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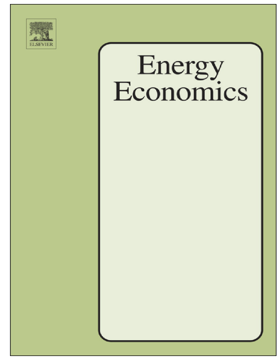

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Can expanding natural gas infrastructure mitigate CO_2 emissions? Analysis of heterogeneous and mediation effects for China

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Abstract: To verify whether the expansion of natural gas infrastructure can effectively mitigate carbon dioxide (CO_2) emissions in China, this study first investigates the impact of natural gas infrastructure on China's CO_2 emissions by employing a balanced panel dataset for 30 Chinese provinces covering 2004-2017. Fully considering the potential heterogeneity and asymmetry, the two-step panel quantile regression approach is utilized. Also, to test the mediation impact mechanism between natural gas infrastructure and CO_2 emissions, this study then analyzes the three major mediation effects of natural gas infrastructure on China's CO_2 emissions (i.e., scale effect, technique effect, and structure effect). The empirical results indicate that expansion of the natural gas infrastructure can effectively mitigate China's CO_2 emissions; however, this impact is significantly heterogeneous and asymmetric across quantiles. Furthermore, through analyzing the mediation impact mechanism, the natural gas infrastructure can indirectly affect CO_2 emissions in China through the scale effect (i.e., gas population and economic effects) and structure effect (i.e., energy structure effect). Conversely, the technique effect (i.e., energy intensity effect) brought by natural gas infrastructure on CO_2 emissions in China has not been significant so far. Finally, policy implications are highlighted for the Chinese government with respect to reducing CO_2 emissions and promoting growth in the natural gas infrastructure.

Keywords: Natural gas infrastructure; CO_2 emissions; Mediation impact mechanism; Heterogeneity and asymmetry; Two-step panel quantile regression

JEL Classification: C31; Q40; Q43; Q54; R11

1. Introduction

The past few decades have witnessed unparalleled growth in the Chinese economy; meanwhile, this rapid growth has brought a series of benefits, such as lifting millions of people out of poverty, accelerating the development of technology, and promoting the welfare of people by reducing consumer prices (Zhang et al., 2019; Zhu and Jiang, 2019). Nevertheless, in tandem with this boom in the economy, there has been rapid growth in carbon dioxide (CO_2) emissions in China (Ma et al., 2020). From 2004 to 2017, the country's CO_2 emissions increased from 4946.5 million tons to 11,533.3 million tons, based on statistics from the China Emission Accounts and Datasets (CEAD; 2018). Considering the rapidly rising CO_2 emissions and the associated global warming, mitigating these emissions is one of the greatest challenges for the Chinese government (Ma et al., 2019).

Therefore, natural gas, as a cleaner transition energy than other fossil energies (i.e., coal and petroleum), has emerged as a widely accepted pathway for reducing CO_2 emissions in China. As reported in the China Energy Statistical Yearbook (CESY; 2018), consumption of natural gas in China increased rapidly between 2004 and 2017, by approximately 6 times, from 40.8 billion cubic meters (bcm) to 234.4 bcm, with an annual average growth rate of 14.4%. Behind this fast-rising demand for natural gas in China, the country's natural gas infrastructure is also rapidly expanding. According to statistics from the China

City Statistical Yearbook (CCSY; 2018), the natural gas storage capacity, an index that reflects growth in the natural gas infrastructure, in China increased by more than 10 times between 2004 and 2017, from 7227.8×10^4 m^3 to $75,365.3\times10^4$ m^3.

Along with rapid expansion of the natural gas infrastructure and rising CO_2 emissions, scholars have started to focus on the potential environmental effects associated with the expansion of natural gas infrastructure (Cesur et al., 2017; Hendrick et al., 2016; Mac Kinnon et al., 2018; Nan et al., 2019). However, to the best of our knowledge, very few studies have explored the potential greenhouse effect of the expansion of natural gas infrastructure, especially for the case of China. Also, given that natural gas infrastructure indirectly affects CO_2 emissions through various mediation effects, it is interesting to explore the mediation impact mechanism between natural gas infrastructure and CO_2 emissions; however, to date, this mediation impact mechanism has not been systematically analyzed. In addition, as shown in Fig. 1, significant differences exist in natural gas infrastructure and CO_2 emissions across various regions in China and, thus, the impact of the natural gas infrastructure on CO_2 emissions can be heterogeneous and asymmetric. However, the potential heterogeneity and asymmetry are often ignored in previous studies.

Insert Fig. 1

To fill the above academic gaps, this study first investigates the role of natural gas infrastructure in CO_2 emissions in China by employing a balanced panel dataset for 30 Chinese provinces covering 2004-2017 and the two-step panel quantile regression approach. Also, to test the mediation impact mechanism, this study analyzes the three major mediation effects of natural gas infrastructure on China's CO_2 emissions (i.e., scale effect, technique effect, and structure effect). Therefore, this study contributes to the existing literature in three aspects: (1) The study tests whether expansion of the natural gas infrastructure can mitigate CO_2 emissions in China and further analyzes the mediation impact mechanism between these two variables. This not only provides a clearer analysis of the impact of natural gas infrastructure on CO_2 emissions in China, but also offers new evidence for developing specific policies to tackle CO_2 emissions and promote growth in the natural gas infrastructure in China; (2) to analyze the mediation impact mechanism between natural gas infrastructure and CO_2 emissions, a panel quantile mediation method is proposed, which extends the current mediation methods from time series to panel data; and (3) most previous studies have ignored the potential heterogeneity and asymmetry of the impact of natural gas infrastructure on CO_2 emissions, which can result in biased and inconsistent findings. To this end, the two-step panel quantile regression approach is utilized to search and analyze the potential heterogeneity and asymmetry in this study.

The rest of the study is structured as follows. Section 2 reviews the relevant literature. Section 3 details the methodology and data. Section 4 reports and discusses the empirical results. Section 5 further discusses the mediation effect between natural gas infrastructure and CO_2 emissions. Section 6 presents conclusions and policy implications.

