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RESEARCH ARTICLE

Research on the relationship between energy consumption and air quality in the Yangtze River Delta of China: an empirical analysis based on 20 sample cities

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Abstract
This paper uses static and dynamic panel regression to measure the effect of energy consumption on air quality of 20 heavily polluted cities in the Yangtze River Delta of China. Further, the influence of the relevant policies on the relationship between energy consumption and air quality is tested with the method of regression discontinuity. This study concluded the following: (1) When energy consumption structure, industrial structure, and energy efficiency are taken into account, the effect coefficient of energy consumption on air quality is 0.4579, meaning that controlling energy consumption tends to improve the air quality positively. (2) The emission of sulfur dioxide is characterized by inertia; the annual increase in sulfur dioxide emissions in the previous year will lead to an increase of 0.427% in the annual emissions. (3) The relationship between energy consumption and air quality of different cities varies, and these cities can be divided into four categories. (4) The relevant policies for improving air quality are effective to some extent. This study indicates that the Yangtze River Delta should focus on actively changing the mode of energy development.

Keywords Energy consumption · Air quality · Yangtze River Delta · Heavily polluted cities

Introduction

In recent years, the problem of poor air quality in China has been becoming increasingly serious, mainly caused by energy consumption driven by economic growth led by industry. Since the Yangtze River Delta region is an area with the fastest economic development and the largest economic aggregate in China, its energy consumption is relatively large and its air is polluted more severely. According to the data published by the Ministry of Environmental Protection, in 2013, the average proportion of days when air quality is qualified in more than 20 cities monitored in this region was 64.2%, which was 3.7% higher than the average of 74 cities countrywide. In 2017 this proportion increased to 74.8%. All the data indicate that the air quality in the Yangtze River Delta has improved significantly in recent years. However, compared with the Pearl River Delta, the overall picture of the air quality in the area is not optimistic. Furthermore, the 2017 environmental bulletin of these cities shows that there are still some areas, such as Huai'an, Xuzhou, and Zhenjiang, with poor air quality. In respect of economic development, the Yangtze River Delta including two provinces and one city is one of the most active areas of economic growth in China and consumes a great quantity of energy, and its average annual rate of growth of energy consumption was 12.60% during the period of 10th Five-Year Plan, higher than the average countrywide growth rate of 10.15% in the same period. Although this rate dropped to 7.55% during the 11th Five-Year Plan period, it was still higher than the national average rate of 6.61% in the same period. Due to higher energy consumption, air quality in the region has deteriorated seriously. The Chinese authorities consistently attach great importance to the control of air pollution in the region and have issued documents such as the plan for the control of atmospheric pollution in key industries in the Yangtze River Delta. The local governments of Jiangsu and Zhejiang provinces have also strengthened the quality control

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of the air environment and taken a series of specific measures which emphasized controlling the total amount of energy consumption, strengthening construction and emissions' reduction, and strictly supervising reduction measures, among other strategies.

The link between energy, environment, and the economy has always been an important topic for scholars. Tiba and Omri (2017) find that energy consumption has enhanced pollutant emissions and damaged environment while promoting economic growth. Luo et al. (2015), Kilkis (2016), and Ke et al. (2017) all argue that energy consumption has an important impact on the environment. Sueyoshia et al. (2017) point out that only achieving a balance between energy and the environment can maintain the sustainable development of the society. In view of the fact that air quality is an important feature of environmental conditions, many studies have explored deeply the relationship between energy consumption and air quality. Amegah and Agyei-Mensah (2017) claim that air quality has deteriorated more and more seriously. Lotta et al. (2017) affirm the impact of energy factors on air pollution. Khan et al. (2016) find a significant positive correlation between energy consumption and air pollution in both the long- and the short-term in Pakistan. Moreover, Pan et al. (2012), Sharmin et al. (2014), Song et al. (2015), and Sghari and Hammami (2016) have come to the same conclusions. In addition, scholars who have generally focused on carbon emissions (Lun et al. 2014; Alam et al. 2016) and sulfur dioxide emissions (Yang et al. 2016) all affirm the effect of energy consumption on the deterioration of air quality. Based on their conclusions, they have put forward a corresponding series of measures to improve energy efficiency (Zhang et al. 2015), establish a system of continuous monitoring and information feedback (Franco et al. 2017; Xu et al. 2017), and increase the development and utilization of biomass energy and renewable energy (Zhang and Cao 2015; Shafie 2016).

Similarly, Chinese scholars have paid considerable attention to air quality issues, mainly to three aspects of this area: First, some studies have tried to identify the factors influencing air quality. Lin and Wang (2016) argue that energy consumption, industrialization, and technological progress are the most important factors causing deterioration of urban air quality. Han et al. (2014) and Jiang et al. (2018) show that the factors affecting air quality are mainly economy, meteorology, society, and energy. Second, other scholars have attempted to explore the relationship between energy consumption and air quality at both quantitative and structural dimensions. In view of the total level, Liu (2015) points out that the use of energy is one of the main factors leading to environmental degradation. In addition, Jia et al. (2013) and Gao et al. (2014) draw similar conclusions. Yan (2011) thoroughly analyzes the basic connotations and constraints of energy consumption constrained by ambient air quality. At the structural dimension, Mai et al. (2014) believe that the consumption structure based on coal energy has brought about both air pollution and economic benefits. Wu et al. (2009), Abu-Madi and Rayyan (2013), and Shi et al. (2015) also confirm the correlation between energy consumption structure and atmospheric environment. It is necessary to mention that some scholars have studied the reality of the Yangtze River Delta. For instance, Bao et al. (2010) forecast the energy production and consumption in China in 2014; extract the relationship among total energy consumption, energy consumption structure, and the carbon emissions; and point out that the air quality in the cities of the Yangtze River Delta has been affected to different degrees. Zhai et al. (2012) identify the pollutant emission factors impacting the air quality and confirm the important influence of energy consumption on the air quality. Third, there are still many studies that discuss air quality monitoring, assessment, or improvement measures, apart from general policies and measures. Xie and Li (2013) and Wei and Ma (2015) have drawn conclusions under different conditions based on situational simulation.

In summary, scholars have studied the long-term, short-term, and dynamic relationships between energy consumption and air quality. These researches laid the foundation for follow-up work. However, there are still some deficiencies in the existing research. First, most of the studies only analyze the relationship between energy consumption and air quality on the whole but do not explore regional differences. Second, these studies mainly focus on static relationships without further revealing the trend of dynamic change. Third, the studies do not address how policies affect the relationship. However, to identify regional differences and dynamic relations between energy consumption and air quality, and objectively evaluate the effect of existing policies, is of great significance for the government to make differential policies and adjust policies dynamically. Therefore, we attempt to advance the research from the above three aspects and come up with some innovative conclusions. The paper is organized as follows: the second part theoretically analyzes the mechanism of energy consumption on the air quality, the third part explains the selection of the variables and the data and then constructs the basic model, the fourth part estimates the model and analyzes its results, the fifth part further estimates the effects of policies on air quality empirically, and the sixth part presents our conclusions.

