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Original Research

Environmental Protection Tax Effect on Reducing $PM_{2.5}$ Pollution in China and Its Influencing Factors

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Abstract

The $PM_{2.5}$ pollution has been globally threatening human health. By monitoring $PM_{2.5}$ concentrations and meteorological data, this study estimated the changes in $PM_{2.5}$ concentrations before and after the implementation of an environmental protection tax law in 30 provincial capital cities in China by conducting a counterfactual curve-fitting simulation method and studied the effects of the environmental protection tax (EEPT) on $PM_{2.5}$. Then, the influencing factors of the EEPT in China were investigated employing a Bayesian LASSO regression model. The environmental protection tax generally reduced the annual $PM_{2.5}$ concentrations in China in 2018. The EEPT in various cities are different. Among the seven significant influencing factors, resident unemployment rate (RUR) and gross domestic product (GDP) were the top two influencing factors, with contributions up to 20.7% and 19.2%, respectively. Proportion of the secondary industry (PSI) (7.9%) and urbanisation rate (UR) (6.7%) were the bottom two influencing factors. The median influencing factors were resident average schooling years (RASY) (17.6%), relief amplitude (RA) (16.5%) and waste gas treatment input (WGTI) (11.5%). Furthermore, GDP and UR associated negatively with the EEPT on $PM_{2.5}$ pollution, whereas the other five variables associated positively with the EEPT on $PM_{2.5}$ pollution.

Keywords: environmental tax, $PM_{2.5}$ pollution, influence factors, Bayesian LASSO model

Introduction

Air pollution has been a global problem with local difference [1]. The main culprits of air pollution are $PM_{2.5}$ that can infiltrate deep into the respiratory system and bloodstreams and cause diseases [1-3]. A high $PM_{2.5}$ concentration is considered one of the main environmental risks to human health [4]. Accordingly, many countries have taken measures to reduce $PM_{2.5}$ concentrations within their territories [2]. An environmental tax is an environmental policy instrument commonly adopted by governments to control air pollution [5]. Since Arthur C. Pigou first proposed environmental taxes in his externality theory [6], the academic community has not yet formed a unified conclusion on the environmental governance effect of environmental taxes. Very few scholars have

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raised questions about environmental taxes [7]. Lin and Li [8] found that the carbon tax has significantly reduced the amount of CO_2 emissions in Finland, but the impacts are negative and not significant in Denmark and Sweden. Certainly, most researchers still have a positive attitude towards the environmental governance effect of environmental taxes. González and Hosoda [9] applied a Bayesian structural time series model to evaluate the impact of an aviation oil fuel tax in Japan on the national aviation fuel demand, and they found that the oil fuel tax reduced the amount of CO_2 emissions from aircrafts. Murray and Rivers [10] studied the effect of the carbon tax in British Columbia and regarded that the carbon tax has reduced greenhouse gas emissions by 5%-15% without affecting the overall economic activities. A study has examined the impacts of the vehicle registration tax reform implemented in Norway in 2007 on the reduction of the average emission intensity of new vehicles [11]. The results show that the implementation of this policy has reduced the average emission intensity of new vehicles.

Some studies have also focused on China's issues. Tang, Shi et al. [12] presented a dynamic CGE model to estimate the economic and environmental effects of China's resource tax reform in 2014 and argued that the policy can curb China's total amount of CO_2 emissions by improving the energy structure. Zhao, He et al. [13] studied the effect of the gasoline consumption tax on CO_2 emissions during a low-oil-price period and found that tax adjustments can still lead consumers to control gasoline consumption, thus reducing CO_2 emissions. Hu, Liu et al. [14] concluded that environmental taxes can effectively curb SO_2 emissions in high-pollution sectors; stimulate demand for clean energy, such as natural gas; and upgrade the energy structure. Zhang, Zheng et al. [15] revealed that emission reduction has been a dominant factor of air quality improvement in China in recent years, and the impact of changes in meteorological conditions was small. The contribution of both to the decline in $PM_{2.5}$ exposure levels in the national population was 91% and 9%, respectively.

Teusch and Braathen [16] used a cost-benefit analysis to assess ex-post effects of environmental taxes. Lin and Li [8] used the difference-in-difference (DID) method to comprehensively assess the effects of carbon taxes on environmental governance in the five Nordic countries, namely, Denmark, Finland, Sweden, the Netherlands, and Norway.