2. Literature review

2.1. Studies on the impact of natural gas infrastructure on CO_2 emissions

With the rapidly increasing consumption of natural gas, researchers have begun to investigate the role of natural gas consumption in affecting CO_2 emissions. For instance, by employing a balanced panel dataset for 30 Chinese provinces covering 1995-2014, Dong et al. (2017) explore the impact of natural gas consumption on CO_2 emissions for the case of China; they conclude that expanding natural gas consumption can effectively reduce China's CO_2 emissions in the long run. Bildirici and Bakirtas (2014), Dong et al. (2018a), and Xu et al. (2019) report the same results for the gas-emission nexus, indicating that the impact of natural gas consumption on CO_2 emissions is linear and negative. When exploring the effect of natural gas consumption on CO_2 emissions, the above studies always assume that the relationship between natural gas consumption and CO_2 emissions is simple linear. However, the relationship between these two variables is not always simple linear; conversely, it may be non-linear. Accordingly, some scholars have investigated whether the non-linear link exists between natural gas consumption and CO_2 emissions, such as Li and Sun (2017), Wang and Lin (2017), and Xu and

Lin (2019).

On the other hand, along with the rapidly increasing demand for natural gas, the corresponding natural gas infrastructure has expanded dramatically. Accordingly, some scholars have started to pay attention to the potential environmental effects associated with the rapidly expanding natural gas infrastructure. For example, Cesur et al. (2017) examine the impact of the expansion of natural gas infrastructure on infant mortality and air pollution in Turkey; they conclude that the expansion of natural gas infrastructure has resulted in a significant decrease in the rate of infant mortality through reducing the level of air pollution. Furthermore, by using a panel dataset for 204 of China's prefecture-level cities covering 2008-2016, Nan et al. (2019) investigate the impact of natural gas infrastructure on the annual average fine particulate matter ($PM_{2.5}$) concentrations in China; they find that the deployment of natural gas pipelines can effectively mitigate China's $PM_{2.5}$ concentrations. In addition, Hendrick et al. (2016) and Mac Kinnon et al. (2018) have conducted similar studies on the potential environmental effects associated with the expansion of natural gas infrastructure. However, very few studies have focused on the potential greenhouse effect of the expansion of natural gas infrastructure, especially for the case of China.

2.2. Studies on other factors affecting CO_2 emissions

In addition to the above factor (i.e., natural gas infrastructure; see section 2.1), based on the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model reformulated by Dietz and Rosa (1997), the factors affecting CO_2 emissions can be divided into population effect, economic effect, and technology effect.

For the population effect, according to Dong et al. (2019) and Zhang and Zhao (2019), population size is frequently presented as an important factor affecting CO_2 emissions. This viewpoint is confirmed by Ghazali and Ali (2019), Wei (2011), and Wang et al. (2019). With respect to the economic effect, many studies have explored the dynamic effect of economic growth on CO_2 emissions (e.g., Al-Mulali et al., 2015; Chen et al., 2020; Dogan and Seker, 2016a, b; Inglesi-Lotz and Dogan, 2018; Narayan and Doytch, 2017; Wang and Feng, 2018), indicating that growth in the economic scale is the main contributor to CO_2 emissions. With regard to the technology effect, as Wang and Feng (2017) indicate, energy consumption structure can play a significant role in influencing CO_2 emissions via various channels. Similarly, Chen et al. (2019), Xu et al. (2020), and several other researchers have explored the effect of the energy consumption structure on CO_2 emissions. In addition, according to Liu and Bae (2018) and Tajudeen et al. (2018), energy intensity can be considered an effective determinant of CO_2 emissions; the dynamic causal linkages between these two variables are also tested in previous works, such as Chen et al. (2018), Feng et al. (2018), Wu et al. (2016), and Zheng et al. (2020).

2.3. Literature gap

Although scholars have started to focus on natural gas infrastructure, certain research gaps still exist. First, despite some studies exploring the environmental effect of expansion of the natural gas infrastructure, very few studies have focused on the impact of natural gas infrastructure on CO_2 emissions, especially for the case of China. Second, considering that natural gas infrastructure indirectly affects CO_2 emissions through various mediation effects, it is interesting to explore the mediation impact mechanism between natural gas infrastructure and CO_2 emissions. However, to the best of our knowledge, very few studies have systematically analyzed this mediation impact mechanism for China. Third, as shown in Fig. 1, significant differences exist in natural gas infrastructure and CO_2 emissions across various regions in China and, thus, the impact of natural gas infrastructure on CO_2 emissions can be heterogeneous and asymmetric. However, previous studies have often ignored the heterogeneity and asymmetry.

3. Methodology and data

3.1. Model construction

To examine the impact of socioeconomic changes on environmental degradation, the STIRPAT model is widely used, as follows:

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

where I, P, A, and T represent environmental effect, population number, per capita affluence, and technology, respectively. After taking natural logarithms, Eq. (1) can be modeled:

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

Based on the conventional STIRPAT model and the above literature review (see Section 2), I in this study is measured by the amount of CO_2 emissions, P is measured by gas population, A is measured by per capita gross domestic product (GDP), and T is proxied by two variables: energy intensity and energy consumption structure. In addition, to investigate the impact of natural gas infrastructure on CO_2 emissions in China, this study extends the STIRPAT model by incorporating the variable of natural gas infrastructure into the model. Consequently, the extended STIRPAT model in this study is as follows in Eq. (3):

$$\ln CO_{2it} = \beta_0 + \beta_1 \ln GP_{it} + \beta_2 GDP_{it} + \beta_3 \ln ES_{it} + \beta_4 \ln EI_{it} + \beta_5 \ln NGI_{it} + \mu_{it} \quad (3)$$

where subscripts i and t denote province and year, respectively; β_1-β_5 are the parameters to be estimated; CO_2 represents the amount of CO_2 emissions; GP indicates gas population, which can be expressed as the population size for utilizing natural gas; GDP describes per capita GDP; ES stands for energy consumption structure, which can be expressed as the share of clean energies including natural gas, nuclear energy, and renewables in the total energy consumption; EI describes energy intensity, which can be expressed as the ratio between primary energy consumption and total GDP; NGI stands for natural gas infrastructure, which can be expressed as the gas storage capacity; and β_0 and μ are the constant term and random error term, respectively. The description of the variables is presented in Table A1 in Appendix A.