Impact mechanism of energy consumption on air quality

Economic growth is one of the most important factors influencing the environment; this is also emphasized by the Kuznets curve. Adu and Denkyirah (2017) argue that economic activities significantly impact the quality of the environment. Zhao et al. (2018) indicate that economic growth and energy consumption are the main causes of environmental pollution. To sum up, economic growth and energy consumption are both important factors in environmental pollution. Therefore, referring to the research of Liu (2015), we believe that air pollution is an important form of environmental pollution and constructs Eq. (1).

$$AP_t = E_t^{\lambda} Y_t^{\mu} \varepsilon_t \tag{1}$$

where AP_t, E_t, and Y_t denote air pollution, energy consumption, and economic aggregate, respectively, in period t, while $\lambda > 0$ and $\mu > 0$ indicate that air pollution will be increased by energy consumption and economic growth. Further, economic growth depends on capital and labor, according to the neoclassical economic growth theory, and the relationship can be expressed as Eq. (2).

$$Y_t = K_t^{\alpha} (A_t L_t)^{\beta} \tag{2}$$

where K, L, and A are capital, labor, and the effectiveness of labor, respectively, with $\alpha > 0$ and $\beta > 0$. Putting Eq. (2) into Eq. (1), we can obtain

$$AP_t = E_t^{\lambda} \left[K_t^{\alpha} (A_t L_t)^{\beta} \right]^{\mu} \varepsilon_t = E_t^{\lambda} K_t^{\alpha\mu} (A_t L_t)^{\beta\mu} \varepsilon_t \tag{3}$$

Taking the logarithm of Eq. (3) and deriving it, we have:

$$\frac{AP_t'}{AP_t} = \lambda \frac{E_t'}{E_t} + \alpha\mu \frac{K_t'}{K_t} + \beta\mu \left(\frac{A_t'}{A_t} + \frac{L_t'}{L_t} \right) \tag{4}$$

Then, replacing the growth rate with$G$, we get:

$$G_{AP_t} = \lambda G_{E_t} + \alpha\mu G_{K_t} + \beta\mu (G_{A_t} + G_{L_t}) \tag{5}$$

Further, adjusting Eq. (5) on the basis of Solow (1956) we obtain the dynamic models of capital, labor, and labor effectiveness, as follows:

$$K_t = aY_t - bK_t \tag{6}$$

$$\hat{L}_t = cL_t \tag{7}$$

$$A_t = dA_t \tag{8}$$

where a, b, c, and$d$are savings rate, depreciation rate of capital, growth rate of labor, and growth rate of technological progress, respectively. Thus, Eq. (6) can be transformed into

$$\frac{K_t}{K_t} = a\frac{Y_t}{K_t} - b \tag{9}$$

In the neoclassical economic growth theories, capital growth tends to be a stable equilibrium. However, according to Eq. (9), if the growth rate of capital remains constant, Y/K must be constant and, thus, the growth rate of Y must equal that of K. Since energy includes traditional energy and new energy, the consumption of the former will decrease the energy aggregate, while the development of new energy will increase the energy supply; therefore, the difference between the speed of traditional consumption and that of new energy development determines the energy consumption. Thus, Eq. (10) is as follows:

$$E_t = (e - ne)E(e > 0) \tag{10}$$

where e and ne are the speed of traditional energy consumption and the speed of new energy development, respectively, and also represent the energy consumption and supply to some extent. If $e - ne > 0$, the consumption speed of traditional energy is greater than that of new energy development, indicating that the increase of energy consumption will aggravate environment pollution. On the contrary, the energy supply tends to rise. Further, under the condition of a balanced economy growth path, we bring energy consumption, labor efficiency, and labor growth rate into Eq. (5) and obtain Eq. (11).

$${G_{AP}}^{*} = \frac{\beta\mu(c + d) + \lambda(e - ne)}{1 - \alpha\mu} \tag{11}$$

where ${G_{AP}}^{*}$ is the growth of air pollution. According to Eq. (11), if $ne = 0$, that is, there is no new energy development, and when c and d keep constant, the variance of ${G_{AP}}^{*}$ depends on that of e. Particularly, if e rises, ${G_{AP}}^{*}$ will increase correspondingly, which means that energy consumption will cause more air pollution. Or else, if$e - ne < 0$, the growth of ${G_{AP}}^{*}$ declines, which indicates that the development of new energy contributes to controlling air pollution. The above analysis highlights the importance of optimizing consumption structure for improving air quality, which viewpoint is supported by Xiang and Song (2015) and Wei and Ma (2015). Furthermore, on the one hand, energy consumption structure optimization requires technological support; on the other hand, the energy consumption structure is constrained by the industrial structure, and the influence of the industrial structure on energy consumption and air quality has been confirmed by many scholars (Zhou et al. 2014a, b; Mi et al. 2015). For these reasons, many researchers have insisted that improving air quality mainly depends on both the structure of energy consumption and the technology paths of energy development. Therefore, we take energy consumption structure, industrial structure, and technology into account when analyzing the effect of the energy consumption on air quality.

Model, variables, and data

Variables and data sources

According to "The Regional Plan for the Yangtze River Delta," approved by the State council in 2020, the Yangtze River Delta includes 25 cites. Because in 2016, the proportion of the days that air quality is standard in Quzhou, Zhoushan, Lishui, Taizhou, and Wenzhou is greater than 85%; this paper has chosen the remaining 20 cities in the Yangtze River Delta as research objects; these are Shanghai (SH), Nanjing (NJ), Wuxi (WX), Lianyungang (LYG), Changzhou (CZ), Suzhou (SZ), Nantong (NT), Yancheng (YC), Yangzhou (YZ), Zhenjiang (ZJ), Taizhou (TZ), Suqian (SQ), Huai'an (HA), Xuzhou (XZ), Hangzhou (HZ), Ningbo (NB), Jiaxing (JX), Huzhou (HUZHOU), Shaoxing (SX), and Jinhua (JH). The basis of selection of the variables involved in this study is as follows.

(1) Air quality. The measurement indicators of air quality that are commonly used include air quality index (AQI), carbon dioxide level, and sulfur dioxide level. Overall, *AQI* can generally reflect the air quality level. However, *AQI* of sample cities is inconsistency in the statistical caliber and there is serious loss of statistical data for some cities, which is difficult to apply to empirical research. Because sulfur dioxide (SO_2) is one of the main harmful gases contributing to air pollution, and it is an important monitoring indicator of *AQI* (Li and Zhang 2008; Chen and Chen 2014; Yu and Lu 2015), we choose SO_2 to measure air quality in this paper. The changes of air quality and sulfur dioxide in the sample period are shown in Fig. 1. To explain the rationale behind choosing a sulfur dioxide indicator, this paper further studies the relationship between the *AQI* (before 2013, *AQI* was calculated as the air pollution index and SO_2 in the Yangtze River Delta from 2000 to 2016. The changes of variables in the sample period are shown in Fig. 1.