To our knowledge, few scholars have conducted in-depth studies on EEPT on $PM_{2.5}$ pollution and its influencing factors in China. The aim of this study is firstly to evaluate the EEPT on $PM_{2.5}$ pollution after the implementation of the environmental protection tax law in China in 2018 and secondly to investigate the influencing factors of EEPT on $PM_{2.5}$ pollution in China. Our study has considered the changes in annual average $PM_{2.5}$ concentrations in the provincial capital cities in China before and after the implementation of the environmental protection tax law by conducting a curve-fitting method for a counterfactual simulation. The influencing factors of EEPT on $PM_{2.5}$ pollution in China were explored by employing a Bayesian LASSO regression model.

Materials and Methods

Study Area and Datasets

Considering the spatial heterogeneity of $PM_{2.5}$ concentrations in provincial areas, city-level areas served as the study areas. As shown in Fig. 1, four provincial cities (Beijing, Tianjin, Shanghai and Chongqing) and 26 provincial capital cities in China were selected. Generally, the most developed area in a provincial region is the corresponding provincial capital city that gathers the relatively administrative, economic and social resources. Compared with the other non-capital cities, the level of tax collection and management in the capital city should be relatively high in a provincial region. This is also why our study selected provincial cities and provincial capital cities as study areas. Due to data unavailability, Haikou city and the provincial capital city in Taiwan Province were not included.

The datasets in this study included three categories: $PM_{2.5}$ daily average concentrations collected from the monitoring sites placed in the 30 study cities (Fig. 1), daily meteorological data of the 30 cities and covariate data of the influencing factors of each city. The raw data of the *in-situ* ground monitoring of $PM_{2.5}$ concentrations from 1 January 2017 to 31 December 2018 were collected from the China National Urban Air Quality Real-time Publishing Platform (http://106.37.208.233:20035/). The daily meteorological data of the 30 cities from 2017 and 2018, involving the daily average temperature, daily average relative humidity, daily average wind speed and daily maximum sustained wind speed, were obtained from a weather data website (https://en.tutiempo.net/climate/china.html). The data of influencing factors in 2018 consisted three classes of covariate variables, namely, socio-economics, environmental protection tax rate and natural environment. The socio-economic data were collected from the official statistical bulletins of the 30 cities in 2018. The environmental protection tax rate data were extracted from the administrative measures for the approval and collection of environmental protection tax of the corresponding provinces. The natural environment data, including the normalised difference vegetation index (NDVI) and terrain elevation, were collected from a website (http://www.resdc.cn).

Estimation Methods of the EEPT

Generally, the changes in $PM_{2.5}$ concentrations stem from two aspects: adjustment of human activities and