3.2. Estimation strategy

3.2.1 Panel unit root tests

Technically, the estimation procedure employed here mainly comprises three steps. In step 1, to investigate the order of integration of the series, various panel unit root tests, the Levin-Lin-Chu (LLC) panel unit root test proposed by Levin et al. (2002), the modified P panel unit root test developed by Choi (2001), the Im, Pesaran, and Shin (IPS) panel unit root test proposed by Im et al. (2003), and the Hadri panel unit root test developed by Hadri (2000) are utilized in this study.

3.2.2 Test for normality

As Bera et al. (2016) indicate, test for normality plays a crucial role in the validity of following specification tests. In other words, if the panel data are not normally distributed, the traditional panel estimated methods are not suitable as they would yield biased results (Shrestha et al., 2017; Trespalacios et al., 2020). Therefore, after implementing the panel unit root tests, the next step in this study is to test for normality in the panel data by using the method proposed by and Galvao et al. (2013). Consider a standard panel-data model as follows:

$$y_{it} = \alpha_0 + \mu_i + e_{it} \tag{4}$$

where $i = 1, \cdots, N;\ t = 1, \cdots T$; α_0 is a constant, μ_i and e_{it} refer to the individual-specific and remainder error component, respectively. Then, this study tests the skewness and kurtosis in the μ_i and e_{it}, separately and jointly, as follows:

$$
\begin{aligned}
&Skewness \begin{cases} s_\mu = \dfrac{\mu_3}{\sigma_\mu^3} = \dfrac{E\left[\mu^3\right]}{\left(E\left[\mu^2\right]\right)^{3/2}} \\ s_e = \dfrac{e_3}{\sigma_e^3} = \dfrac{E\left[e^3\right]}{\left(E\left[e^2\right]\right)^{3/2}} \end{cases} \\
&Kurtosis \begin{cases} k_\mu = \dfrac{\mu_4}{\sigma_\mu^4} = \dfrac{E\left[\mu^4\right]}{\left(E\left[\mu^2\right]\right)^{2}} \\ k_e = \dfrac{e_4}{\sigma_e^4} = \dfrac{E\left[e^4\right]}{\left(E\left[e^2\right]\right)^{2}} \end{cases}
\end{aligned} \tag{5}
$$

where s_μ and s_e indicate the skewness in the μ_i and e_{it}, respectively, while k_μ and k_e denote the kurtosis in the μ_i and e_{it}, respectively.

In addition, the null hypotheses of skewness can be shown as:

$$H^{s_\mu}:\ s_\mu = 0\ \ and\ \ H^{s_e}:\ s_e = 0 \tag{6}$$

The null hypotheses of kurtosis can be shown as:

$$H^{k_\mu}:\ k_\mu = 3\ \ and\ \ H^{k_e}:\ k_e = 3 \tag{7}$$

The null hypotheses for joint testing are shown as:

$$\begin{cases} H^{s_\mu \& k_\mu}:\ s_\mu = 0\ \ and\ \ k_\mu = 3 \\ H^{s_e \& k_e}:\ s_e = 0\ \ and\ \ k_e = 3 \end{cases} \tag{8}$$

3.2.3 Two-step panel quantile regression approach

At the last step (i.e., step 3), this study estimates the long-run parameters for Eq. (3). As the data in the energy and environment areas are always not normally distributed and asymmetric (Cheng et al., 2019; Galvao et al., 2013; Yan et al., 2019), the conditional mean regression approaches (e.g., the fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) estimators) are not suitable and would produce unreliable results. Conversely, the quantile regression approach developed by Koenker and Bassett (1978, 1982) can overcome this shortcoming and, thus, provide more robust estimation results. Accordingly, to take the impact effects and unobserved individual heterogeneity in panel data into consideration, this study considers the following model:

$$Q_{y_{it}}\left(\tau|\square\right)=\alpha_{\tau}'x_{it}+\beta_{i},\quad i=1,\cdots,N;\ \ t=1,\cdots T \tag{9}$$

To address the unobserved individual heterogeneity in Eq. (9), Canay (2011) proposes a two-step panel quantile method. This approach considers the fixed effect as a pure location shifter. The first step is to apply the standard panel model with fixed effect as follows:

$$y_{it}=x_{it}^{T}\cdot\beta+\mu_{i}+\varepsilon_{it} \tag{10}$$

where μ_i is the unobserved fixed effect. Then, we can subtract the fixed effect obtained in Eq. (9) from the response variable:

$$\hat{y}_{it}=y_{it}-\hat{\mu}_{i} \tag{11}$$

From Eq. (11), we see that the $\hat{y}_{it}$ is free of the influence of unobserved heterogeneity. Thus, following Koenker and Bassett (1978), we can use quantile regression to estimate the model in this study (i.e., Eq. (3)), which is as follows:

$$\underset{\alpha}{\operatorname{argmin}}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{t=1}^{T}w_{k}\rho_{\tau k}\left\{\hat{y}_{it}-\alpha_{\tau}'x_{it}\right\} \tag{12}$$

where $k=1,\cdots K;\ i=1,\cdots,N;\ t=1,\cdots T$, $\rho_{\tau k}\left(y\right)=y\left(\tau-1_{y<0}\right)$ is the traditional check function, 1_A is the indicator function of set A. Notably, K is the index for quantiles, and $w_k=1/K$ is the weight on k-th quantile, which controls the proportion of different quantile levels in this estimation (Cheng et al., 2018).

3.3. Data source and description

To investigate the role of natural gas infrastructure in CO_2 emissions in China, this study employs a balanced panel dataset for 30 Chinese provinces covering 2004-2017 due to data unavailability. Notably, Tibet, Hong Kong, Macao, and Taiwan are not considered in this study due to data availability issues. The data on CO_2 emissions (denoted by CO_2) are obtained from the CEAD (2018). Furthermore, the data on per capita GDP (denoted by GDP) and energy intensity (denoted by EI) are from the China Statistics Yearbook (CSY; 2018), while the CESY (2018) provides the data on energy consumption structure (denoted by ES). In addition, the data on gas population (denoted by GP) and natural gas infrastructure (denoted by NGI) are sourced from the CCSY (2018). The descriptive statistics (i.e., maximum value, minimum value, mean value, standard deviation, 1 Quartile, and 3 Quartile) of the variables are shown in Table 1.