As can be seen from Fig. 1, the changes of sulfur dioxide and air quality are basically the same in the sample period, and the inconsistency occurs in 2003, 2006, 2012 and 2013. Besides, the *AQI* has been in a state of decline since 2015. This implies that the change of sulfur dioxide emissions occurred before the corresponding change of the *AQI*, which indicates that the change of sulfur dioxide emissions may have affected the change of air quality. Further, a Granger causality test was conducted in respect of the sulfur dioxide emissions and the *AQI*, and the results demonstrate that the sulfur dioxide emissions Granger caused the *AQI*. Based on the above analysis of the relationship between the SO_2 and the *AQI*, and the availability of the *AQI*, this paper selects industrial sulfur dioxide emissions SO_2 as a substitute variable of air quality; the sample period is 2000–2016.

(2) Total energy consumption. This paper selects the total energy consumption (*EC*) of sample cities from 2000 to 2016.

(3) Control variables. Energy consumption structure (EC_S), industrial structure (S), energy efficiency (E), and economic aggregate are introduced as control variables in this paper. EC_S in this paper is the proportion of coal consumption in total energy consumption. Besides, according to the total accounting standard of production method adopted by the National Bureau of Statistics of China, this paper selects the proportion of added value of tertiary industry as the substitute variable of S. Further, referring to energy efficiency defined by Wang et al. (2014), this paper uses energy efficiency to indicate the overall contribution of technical investment, expressed as "unit energy consumption", which is the reciprocal of energy intensity.

Due to the limited availability of the statistical data, we use a variety of methods to acquire data. Variable description, data source, and acquisition method are shown in Table 1.

Decoupling analysis of energy consumption and sulfur dioxide

To unify the standardized dimension and reduce the interference of heteroscedasticity in the test validity, all related variables are taken as natural logarithm and a unit root test is carried out. The test results show that all variables are I (1) sequences. On this basis, the cointegration test is carried out, and we find that under the confidence level of 1%, there exists a long-term stable equilibrium relationship between air quality, energy consumption, energy consumption structure, industrial structure, and energy efficiency in sample cities. Further, a Granger causality test is carried out. To prevent false regression, this paper tests the difference of the logarithm of original sequence, and the results are shown in Table 2.

We find that there is a bidirectional causal relationship between sulfur dioxide emissions and total energy consumption in sample cites, and the control variable is also the Granger causes of sulfur dioxide emissions. From the above analysis, we can acknowledge that there is a bidirectional causal relationship between energy consumption and sulfur dioxide emissions, which interfere with each other in the process of movement and development, that is, there is a "coupling" relationship between energy consumption and sulfur dioxide emissions (Yu et al. 2013).

The "decoupling" is breaking the coupling relationship between economic growth and environmental hazards and reducing the impact on the environment. According to the decoupling theory, if the reduction of sulfur dioxide emissions is larger than the reduction of energy consumption, this can be considered as relative decoupling. As the trend of change of both is basically the same, they are not decoupled (Du et al. 2015). Relative decoupling of energy consumption and sulfur dioxide emissions occurs when the growth rate of sulfur dioxide deterioration is slower than that of energy consumption. This indicates that it is

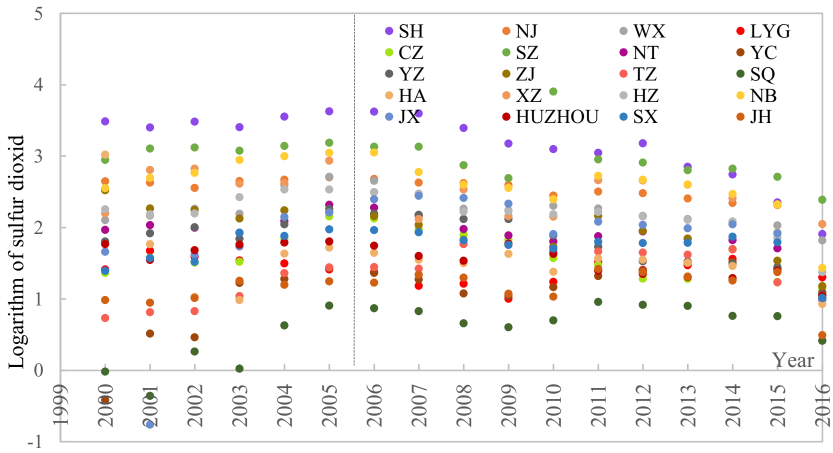

Fig.1 Changes of air quality and sulfur dioxide in the Yangtze River Delta from 2000 to 2016

meaningful to study air quality from the perspective of energy consumption (Du et al. 2015). Further, it is acknowledged that controlling the growth of energy consumption can effectively improve air quality. Referring to the structure of the energy decoupling index of Yu et al. (2013), the decoupling index of energy consumption and air quality in Jiangsu province is established, as in Eq. (12):

$$K_{it} = \frac{SO_2\text{-}\{K_{it}\}}{EC\text{-}\{K_{it}\}} \tag{12}$$

where K_{it} is the decoupling index of sulfur dioxide of $\mathrm{i_{th}}$ region in the $\mathrm{t_{th}}$ year, $EC\_\{K_{it}\}$ represents the energy consumption index of $\mathrm{i_{th}}$ region in the $\mathrm{t_{th}}$ year, and $SO_2\_\{K_{it}\}$ represents the sulfur dioxide emissions of $\mathrm{i_{th}}$ region in the $\mathrm{t_{th}}$ year. In this paper, the sample range is 2000–2016; thus the calculation of $EC_\{K_{it}\}$与$SO_2_\{K_{it}\}$ is based on 2000. On the basis of this, the decoupling coefficient of energy consumption and sulfur dioxide emissions in Yangtze River Delta from 2000 to 2016 is obtained, as shown in Fig. 2.

We find, except for Yancheng city, the decoupling coefficient of sample cities in 2009 and later is between 0 and 1, which represents a relatively decoupled state. However, the decoupling coefficient in Yancheng and other cities before 2009 is not less than 1. This may be related to factors such as policy lag, the intensity of inter-regional policy implementation, technical level, resource situation, and economic basis. The above analysis shows that there is a practical significance in studying the influence of energy consumption on sulfur dioxide in sample cities.