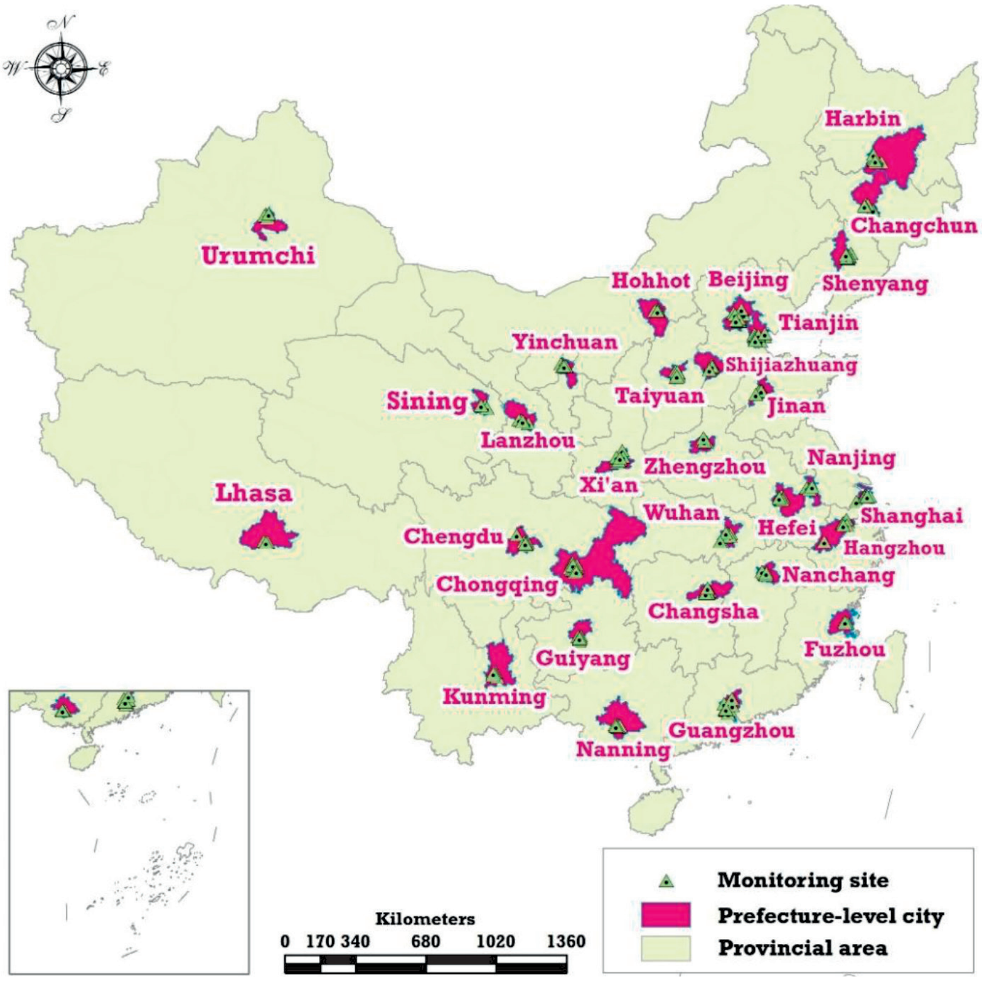

Fig. 1. Distribution of the study areas, provincial capital cities and air pollution monitoring sites in China.

natural conditions. The adjustment of human activities, especially industrial emission activities, can often occur under legal environmental regulations. According to the China Environmental Bulletin in 2017 and 2018 (http://www.mee.gov.cn /hjzl/zghjzkgb/lnzghjzkgb/), except for the enforcement of the environmental protection tax law in 2018, China has basically implemented the same environmental policies and measures in the said two years. Hence, our study argued that the adjustment of human activities was caused by the implementation of the environmental protection tax law. Furthermore, the change in annual average $PM_{2.5}$ concentrations, resulting in the adjustment of human activities, is the EEPT, denoted herein as $\Delta_{i,human,2018}$. If the counterfactual $PM_{2.5}$ concentrations, under the condition that environmental protection tax law would not be implemented, denoted by $\rho^{cou}_{i,human,2018}$, can be estimated, then the EEPT, denoted by $\Delta_{i,human,2018}$, may be calculated as follows:

$$\Delta_{i,human,2018} = \rho^{cou}_{i,human,2018} - \rho^{real}_{i,human,2018} \quad (1)$$

...where $\rho^{real}_{i,natural,2018}$ is the real $PM_{2.5}$ annual average concentrations under the enforcement of the environmental protection tax law in the i-th city in 2018. Meanwhile, the real and counterfactual total $PM_{2.5}$ annual average concentrations in the i-th city in 2018, denoted by $\rho^{real}_{i,2018}$ and $\rho^{cou}_{i,2018}$, respectively, can be expressed as follows:

$$\rho^{real}_{i,2018} = \rho^{real}_{i,human,2018} + \rho^{real}_{i,natural,2018} \quad (2)$$

$$\rho^{cou}_{i,2018} = \rho^{cou}_{i,human,2018} + \rho^{real}_{i,natural,2018} \quad (3)$$