Insert Table 1

4. Empirical findings and discussion

4.1. Results of panel unit root test

The results of LLC, modified P, IPS, and Hadri panel unit root tests are reported in Table 2, implying that the null hypothesis of the existence of a unit root is strongly rejected for all the variables at the 1% significance level. In other words, all the variables are stationary at level. Accordingly, there is no need to conduct the panel unit root tests at first difference or to conduct panel cointegration tests (Yan et al., 2020). Also, these findings allow us to use the panel quantile regression approach to further explore the impact of natural gas infrastructure on China's CO_2 emissions in the next step.

Insert Table 2

4.2. Results of normality test

Before estimating the long-run linkages between the variables, this study tests for the normality in the panel data; the results are listed in Table 3. From this table, one can see that the variable CO_2 is not normally distributed, asymmetric, and left-skewed. These findings indicate that the conditional mean regression methods are not suitable in this study and would yield biased results. In other words, the panel quantile regression approach should be employed in this study.

Insert Table 3

4.3. Results of two-step panel quantile regression approach

Table 4 reports the estimation results of Eq. (3) by using the two-step panel quantile regression approach for the 10th, 25th, 50th, 75th, and 90th percentiles of the conditional CO_2 emissions (i.e., $\ln CO_2$). Also, to intuitively and clearly show the various change patterns of the coefficients of factors at different quantile levels,

Fig. 2 is drawn based on the results in Table 4. From Table 4 and Fig. 2, one can see that the impacts of various factors on CO_2 emissions (i.e., $\ln CO_2$) are heterogeneous.

According to the estimated coefficients of $\ln NGI$ shown in Table 4, the expansion of natural gas infrastructure has a negative impact on CO_2 emissions in China; however, this impact is significantly heterogeneous and asymmetric across quantiles. Specifically, as shown in Fig. 2, the absolute value of the coefficient of $\ln NGI$ slightly increases from 0.0089 in the 10th quantile to 0.0131 in the 50th quantile and decreases thereafter. This implies that the change pattern of the mitigation impact for natural gas infrastructure exhibits an inverted U-shaped curve. In other words, the mitigation impact of natural gas infrastructure on CO_2 emissions in China increases at the initial phase and then decrease after reaching a peak. In addition, another interesting point is worth mentioning: As seen in Table 4 and Fig. 2, the coefficient of $\ln NGI$ is not significant at the lower quantile (i.e., 10th) or upper quantile (i.e., 90th). This finding suggests that the expansion of natural gas infrastructure will not significantly affect the CO_2 emissions in the provinces with lower levels of CO_2 emissions (e.g., Hainan, Qinghai, Beijing) or upper levels of CO_2 emissions (e.g., Hebei, Shanxi, Shandong). This may be because in the provinces with lower levels of CO_2 emissions (e.g., Hainan, Qinghai, Beijing), the natural gas infrastructure is adequate and, thus, the marginal carbon mitigation effect of expanding natural gas infrastructure is no longer significant. Conversely, for provinces with upper levels of CO_2 emissions (e.g., Hebei, Shanxi, Shandong), the mitigation effect of the expansion of natural gas infrastructure on CO_2 emissions might be obscured by increasing economic growth and dirty fossil fuels consumption (i.e., coal and petroleum). In other words, for the provinces with middle-level CO_2 emissions (e.g., Chongqing, Sichuan, Zhejiang), the natural gas infrastructure offers much greater potential for emissions mitigation.

With respect to $\ln GP$, $\ln GDP$, $\ln ES$, and $\ln EI$, as seen in Table 4, all the estimated coefficients of the variables are statistically significant and have the correct signs, as discussed in Section 2.3. Specifically, for all quantile levels, China's CO_2 emissions are significantly and positively affected by gas population, per capita GDP, and energy intensity, while the energy consumption structure (measured by the share of clean energies including natural gas, nuclear energy, and renewables in the total energy consumption) has a significant and negative effect on China's CO_2 emissions. However, it is noteworthy that the impacts of the above influencing factors (i.e., GP, GDP, ES, and EI) on CO_2 emissions are significantly heterogeneous and asymmetric across quantiles. In general, the impact of GP, GDP, and EI on CO_2 emissions in China displays an upward trend across all quantiles, while the change trend of the mitigation impact of ES on CO_2 emissions exhibits an U-shaped curve. This implies that the mitigation impact of adjusting the energy consumption structure (i.e., improving the share of clean energies including natural gas, nuclear energy, and renewables) on CO_2 emissions in China will be stronger at the lower quantile or upper quantile, indicating that the provinces with lower or upper levels of CO_2 emissions are more vulnerable to changes in the energy consumption structure.

Insert Table 4

Insert Fig. 2

4.4. Robustness analysis

To test the stability of the estimated parameters obtained from the two-step panel quantile regression approach in Table 4, we use the fixed effect regression approach to estimate the long-run parameters in Eq. (3). The comparison of results between the two-step quantile regression approach and fixed effect regression approach are presented in Table 5. As shown, the regression result obtained by the fixed effect regression technique is consistent with that of the two-step quantile regression approach. Consequently, the parameters of our models acquired from the two-step quantile regression approach are considered stable.

Insert Table 5

5. Further discussion on the mediation effect between natural gas infrastructure and CO_2 emissions

5.1. Causal mediation analysis

The above empirical results indicate that expanding the natural gas infrastructure can effectively mitigate CO_2 emissions in China, which raises another interesting question: How does the natural gas infrastructure affect China's CO_2 emissions? Do mediation effects exist between the natural gas infrastructure and CO_2 emissions in China? Based on the previous analysis and Eq. (3), this study assumes that China's natural gas infrastructure affects its CO_2 emissions through three major mediation effects: scale effect (i.e., GP and GDP), structure effect (i.e., ES), and technique effect (i.e., EI). The traditional mediation methods are based on time series, which are no longer suitable for analyzing the panel data. Therefore, in this study, we propose a panel quantile mediation method by extending the work of Imai et al. (2010). The key identifying assumption functions can be written as follows:

$$\ln CO_{2it} = b_1 \ln NGI_{it} + \alpha_1' X_{it} + \varepsilon_{it} \tag{13}$$

$$M_{it} = b_2 \ln NGI_{it} + \alpha_2' X_{it} + \delta_{it} \tag{14}$$

$$\ln CO_{2it} = b_3 \ln NGI_{it} + b_4 M_{it} + \alpha_3' X_{it} + e_{it} \tag{15}$$

where M_{it} denotes the mediators between natural gas infrastructure and CO_2 emissions, including GP, GDP, ES, and EI. X_{it} indicates a vector of the observed pre-treatment confounders. According to the analysis approach for the mediation effect proposed by Baron and Kenny (1986), b_1 indicates the total treatment effect. Moreover, b_3 denotes the average direct effect, which reflects the direct effect of natural gas infrastructure on CO_2 emissions after considering the mediation effect of M_{it}. In addition, $b_1 - b_3$ refers to the average casual mediation effect, which reflects the mediation effect (also called indirect effect) of natural gas infrastructure on CO_2 emissions.