Basic model

Based on the above analysis, first, we find the relationship map between energy consumption and air quality of sample cities is linear in most cities. Further, it can be seen from the results of a Likelihood ratio test and Hausman test that a fixed effect model should be established. Equation (13) is built to examine the long-term influence of energy consumption on air quality.

$$\begin{aligned} lnSO_{2it} &= C + \alpha_{1i} + \beta_1 lnEC_{it} + \gamma_1 lnEC_{Sit} + \lambda_1 lnS_{it} \\ &\quad + \delta_1 lnE_{it} + \varepsilon_{it} \end{aligned} \tag{13}$$

Where i represents the i_{th} city ($i = 1, 2, \cdots, 20$), t ($t = 2000, 2001, \cdots, 2016$) represents the year, and α_{1i} reflects the random effects of each city (consisting of random variable items). β_1, γ_1, λ_1, and δ_1 indicate the changes of sulfur dioxide emissions caused by the relative changes of total energy consumption, energy consumption structure, individual structure, and energy efficiency, respectively. In addition, considering the inertia characteristics of sulfur dioxide emissions and the dynamics of the model, previous emissions have an influence on current emissions. Therefore, by adding the first-order lag item, a dynamic adjustment model effect model is obtained, as shown in Eq. (14):

$$\begin{aligned} lnSO_{2it} &= C_i + \alpha_{2i} + \beta_{2i} lnEC_{it} + \gamma_{2i} lnEC_{Sit} + \lambda_{2i} lnS_{it} \\ &\quad + \delta_{2i} lnE_{it} + \eta_i lnSO_{2it-1} + \varepsilon_{it} \end{aligned} \tag{14}$$

where i represents the i_{th} city ($i = 1, 2, \cdots, 20$), t ($t = 2000, 2001, \cdots, 2016$) represents the year, and α_{2i} reflects the random effects of each city (consisting of random variable items). β_2, γ_2, λ_2, and δ_2 indicate the changes of sulfur dioxide emissions caused by the relative changes of total energy consumption, energy consumption structure, individual structure, and energy efficiency, respectively. η_i represents the influence of previous emissions on the current emissions.

Further, Casson et al. (2010) points out that the environmental Kuznets curve (EKC) could be inverted U-shaped only under the influence of government intervention, environmental regulations, and technology diffusion. Zhang and Zhong (2009) also verify the influence of government environmental policies on the relationship between environment and income. In view of this, this paper tries to further investigate the influence of related policies on the relationship between energy

Table 1 Variables description and data source

Variables	Unit	Data source and acquisition method
AQI/API	μg/m^3	Environmental Protection Department of the People's Bureau of Statistics of China
SO_2	10^4t	Data of Suqian in 2000–2002 come from the Suqian Statistical Yearbook (2001–2013). Data of Huai'an in 2000 and 2001 are calculated by multiplying the amount of sulfur dioxide emissions per square kilometer by the land area (km^2); the data come from the China Energy Statistical Yearbook (2001, 2002). The data in other cities in 2000–2002 come from the Statistical Yearbook of each city (2001–2003), and the data of each city in 2003–2015 come from the Statistical Yearbook of Chinese Cities (2004–2016). The data of each city in 2016 come from the Statistical Yearbook of each city (2017)
EC	10^4tce	The data of Changzhou in 2000–2008, Huzhou in 2000–2010, Jinhua in 2001–2016, and Hangzhou in 2000–2016 is replaced by the sum of standard coal that various types of energy consumption are converted into. The total consumption of various energy sources in related cities are, respectively, from the Changzhou Statistical Yearbook (2001–2008), the Huzhou Statistical Yearbook (2001–2011), the Hangzhou Statistical Yearbook (2001–2017), and the Jinhua Statistical Yearbook (2002–2017). The reference coefficient for converting various types of energy consumption into standard coal comes from the China Energy Statistical Yearbook 2016. The data of Suqian in 2000, 2001, and 2004 are missing. We use the data calculated by multiplying the total energy consumption of Jiangsu province by the proportion of the total industrial output value of Suqian to that of Jiangsu province, and the remaining data come from the Suqian Statistical Yearbook (2003, 2004, 2006–2017). For 2000, the energy consumption of Jinhua is multiplied by the total energy consumption of Zhejiang province and the proportion of the total industrial output value of Jinhua to that of Zhejiang province. Energy consumption in other cities comes from the Statistical Yearbook of each city (2001–2017)
GDP	10^9Yuan	Statistical Yearbook (2001–2017) of each city
EC_S	/	The data of Yancheng coal consumption in 2000–2004; Suqian coal consumption in 2000, 2001, and 2004; and Taizhou coal consumption in 2004 are calculated by multiplying Jiangsu coal consumption by the proportion of the total industrial output value of each city in Jiangsu. Jinhua coal consumption in 2000 is calculated by multiplying Zhejiang coal consumption by the proportion of the Jinhua industrial output value in Zhejiang. The remaining data come from the Statistical Yearbook. The data of coal consumption in Nantong in 2000 come from the Nantong Environmental Bulletin 2004, the data of Yancheng in 2013 come from the Yancheng Environmental Bulletin 2013, and other data come from Statistical Yearbooks over the years. The data of other cities are all from the Statistical Yearbook of each city (2001–2017)
S	/	The added value of the tertiary industry in Shanghai and Yancheng comes from their Statistical Yearbook (2001–2016). Data in Huai'an in 2000–2004 comes from the Statistical Bulletin of National Economic and Social Development in Huai'an (2000–2004), and the data from 2005 to 2016 come from the Statistical Yearbook of Huai'an (2006–2017). The data in other cities comes from the Statistical Yearbook of each city (2017)
E	10^9 Yuan/10^4tce	GDP/total energy consumption

consumption and air quality based on Eq. (13). As far as the method is concerned, because the regression discontinuity (RD) can assume that the samples around the breakpoint are randomly distributed, it can be considered that other characteristics of these samples are the same and that there is no significant difference. This solves the problem of missing variables in the empirical process (Hahn et al. 2001) and has great advantages in policy evaluation and casual inference. Therefore, this paper uses RD to further explore the role of policy.

In general, without policy interference, the level of sulfur dioxide emissions should change smoothly with time, and the breakpoint is considered to be caused by exogenous policy factors. Based on this, firstly, the breakpoint position is judged and policy screening is carried out according to the breakpoint position. Referring to definition of virtual variables (Liu et al. 2016), this paper introduces virtual variables to represent policies; the control group is before the breakpoint, and, after the breakpoint, the treatment group is influenced by policy. Specifically, if the implementation of the policy is the specified content that the affected objects must strictly complete, the simplest method of regression discontinuity, namely deterministic regression discontinuity, can be used. However, due to geographical factors, the strength of policy implementation, and other factors, it may not be possible to fully guarantee the completion of the specified content in a certain period of time;