Technically, the estimation procedure of causal mediation analysis between natural gas infrastructure and CO_2 emissions in China mainly comprises two steps. **First**, the estimation procedure above (see Section 3.2) is employed to check whether the average casual mediation effect (i.e., $b_1 - b_3$) is statistically significant. Specifically, if the average casual mediation effect (i.e., $b_1 - b_3$) is statistically significant, the mediation effect (also called indirect effect) exists between natural gas infrastructure and CO_2 emissions. In addition, this study will use the bootstrapping approach (Preacher and Hayes, 2008) to check whether this mediation effect is statistically significant. **Second**, after confirming the existence of the mediation effect, the directionality of the relationship between natural gas infrastructure and mediation variables (i.e., GP, GDP, ES, and EI) will be identified, which can provide much more productive and more complete information about the mediation impact mechanism between natural gas infrastructure and CO_2 emissions in China.

5.2. Results of causal mediation analysis

Following the analysis method described above (see Section 5.1), the average casual mediation effects (i.e., $b_1 - b_3$) of all the mediators (i.e., GP, GDP, ES, and EI) are estimated; the results are listed in Table 6. From this table, one can see that the average casual mediation effects of GP, GDP, and ES are statistically significant, implying that GP, GDP, and ES are significant mediators between natural gas infrastructure and CO_2 emissions in China. In other words, natural gas infrastructure can indirectly affect CO_2 emissions in China through the scale effect (i.e., GP and GDP) and structure effect (i.e., ES). Conversely, as seen in Table 6, EI is not the mediator between natural gas infrastructure and CO_2 emissions in China, indicating that, to date, the technique effect (i.e., EI) brought by natural gas infrastructure on CO_2 emissions in China has not been significant. In fact, EI is related to the total energy consumption, while the natural gas infrastructure largely reflects the consumption for natural gas; however, the current level of natural gas consumption in China is still low and not exploited sufficiently to affect the total energy consumption. Thus, the natural gas infrastructure cannot significantly and indirectly affect CO_2 emissions in China through the technique effect (i.e., EI) (Dong et al., 2018b).

Insert Table 6

Next, to explore more complete information about the mediation impact mechanism between natural gas infrastructure and CO_2 emissions in China, the effects of natural gas infrastructure on the mediation variables (i.e., GP, GDP, ES, and EI) are further explored by estimating b_2 in Eq. (14); the results are reported in Table 7. Based on this table, in general, natural gas infrastructure can significantly and positively affect GP, GDP and ES; conversely, the effect of natural gas infrastructure on EI is not significant, which also answers the question we raised earlier of why EI cannot be the mediator between natural gas infrastructure and CO_2 emissions in China. In addition, based on the results of Tables 6 and 7, the mediation impact mechanism between natural gas infrastructure and CO_2 emissions in China can be drawn as in Fig. 3.

Insert Table 7

Insert Fig. 3

6. Conclusion and policy implications

By employing a balanced panel dataset for 30 Chinese provinces covering 2004-2017 and the two-step panel quantile regression approach, this study aims to investigate the role of natural gas infrastructure in CO_2 emissions in China. Also, to test the impact mechanism, this study analyzes the three major mediation effects of natural gas infrastructure on China's CO_2 emissions (i.e., scale effect, technique effect, and structure effect).

Several interesting findings are highlighted, as follows:

(1) Expansion of the natural gas infrastructure has a negative impact on CO_2 emissions in China; however, this impact is significantly heterogeneous and asymmetric across quantiles.

(2) China's CO_2 emissions are significantly and positively affected by gas population, per capita GDP, and energy intensity, while the energy consumption structure has a significant and negative effect on China's CO_2 emissions. Also, the

above impacts are significantly heterogeneous and asymmetric across quantiles.

(3) With respect to the mediation impact mechanism between natural gas infrastructure and CO_2 emissions in China, natural gas infrastructure can indirectly affect CO_2 emissions in China through the scale effect (i.e., GP and GDP) and structure effect (i.e., ES). Conversely, the technique effect (i.e., EI) brought by natural gas infrastructure on CO_2 emissions in China has not been significant.

The above findings suggest important policy implications. First, as the estimated results indicate, expansion of the natural gas infrastructure can effectively mitigate CO_2 emissions in China. In fact, the development level of natural gas infrastructure in China is considerably lower than the levels seen in other developed countries, such as the United States. Thus, to further tackle CO_2 emissions, more emphasis should be placed on the development and deployment of natural gas infrastructure for China, such as expanding gas storage capacity and improving the length of gas supply pipelines.

Second, since the natural gas infrastructure can indirectly affect China's CO_2 emissions through the scale effect and structure effect, Chinese policymakers can develop specific policies to reduce CO_2 emissions by adjusting the scale mediation effect (i.e., gas population and economic scale) and structure mediation effect (i.e., energy consumption structure). On the other hand, the Chinese government should try to adjust the technique mediation effect brought by natural gas infrastructure by improving the link between expansion of the natural gas infrastructure and the total energy consumption for China.

Third, considering that the impacts of natural gas infrastructure and other driving factors on CO_2 emissions are significantly heterogeneous and asymmetric, sufficient differentiation in emission-reduction policies should be developed for different quantiles (i.e., different subpanels). For example, natural gas infrastructure cannot effectively mitigate CO_2 emissions at the lower or upper quantile provinces; conversely, the natural gas infrastructure in provinces with middle-level CO_2 emissions (e.g., Chongqing, Sichuan, Zhejiang) offers much greater potential for emissions mitigation. Accordingly, the middle-quantile provinces should further promote their marginal carbon mitigation effect of natural gas infrastructure by increasing investments in natural gas infrastructure.