Table 2 Granger causality test results

Process	Lags	P value	Process	Lags	P value
$dlnSO_2 \rightarrow dlnEC$	0	0.0543*	$dlnEC \rightarrow dlnSO_2$	1	0.0152**
$dlnSO_2 \rightarrow dlnEC_S$	0	0.6777	$dlnEC_S \rightarrow dlnSO_2$	0	0.9616
$dlnSO_2 \rightarrow dlnS$	1	0.8001	$dlnS \rightarrow dlnSO_2$	1	0.0022***
$dlnSO_2 \rightarrow dlnE$	0	0.2307	$dlnE \rightarrow dlnSO_2$	0	0.4413
$dlnEC \rightarrow dlnEC_S$	0	0.0128**	$dlnEC_S \rightarrow dlnEC$	0	0.0929*
$dlnEC \rightarrow dlnS$	0	0.0064***	$dlnS \rightarrow dlnEC$	0	0.0002***
$dlnEC \rightarrow dlnE$	8	0.7188	$dlnE \rightarrow dlnEC$	8	0.0710*
$dlnEC_S \rightarrow dlnS$	0	0.0591*	$dlnS \rightarrow dlnEC_S$	0	0.4118
$dlnEC_S \rightarrow dlnE$	0	0.4791	$dlnE \rightarrow dlnEC_S$	0	0.0390**
$dlnS \rightarrow dlnE$	0	0.0409***	$dlnE \rightarrow dlnS$	0	0.0109**

thus, a fuzzy regression discontinuity design method (Lee and Lemieux 2010) is adopted, and it is estimated by the two-stage least squares method (TSLS), which is equivalent to tool variables (Cook 2008; Meng 2013). The regression model of tool variables is built as Eq. (15):

$$lnSO_{2it} = C + \alpha lnEC_{it} + \beta lnEC_{Sit} + \gamma lnS_{it} + \lambda lnE_{it} + \delta lnZC_{it} + \varepsilon_{it} \tag{15}$$

where i represents the i_{th} city and t represents the year. SO_{2it} is sulfur dioxide emissions.α, β, γ, λ, and δ indicate the changes of sulfur dioxide emissions caused by the relative changes of total energy consumption, energy consumption structure, industrial structure, and energy efficiency. Policies ZC are endogenous variables, and years and regions are instrumental variables of the model.

Empirical results and analysis

General model estimated results

The paper adopts Least Squares to estimate Eq. (13), examining the long-term effects of relevant variables on air quality. The results are shown in Table 3.

Several conclusions can be drawn from Table 1, as follows:

Considering the common effect of all variables, a 1% change of energy consumption structure, industrial structure, and energy efficiency will result in a 0.291%, − 1.595%, and − 0.185% change of sulfur dioxide emissions, respectively. And a 1% increase of total energy consumption will result in a 0.458% increase of sulfur dioxide emissions. These indicate that the role of the structure and technology path and the effective control of total energy consumption are important for improving air quality. Besides, in terms of sequence characteristics alone, within the sample interval, the changes in energy consumption structure, industrial structure, and energy efficiency of the sample cities are obvious, showing that policy implementation, technology, and policy support have a positive effect on promoting structural optimization and efficiency improvement.

Of the 20 sample cities, energy consumption in Lianyungang, Changzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Suqian, Huai’an, Xuzhou, Jiaxing, Huzhou, Shaoxing, and Jinhua is negatively related to the emissions of sulfur dioxide. All the cities, except for Jiaxing, Huzhou, Shaoxing, and Jinhua, belong to Jiangsu province. In recent years, Jiangsu Province has attached great importance to industrial restructuring and technological innovation, and the government has also issued a series of related policies.

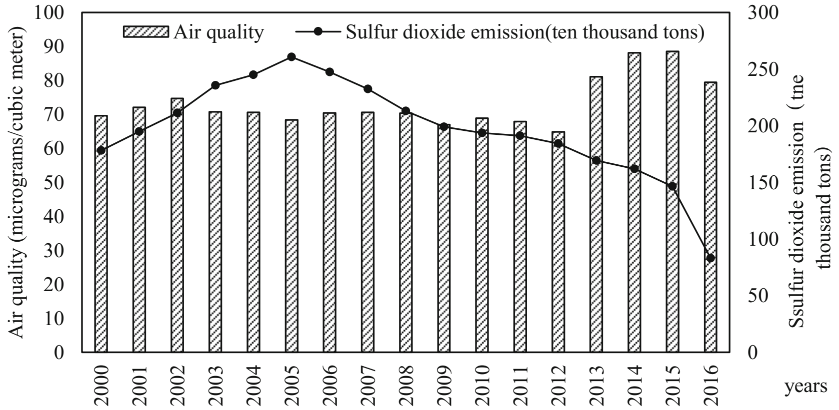

Fig. 2 Decoupling coefficients of energy consumption and sulfur dioxide emissions in the Yangtze River Delta from 2000 to 2016

Table 3 A fixed-effect model estimated result

Variables	Coefficient	Standard deviation		T statistics		P value	
C	− 2.7772	0.7187		− 3.8643		0.0001***	
$lnEC$	0.4745	0.0635		7.4693		0.0000***	
$lnEE_S$	0.2909	0.1050		2.7701		0.0059***	
lnS	− 1.5945	0.3730		− 4.2744		0.0000***	
lnE	− 0.1848	0.0875		− 2.1127		0.0354**	
C_1	1.0216	C_6	0.5390	C_{11}	−0.4348	C_{16}	0.0963
C_2	0.4579	C_7	−0.1023	C_{12}	−0.3519	C_{17}	−0.1449
C_3	0.1342	C_8	−0.6423	C_{13}	−0.2739	C_{18}	−0.2068
C_4	−0.1740	C_9	−0.0972	C_{14}	−0.0301	C_{19}	−0.1828
C_5	−0.1077	C_{10}	−0.0987	C_{15}	0.6340	C_{20}	−0.1366
R^2		0.8181		F value		61.8014	
Adjusted R^2		0.8049		Dependent variable mean		1.8880	
Regression standard deviation		0.3236		Dependent variable variance		0.7367	
Residual square sum of square		33.0986		D-W statistics		0.7084	

******, , and correspond to rejection of the null hypothesis at the 1%, 5%, and 10% confidence levels (the same below)

Jiaxing, Huzhou, Shaoxing, and Jinhua in Zhejiang province have relatively high levels of economic development and openness. The government has also made major investments in industrial restructuring and technological innovation, and the effect of improving air quality has become more apparent. Taking Jinhua as an example, since the Zhejiang Provincial Government agreed to establish a provincial-level high-tech industrial park in 1998, the high-tech industry has entered a period of rapid development, which had an important role in promoting regional industrial restructuring, industrial upgrades, and energy efficiency improvement. In addition, Jinhua City issued the "Implementation Opinions on Accelerating the Development of Jinhua's Global Tourism" in September 2016. The tertiary industry has been greatly promoted, and the industrial structure has been optimized. These results all highlight the importance of multipath reduction of total energy consumption to improve air quality.

Dynamic model estimation results

This paper adopts the generalized method of moments (GMM) estimated method proposed by Arellano and Bond (1991) to estimate Eq. (14). The results are shown in Table 4.

Several conclusions can be drawn from Table 4, as follows:

A 1% change of energy consumption and energy consumption structure, respectively, will result in a 0.284% and 0.151% pulling action of sulfur dioxide. However, a 1% increase of industrial structure and energy efficiency, respectively, will result in a 2.361% and 0.067% inhibition action of sulfur dioxide. Compared with the results of general model estimation, the results show that: First, the total energy consumption and energy consumption structure have reduced the driving effect of sulfur dioxide. Second, industrial structure optimization increases the inhibition of sulfur dioxide. However, the increase in energy efficiency has reduced the inhibitory effect of sulfur dioxide. This is because technological factors (energy efficiency) influence the emission of sulfur dioxide through the guidance of the industrial structure, but the emission reduction effect caused by technical factors through the guidance of the industrial structure is easily affected by inertia. Third, sulfur dioxide emissions have certain inertial characteristics. The 1% increase in sulfur dioxide emissions in the previous period has a positive impact on 0.428% of current emissions.

Considering the inertial characteristics of sulfur dioxide emissions, energy consumption is decoupled from sulfur dioxide emissions in Jiaxing, Zhenjiang, Suzhou, Wuxi, Nanjing, Suqian, and Shanghai, but only Jiaxing city has a coefficient greater than 0.5. In terms of structural path, first, the optimization of energy consumption structure in Lianyungang, Zhenjiang, Nanjing, Changzhou, Huzhou, Wuxi, Shanghai, Nantong, Yangzhou, Xuzhou, and Hangzhou has an inhibitory effect on sulfur dioxide emissions, but the degree is different. The suppression coefficients of Shanghai, Nantong, Yangzhou, Xuzhou, and Hangzhou are all above 1. Second, the optimization of industrial structure in Jiaxing, Nanjing, Wuxi, Changzhou, Lianyungang, Zhenjiang, Suzhou, Yangzhou, and Ningbo also has an inhibitory effect on sulfur dioxide, and the degree is different. The coefficients of interaction of Jiaxing, Nanjing, Wuxi, Changzhou, Lianyungang, Zhenjiang are all above 1. In terms of efficiency path, except for Changzhou, Shaoxing, Nanjing, Shanghai, Suzhou, Jiaxing, and Zhenjiang, the increase in energy efficiency in other cities have an inhibitory effect on

Table 4 GMM estimation result of dynamic action model

Region	*lnEC*	*lnECS*	*lnS*	*lnE*	*lnSO2*(−1)	J statistic
SH	−0.0159 (0.1674)	1.3130 (0.6907)	2.3751 (2.8505)	0.2517(0.5203)	1.7889(0.4258)	0.1014
NJ	0.0221(0.0474)	0.1705(0.1074)	−1.2080(1.1961)	−0.0641(0.0773)	0.6920(0.3994)	0.0690
WX	0.1675(0.4205)	0.7961(0.9662)	−1.3775(3.3642)	0.0125(1.0631)	0.0828(0.3871)	0.0773
LYG	−0.2418(0.1156)	−0.5676(0.2469)	−0.8396(0.4654)	0.3230(0.1551)	1.1424(0.1570)	0.0048
CZ	0.2518(0.4437)	−0.2591(1.6337)	0.8278(2.2095)	−1.0031(0.5218)	0.6799(0.0677)	0.0942
SZ	−0.0307(0.0423)	−0.4366(0.4388)	1.2418(2.0556)	−0.7580(0.9925)	1.3990(0.7535)	0.0593
NT	0.3471(0.1401)	3.6491(0.9533)	0.3024(1.2742)	−1.5376(0.5204)	1.0398(0.6693)	0.0551
YC	0.0097(0.1506)	−1.5876(0.4511)	0.1539(0.6778)	0.1795(0.1218)	0.6467(0.1949)	0.0047
YZ	0.5130(0.2516)	−1.4670(1.0166)	6.0957(3.8767)	−1.2975(0.5415)	2.1149(1.0865)	0.0100
ZJ	−0.1395(0.1753)	0.6433(1.0961)	−2.1763(1.1768)	0.2448(0.3442)	0.5628(0.5761)	0.0713
TZ	−0.1739(0.2130)	0.9392(0.9484)	−1.8368(1.2089)	−0.4768(0.6652)	1.2699(0.1903)	0.0101
SQ	−0.4323(0.3978)	0.3885(0.4798)	−1.0454(0.7652)	1.1647(0.8367)	0.2933(0.5672)	0.0019
HA	0.0805(1.2586)	−3.9891(12.9406)	3.9350(8.7001)	−2.2526(4.7021)	1.3925(5.4404)	0.0010
XZ	1.6768(0.9794)	3.7678(1.6923)	12.6731(7.3860)	−4.8991(2.8170)	0.1559(0.6320)	0.0317
HZ	−0.8104(0.3446)	−0.9588(0.7469)	−3.7818(1.1906)	0.9655(0.4475)	1.7900(0.5001)	0.0595
NB	1.2222(1.2610)	0.9046(0.3262)	11.7122(13.8397)	−4.6056(4.2714)	0.3982 (0.4517)	0.1235
JX	0.5130(0.2786)	2.4105(0.5155)	0.4864(1.7562)	−1.4460(0.4699)	0.0333 (0.0678)	0.0008
HUZHOU	0.9853(0.9301)	3.3174(3.5316)	−0.4494(1.2371)	−1.0167(0.8080)	−2.7031 (2.8513)	0.0289
SX	0.4348(1.3499)	−0.2809(2.9752)	2.2783(4.7357)	−0.8976(0.9876)	0.6723 (1.6782)	0.0233
JH	0.4000(2.3283)	−0.1641 (1.6559)	−0.2735(0.9733)	−0.1238(0.2032)	−1.2502 (2.3283)	0.0208
Synthesis	0.2837(0.0537)	0.1514(0.0338)	−2.3608(0.4675)	−0.0672(0.0296)	0.4278(0.0485)	14.5260

sulfur dioxide emissions. The coefficients of Hangzhou, Huzhou, Taizhou, Xuzhou, Nantong, Jinhua, Yangzhou and Yancheng all exceed 1. The largest emissions' reduction is seen in Hangzhou and Huzhou, followed by Taizhou, Xuzhou, Nantong, Jinhua, Yangzhou, Yancheng, Huai'an, Suqian, Wuxi, Ningbo and Lianyungang. For Changzhou, Shaoxing, Nanjing, Shanghai, Suzhou, Jiaxing, and Zhenjiang, the role of the technology pathway in suppressing emissions has not yet appeared, but on the contrary, it has produced weak pulls. Further, due to differences in the degree of economic development, resources, and policy orientations in different regions, the impacts of energy consumption on air quality will inevitably be different. To further explore the laws, based on the estimated results of the dynamic model, a cluster analysis was performed on sample cities with K-means clustering method. The results are shown in Fig. 3.