Nevertheless, this study only provides preliminary empirical evidence on the impact of natural gas infrastructure on CO_2 emissions in China, and some limitations still exist. Notably, in addition to the indicator used in this study (i.e., gas storage capacity), other indicators, such as natural gas pipelines, are also important for the expansion of natural gas infrastructure. However, in this study, we do not use natural gas pipelines to measure natural gas infrastructure due to data unavailability. Consequently, to further analyze the impact of natural gas infrastructure on CO_2 emissions in China, future research should add natural gas pipelines into our econometric model as another indicator for measuring natural gas infrastructure.

CRediT authorship contribution statement

Kangyin Dong: Data curation, Writing - Original Draft, Funding acquisition. **Xiucheng Dong:** Conceptualization, Supervision, Funding acquisition. **Xiaohang Ren:** Methodology, Writing - Review & Editing, Software.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure statement

No potential conflict of interest was reported by the authors.

Appendix A

Table A1. Definition and description of the variables.

Variable	**Definition**	**Unit**
CO_2	The amount of CO_2 emissions	Metric tons
GP	Gas population	10^4 persons
GDP	Per capita real GDP	Yuan
ES	Energy structure, which is measured by the share of clean energies including natural gas, nuclear energy, and renewables	%
EI	Energy intensity, which is measured by the ratio between primary energy consumption and total GDP	Tce/10^4 yuan
NGI	Natural gas infrastructure, which is measured by the gas storage capacity	10^4 m^3

Table A2. List of abbreviations.

Abbreviations			
Bcm	Billion cubic meters		
CEAD	China Emission Accounts and Datasets	$PM_{2.5}$	Fine particulate matter
CESY	China Energy Statistical Yearbook	GDP	Gross domestic product
CCSY	China City Statistical Yearbook	GP	Gas population
CO_2	Carbon dioxide	IPS	Im, Pesaran, and Shin
DOLS	Dynamic OLS	LLC	Levin-Lin-Chu
EI	Energy intensity	NGI	Natural gas infrastructure
ES	Energy structure	OLS	Ordinary least squares
FMOLS	Fully modified OLS	STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology

Appendix B. Supplementary data

Supplementary data to this article can be found online at

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Tables

Table 1. Descriptive statistics of the variables (after logarithm).

Table 2. Results of panel unit root tests at levels.

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Table 5. Comparison of the estimates between the two-step quantile regression approach and fixed effect regression approach.

Table 6. Results of the average casual mediation effects for the mediators.

Table 7. Results of the effect of natural gas infrastructure on the mediators.

Table 1. Descriptive statistics of the variables (after logarithm).

Statistics	$\ln CO_2$	$\ln GP$	$\ln GDP$	$\ln ES$	$\ln EI$	$\ln NGI$
Max.	3.191	3.479	5.111	1.808	0.636	4.689
Min.	0.878	-0.310	3.635	1.183	-0.594	-0.097
Mean	2.344	2.507	4.475	1.500	-0.019	2.340
Std. Dev.	0.358	0.651	0.294	0.123	0.228	0.757
1. Quartile	2.146	2.197	4.276	1.407	-0.201	1.986
3. Quartile	2.590	2.960	4.675	1.583	0.155	2.737

Note: Max., Min., and Std. Dev. denotes maximum, minimum, and standard deviation respectively, while 1. Quartile and 3. Quartile indicate the 25th and 75th empirical quartiles, respectively.

Table 2. Results of panel unit root tests at levels.

Variable	LLC test	Modified P test	IPS test	Hadri test
$\ln CO_2$	-7.361***	12.700***	-9.443***	25.341***
$\ln GP$	-37.768***	57.852***	-25.285***	20.864***
$\ln GDP$	-17.399***	23.548***	-9.738***	44.344***
$\ln ES$	-8.136***	25.944***	-7.695***	11.755***
$\ln EI$	-6.159***	35.311***	-8.394***	14.419***
$\ln NGI$	-22.876***	45.748***	-14.372***	11.524***

Note: *** illustrates statistical significance at the 1% level and the null hypothesis is unit root.

Table 3. Results of normality test for CO_2.

Test	Coefficient	Standard Error	z	P-value
Skewness_e	-0.7963	0.2392	-3.3300	0.001
Kurtosis_e	1.9867	1.0262	1.9400	0.053
Skewness_u	-0.4940	0.3678	-1.3400	0.179
Kurtosis_u	0.1259	0.6289	0.2000	0.841
Joint test for Normality on e:	14.83			0.0006
Joint test for Normality on u:	1.84			0.3976

Note: *u* and *e* refer to the individual-specific and the remainder error component, respectively (detailed please see Section 4.2).

Table 4. Panel quantile regression results.

Dependent variable: $\ln CO_2$					
Variables	**Quantiles**				
	10th	**25th**	**50th**	**75th**	**90th**
$\ln GP$	0.0238	0.0199***	0.0260***	0.0339***	0.0286***
	(0.9756)	(2.8938)	(4.3003)	(6.4651)	(4.5586)
$\ln GDP$	1.1268***	1.1149***	1.1256***	1.1319***	1.1594***
	(40.8140)	(61.2356)	(54.9993)	(67.4020)	(69.5952)
$\ln ES$	-0.8172***	-0.7533***	-0.7579***	-0.7117***	-0.7716***
	(-19.1591)	(-21.4572)	(-30.1729)	(-26.2949)	(-13.9401)
$\ln EI$	0.7667***	0.8267***	0.8561***	0.9076***	0.9074***
	(19.9491)	(29.8852)	(36.9677)	(34.4270)	(36.4282)
$\ln NGI$	-0.0089	-0.0099**	-0.0131***	-0.0102**	-0.0090
	(-1.0390)	(-1.5942)	(-2.4842)	(-2.0933)	(-1.4284)
Constant	-1.5497***	-1.5502***	-1.5750***	-1.6708***	-1.6596***
	(-14.6052)	(-16.9087)	(-18.7738)	(-23.2969)	(-14.6494)

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively and the values in parentheses represent t-statistics.

Table 5. Comparison of the estimates between the two-step quantile regression approach and fixed effect regression approach.