According to the clustering results, sample cities can be divided into four categories. The first category consists of Nanjing, Wuxi, Lianyungang, Changzhou, Yancheng, Zhenjiang, Taizhou, Suqian, Huai'an, Hangzhou, Huzhou, and Jinhua; the relevant variables have a strong inhibitory effect on sulfur dioxide. The second category consists of Suzhou, Nantong, Jiaxing, and Shaoxing, with a relatively strong inhibitory effect. The third category consists of Shanghai, Yangzhou, and Ningbo, with a general inhibitory effect. The fourth category consists of Xuzhou, with weak inhibition effect. Overall, first, Hangzhou City's relevant variables have the strongest inhibitory effect on sulfur dioxide. In reality, Hangzhou has a good natural environment and industrial environment, providing good conditions for the optimization of industrial structure; besides, Hangzhou is a national pilot city for informatization, and its high-tech industries have developed rapidly. In addition, the Hangzhou Municipality has fully completed the improvement and the environmental law enforcement is relatively high, providing a guarantee for

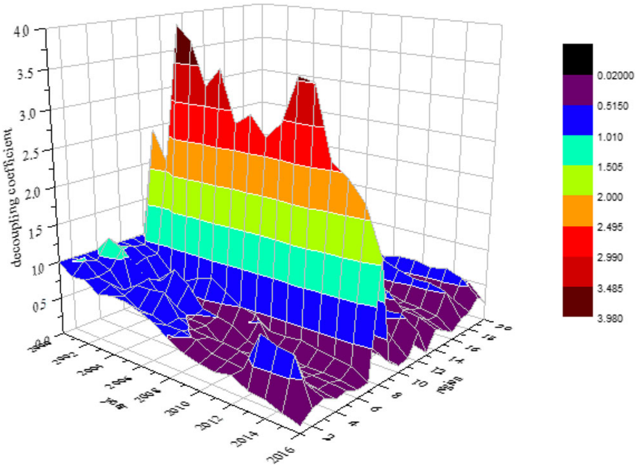

Fig. 3 Urban classified results based on the relationship between energy consumption and air quality

promoting the reduction of major pollutants and improving the environmental quality. Second, there is no direct relationship between the degree of energy consumption impact on air quality and the absolute level of regional economic development. All categories, especially the third category, clearly include cities with large differences in economic development, such as Shanghai and Yangzhou. Relatively speaking, the relationship between energy consumption and air quality is related not only to variables such as energy consumption structure, industrial structure, and energy efficiency but also to geographical distribution, policy formulation, and implementation. Third, the effect of energy consumption on air quality is not directly related to the provinces to which the cities belong. For example, both Nanjing and Nantong belong to Jiangsu province, but the comprehensive inhibitory effect of Nanjing's relevant variables on emissions is 0.388, while Nantong's pulling effect is 3.801.

Effect of related policies on the relationship between energy consumption and air quality

Policy choice and function measurement

Based on the above analysis, this paper tries to further examine the influence of policies on energy consumption, air quality, and the relationship between energy consumption and air quality. Due to the variation of the original SO_2 emission sequence being relatively large, it is difficult to determine the breakpoint position. Therefore, the logarithm of the sulfur dioxide sequence will not affect the changing trend of the original sequence. Figure 4 shows the logarithm change of sulfur dioxide emissions in sample cities from 2000 to 2016.

It can be seen that sulfur dioxide emissions in 20 sample cities all showed obvious breakpoints around 2007 and decreased after 2007, which may be caused by policy influence. Although, there are many policies directly aimed at environmental pollution in the sample period, this paper mainly considers policies around 2007. Combined with the analysis results in Fig. 4, this paper selects "Measures for Environmental Monitoring Management" (Decree No. 39 of the State Environmental Protection Administration, hereinafter referred to as "Measures") as the investigation object. To strengthen the management of environmental monitoring, the "Measures" were formulated on September 1, 2007, in accordance with "The Environmental Protection Law" and other relevant laws and regulations. The implementation of the "Measures" has become an important support condition for promoting energy conservation and emission reduction. After the implementation of the "Measures," the emissions of related pollutants decreased in 2007. Referring to the definition of virtual variables by Liu et al. (2016), virtual variables in this paper represent the "Measures" (2007Q3 and later, $ZC = 1$; otherwise, $ZC = 0$). Before 2007, it was the control group that was influenced by policies, and after 2007, it was the treatment group. A TSLS method is used to estimate Eq. (15). The estimated results are shown in Table 5.

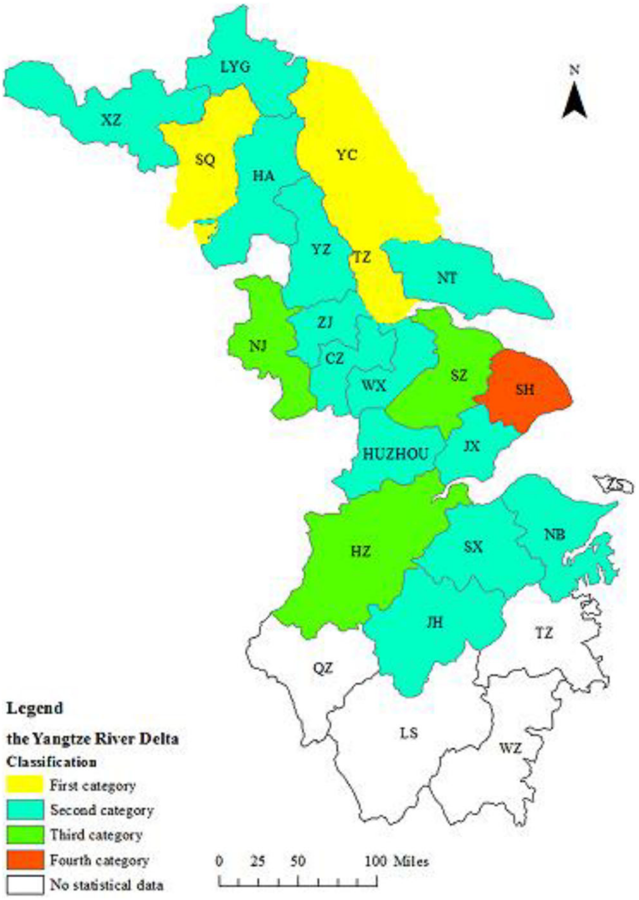

Fig. 4 The changes of the logarithm of sulfur emissions in sample cities in the Yangtze River Delta from 2000 to 2016

According to the estimation results, after the implementation of the "Measures", sulfur dioxide emissions are obviously inhibited generally, with a coefficient of 0.865, and this function is persistent. In practice, the environmental monitoring system is one of the three systems supporting total pollutant emissions' reduction. The implementation of the "Measures" makes the emission reduction indicators system more scientific and effective. In addition, to warn of all kinds of