Dependent variable: $\ln CO_2$						
Variables	**Quantile regression approach**					**Fixed effect regression approach**
	10th	**25th**	**50th**	**75th**	**90th**	
$\ln GP$	0.0238	0.0199***	0.0260***	0.0339***	0.0286***	0.0359***
	(0.9756)	(2.8938)	(4.3003)	(6.4651)	(4.5586)	(2.8984)
$\ln GDP$	1.1268***	1.1149***	1.1256***	1.1319***	1.1594***	1.1364***
	(40.8140)	(61.2356)	(54.9993)	(67.4020)	(69.5952)	(18.7323)
$\ln ES$	-0.8172***	-0.7533***	-0.7579***	-0.7117***	-0.7716***	-0.7609***
	(-19.1591)	(-21.4572)	(-30.1729)	(-26.2949)	(-13.9401)	(-7.5902)
$\ln EI$	0.7667***	0.8267***	0.8561***	0.9076***	0.9074***	0.8624***
	(19.9491)	(29.8852)	(36.9677)	(34.4270)	(36.4282)	(8.6911)
$\ln NGI$	-0.0089	-0.0099**	-0.0131***	-0.0102**	-0.0090	-0.014*
	(-1.0390)	(-1.5942)	(-2.4842)	(-2.0933)	(-1.4284)	(-1.6383)
Constant	-1.5497***	-1.5502***	-1.5750***	-1.6708***	-1.6596***	-1.6412***
	(-14.6052)	(-16.9087)	(-18.7738)	(-23.2969)	(-14.6494)	(-5.0848)

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively and the values in parentheses represent t-statistics.

Table 6. Results of the average casual mediation effects for the mediators.

Estimated parameter: $b_1 - b_3$ in Eq. (13)-(15)					
Variables	**Quantiles**				
	10th	**25th**	**50th**	**75th**	**90th**
$\ln GP$	0.0036 (0.9352)	0.0030*** (2.0647)	0.0039*** (3.4267)	0.0051*** (5.5631)	0.0043*** (2.5858)
$\ln GDP$	0.0203*** (3.6156)	0.0200*** (3.3939)	0.0202*** (3.4506)	0.0203*** (3.4443)	0.0208*** (3.5352)
$\ln ES$	-0.0035** (-2.1171)	-0.0033** (-2.1247)	-0.0033** (-2.1290)	-0.0031** (-2.1333)	-0.0033** (-2.1261)
$\ln EI$	0.0015 (0.7033)	0.0016 (0.7573)	0.0016 (0.7477)	0.0017 (0.7359)	0.0017 (0.7339)

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively and the values in parentheses represent t-statistics.

Table 7. Results of the effect of natural gas infrastructure on the mediators.

Estimated parameter: b_2 in Eq. (14)					
Mediators	**Quantiles**				
	10th	**25th**	**50th**	**75th**	**90th**
$\ln GP$	0.1087^{**}	0.1729^{***}	0.1620^{***}	0.1510^{***}	0.0550
	(2.4117)	(8.4174)	(12.8524)	(8.7659)	(1.5047)
$\ln GDP$	0.0204^{**}	0.0122^{*}	0.0185^{***}	0.0185^{***}	0.0091
	(2.0783)	(1.7323)	(4.0566)	(2.9986)	(1.5081)
$\ln ES$	0.0087^{***}	0.0083^{**}	0.0047^{**}	0.0020	-0.0049
	(4.8753)	(4.2046)	(2.2391)	(0.9852)	(-0.8185)
$\ln EI$	0.0047	0.0055^{*}	0.0027	-0.0006	-0.0015
	(0.9172)	(1.9022)	(0.9620)	(-0.2214)	(-0.3925)

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% respectively and the values in parentheses represent t-statistics.

Figures

Fig. 1. Spatial characteristics of CO_2 emissions and natural gas infrastructure in 2017 in China.

Fig. 2. Change in panel quantile regression coefficients.

Fig. 3. Mediation impact mechanism between natural gas infrastructure and CO_2 emissions in China.

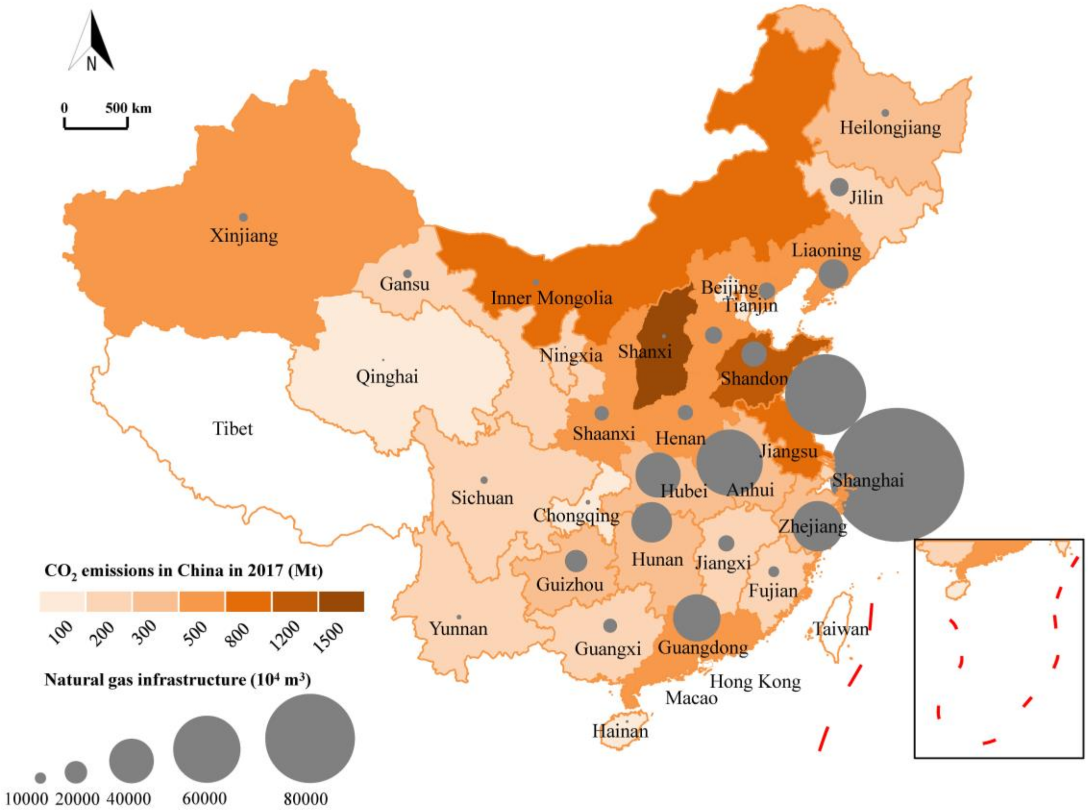

Fig. 1. Spatial characteristics of CO_2 emissions and natural gas infrastructure in 2017 in China. ***Data sources:*** CEAD, 2018; CCSY, 2018.