Table 5 The TSLS estimation results of the breakpoint model

Variables	Coefficient	Standard deviation	*Z* statistics	*P* value
C	− 4.3126	0.4874	− 8.8500	0.0000***
LNEC	0.8470	0.0425	19.9500	0.0000***
LNECS	0.2801	0.0669	4.1900	0.0000***
LNS	− 0.7157	0.2337	− 3.0600	0.0020***
LNE	0.1996	0.0673	2.9700	0.0030***
ZC	− 0.8648	0.0955	− 9.05	0.0000***

Table 6 Results of robustness test

	α estimation value	Standard error	T statistics	P value
Control variable is not added	0.5546	0.0241	23.0200	0.0000***
Add the energy consumption structure	0.5882	0.0274	21.46	0.0000***
Add the energy consumption structure and industrial structure	0.7421	0.0312	23.76	0.0000***
Add all the variables	0.5985	0.0394	15.18	0.0000***

environmental emergencies accurately and meet the environmental management needs, the "Measures" require that data must be provided truly, and the changes of pollutant emissions from pollution sources can be tracked in time, which is of great significance to the improvement of environmental quality. Further, compared with those model results that is not considering policies, the relationship between energy consumption and sulfur dioxide emissions varies. First, the effect of energy consumption and energy consumption structure on sulfur dioxide emissions changes, but the direction remains the same. Specifically, for every 1% change in energy consumption and energy consumption structure, the sulfur dioxide emissions increase by 0.249% and 0.005%, respectively. This indicates that the policy implementation enhances the influence of energy consumption and energy consumption structure on the sulfur dioxide emissions. Second, the effect degree and direction of industrial structure and energy efficiency on sulfur dioxide have changed. For every 1% change in industrial structure, the sulfur dioxide emissions change, from − 1.595% when no policy is considered to 0.418%; for every 1% change in energy efficiency, the sulfur dioxide emissions change, from − 0.185% when no policy is considered to 0.127%. This result implies that, in the sample interval, the guiding role of policies on industrial structure optimization and energy efficiency improvement fail to appear, which may be related to the policy time lag.

Rationality and robustness test

Rationality test of instrumental variable method

First, the exogenous test is carried out. According to the Sargan statistics, over-detection is carried out, and the P value is 0.9512, accepting the original hypothesis that region and year are exogenous and unrelated to the disturbance term. Further, the estimation results of the weak tool variables show that Shea's partial R^2 value is 0.460, the F statistic is 177.624, and the P value corresponding to the F statistic is 0.000. Thus, we reject the original hypothesis and deduce that there are no weak tool variables. However, to ensure robustness, the limited information maximum likelihood method (LIML), which is less sensitive to weak variables, is used. The results show that the estimated coefficient value of LIML method is very close to the TSLS results, which also indicates that there are no weak tool variables, that is, tool variables (regions, years) have great explanatory power to endogenous variables. Therefore, the choice of tool variables is reasonable. Further, the premise of using the instrumental variable method is that there are endogenous variables; thus, this paper carries out a Hausman test on endogenous variables, which is policy. The original hypothesis is that all explanatory variables are exogenous, which means that endogenous variables do not exist. According to the test results, the P value is 0.000, rejecting the original hypothesis and considering the policy to be an endogenous variable. Due to the fact that traditional Hausman's test should be based on the same variance, it is more convincing to use the instrumental variable method and then conduct the heteroscedastic robust Durbin–Wu–Hausman test. The test results indicate that the P value is 0.000, rejecting the original hypothesis. In conclusion, it is reasonable to choose policies as endogenous variables in this paper, and the method selection is applicable.

Robustness test

To examine the rationality of the estimation results, this paper further conducts the robustness tests on related variables. Referring to the research of Lei et al. (2015), in principle, the unobservable factors and influencing factors that do not change with time between the processing group and the control group of regression discontinuity design are either the same or similar, and the addition or absence of control variables will not affect the final result. The step-by-step addition method is used to analyze the sensitivity of Eq. (15), and the results are shown in Table 6.

As can be seen from Table 6, compared with no control variables, after successive addition of energy consumption structure, industrial structure, and energy efficiency, this positive influence of energy consumption on sulfur dioxide emissions has not changed and the change of coefficient is not large, which verifies the robustness of the model estimation results.

Conclusions and suggestions

The main finds that there is a long-term equilibrium relationship between energy consumption and air quality in the

Yangtze River Delta of China. The increase in both total energy consumption and the proportion of coal consumption leads to the emission pull effect. Optimization of industrial structure and improvement of energy efficiency can effectively restrain emissions. Overall, the inhibitory effect of the industrial structure path is superior to the technical path. In addition, the deterioration of air quality has an inertial effect, and for each city, the magnitude of inertia and the direction of action are not consistent. Moreover, the relationship between energy consumption and air quality has differences between cities. The strength of the relationship between the two is not directly related to the absolute level of regional economic development. Furthermore, the relevant policies of Chinese government for improving air quality are effective to some extent. It is to be noted that the conclusions of the general relationship between energy consumption and air quality are consistent with Han et al. (2014), Shi et al. (2015), Khan et al. (2016), Tiba and Omri (2017), etc. As for the research on Yangtze River Delta of China, we draw the similar conclusions with Bao et al. (2010) and Zhai et al. (2012) from the static perspective, but our findings on the regional differences of the relationship, the inertial effect of air quality deterioration, and the effect of polices are new.

In practice, as a region in China with high energy consumption, the Yangtze River Delta should focus on actively changing the mode of energy development. First, full play should be given to the role of structure paths to reduce the total amount of energy consumption. The focus of policies should be optimization of energy consumption structure and industrial structure. On the one hand, it is necessary to further promote the strategic adjustment of the energy structure and the clean and efficient use of fossil energy should be vigorously promoted. On the other hand, the Yangtze River Delta should be guided by the adjustment of industrial structure of low energy consumption, low pollution, and high efficiency to further optimize the industrial structure. Except for promoting three industrial adjustments, more emphasis should be placed on two aspects, one is optimizing the internal structure of industrial sector, and another is strictly controlling of new capacity and orderly withdrawal of excess capacity. Second, the policy makers should adopt subsidy and incentive policies to guide enterprises to increase technical input and to promote technological progress and even energy conversion efficiency. Third, for the cities that the relevant variables have a strong or relatively strong inhibitory effect on air quality, it is necessary to control the key factors influencing air quality according to the reality of "economic-environment" relationship. In general, it should optimize energy consumption structure in the short-term, and focus on technology promotion and industrial structure consummation in the long-term. For the cities that the relevant variables have a general or weak inhibitory effect, structural optimization and technology promotion policies should still be emphasized in the long-term; but in the short-term, policies should be focused on "governance", such as penalties for air pollution rather than "guidance." Finally, cities should strengthen their policy coordination and establish an effective cross-regional policy system.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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