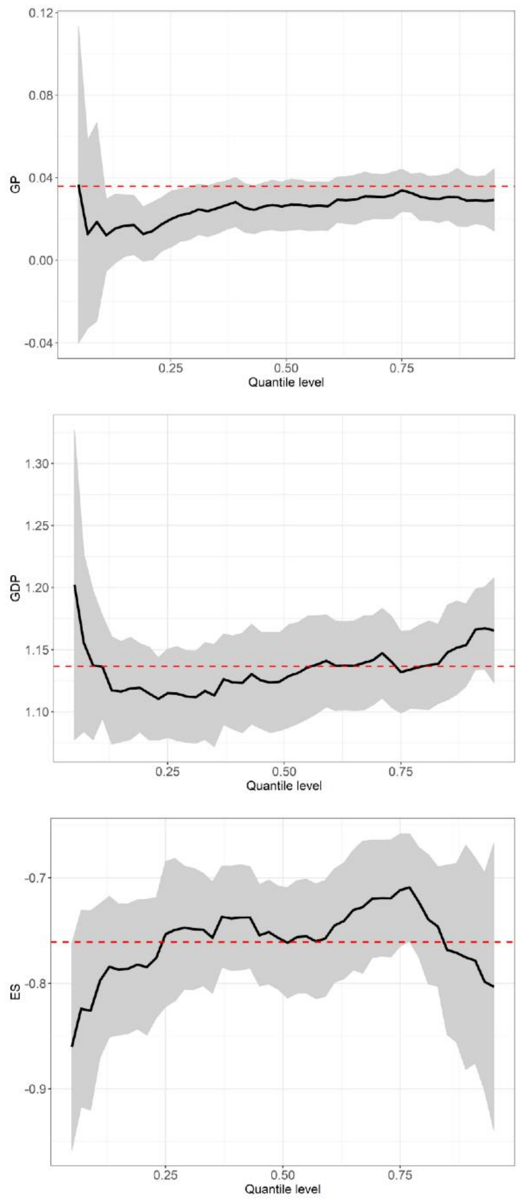

Fig. 2. Change in panel quantile regression coefficients. ***Notes:*** The x-axis denotes the conditional quantiles of CO_2 emissions and the y-axis indicates the coefficient values of various variables. Shaded areas correspond to 95% confidence intervals of quantile estimation. The red line denotes the coefficient values of panel data model with fixed effect.

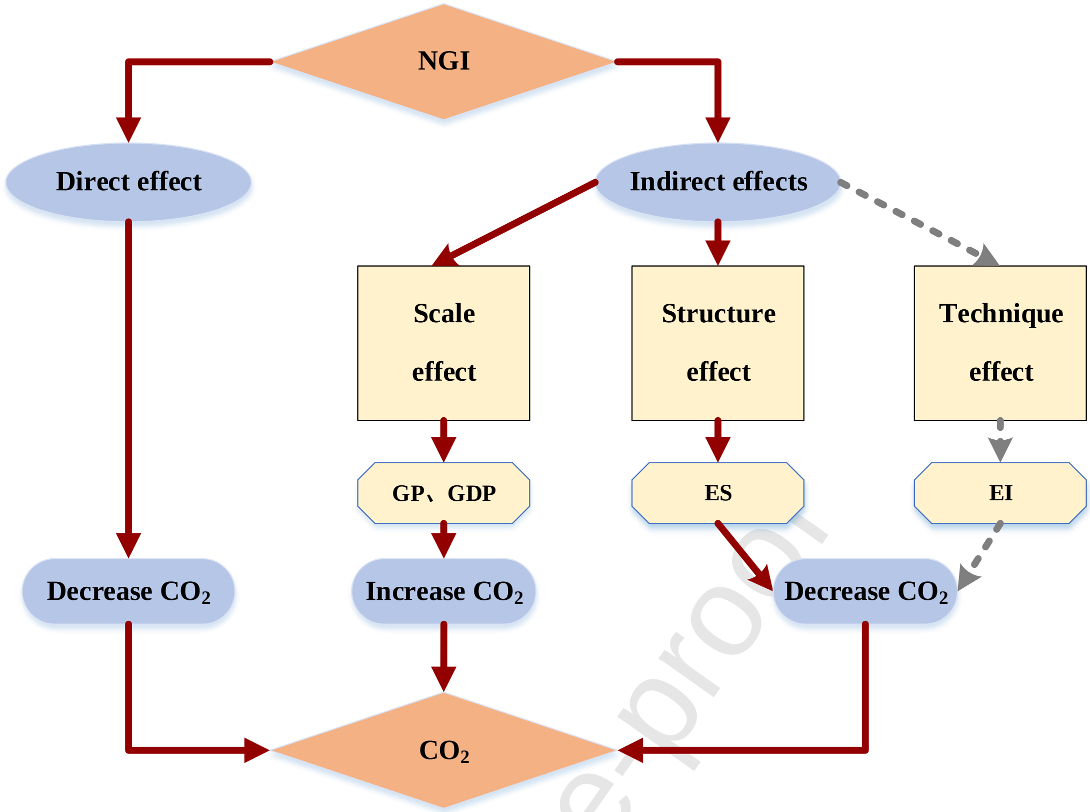

Fig. 3. Mediation impact mechanism between natural gas infrastructure and CO_2 emissions in China.

CRediT author statement

Kangyin Dong: Data curation, Writing - Original Draft, and Funding acquisition.

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Highlights

- The greenhouse effect of China's natural gas infrastructure (NGI) is explored.
- The mediation impact mechanism between NGI and carbon dioxide (CO_2) emissions in China is analyzed.
- NGI can heterogeneously and asymmetrically reduce CO_2 emissions in China.
- NGI affects China's CO_2 emissions via the scale and structure effects.
- The technique effect brought by NGI is not significant to date.