...where $\rho^{real}_{i,natural,2018}$ represents the real $PM_{2.5}$ annual average concentrations caused by natural conditions in the i-th city in 2018. Equation (4) can be obtained by subtracting the result of Equation (3) from that of Equation (2):

$$\Delta_{i,human,2018} = \rho^{cou}_{i,2018} - \rho^{real}_{i,2018} \quad (4)$$

...where $\rho^{real}_{i,2018}$ is the observed data, and $\rho^{cou}_{i,2018}$ needs to be estimated. The daily $PM_{2.5}$ concentrations in a city in one year can be determined through meteorological parameters [17, 18], such as temperature and humidity. For a city, if the meteorological parameters can predict or model daily $PM_{2.5}$ concentrations in 2017, then the model coefficients reflect the associations between daily $PM_{2.5}$ concentrations and human activities and natural conditions in that year. Then, the counterfactual daily $PM_{2.5}$ concentrations can be estimated by inputting the meteorological parameters in 2018 to the model fitted from the data of 2017. The related expressions are as follows:

$$\rho_{i,d,2017}^{real} = F_{i,2017}\left(M_{i,d,2017}\right) + \varepsilon_i \tag{5}$$

$$\rho_{i,d,2018}^{cou} = F_{i,2017}\left(M_{i,d,2018}\right) + \varepsilon_i \tag{6}$$

...where $\rho_{i,d,2017}^{real}$ and $\rho_{i,d,2018}^{cou}$ are the real daily average $PM_{2.5}$ concentrations in the i-th city on the d-th day in 2017 and counterfactual daily average $PM_{2.5}$ concentrations in the i-th city in 2018, respectively. $M_{i,d,2017}$ and $M_{i,d,2018}$ are the meteorological parameters in the i-th city on the d-th day in 2017 and 2018, respectively. $F_{i,2017}(M_{i,d,2017})$ is the fitted model based on the data of 2017. ε_i represents the Gauss random effect. $F_{i,2017}(M_{i,d,2018})$ is the estimate of daily $PM_{2.5}$ concentrations under conditions of human activities in 2017 and meteorological conditions in 2018. Accordingly, we assume that the difference in human activities between 2017 and 2018 is caused by the enforcement of the environmental protection tax law. Consequently, $F_{i,2017}(M_{i,d,2018}) + \varepsilon_i$ may estimate counterfactual daily $PM_{2.5}$ concentrations under the condition without the environmental protection tax law.

Based on the data experiment, the sorted daily $PM_{2.5}$ concentrations can be accurately predicted by the sorted daily average temperature in a whole calendar year, rather than the other three meteorological parameters. The corresponding fitting function is a piecewise function composed of linear and logistic growth functions:

$$\rho_{i,(d),2017}^{real} = F_{i,2017}\left(T_{i,(d),2017}\right) = \begin{cases} \beta_i T_{i,(d),2017} + \alpha_i, & T_{i,Min,2017} \le T_{i,(d),2017} < T_{i,0,2017} \\ \frac{\delta}{\gamma_i + \eta_i * \exp\left(\nu_i T_{i,(d),2017}\right)}, & T_{i,0,2017} \le T_{i,(d),2017} \le T_{i,Max,2017} \end{cases} \tag{7}$$

...where $\rho_{i,(d),2017}^{real}$ is the sorted daily $PM_{2.5}$ concentrations in the i-th city in 2017, subscript (d) denotes the serial number of the sorted days of a calendar year, $T_{i,(d),2017}$ is the sorted daily average temperature in the i-th city in 2017, $T_{i,0}$ is a demarcation point, and $T_{i,Min,2017}$ and $T_{i,Max,2017}$ are the minimum and maximum temperature in the i-th city in 2017, respectively. The other variables are fitting coefficients. Then, the EEPT and per centum of the EEPT, denoted by E_i and π_i, respectively, may be calculated as follows:

$$E_i = \frac{\sum_{(d)=1}^{365}\left(F_{i,2017}\left(T_{i,(d),2018}\right)\right) - \sum_{(d)=1}^{365}\left(\rho_{i,(d),2018}^{real}\right)}{365} \tag{8}$$

$$\pi_i = \frac{\sum_{(d)=1}^{365}\left(F_{i,2017}\left(T_{i,(d),2018}\right)\right) - \sum_{(d)=1}^{365}\left(\rho_{i,(d),2018}^{real}\right)}{\sum_{(d)=1}^{365}\left(F_{i,2017}\left(T_{i,(d),2018}\right)\right)} \tag{9}$$

Bayesian LASSO Regression Model

To overcome the problem of multicollinearity among the variables and select striking influence variables, the Bayesian LASSO regression model [19] was employed in this paper. The Bayesian LASSO regression model is the Bayesian version of the ordinary LASSO regression model [20] interpreted by Bayesian posterior mode estimates when the regression parameters have independent and identical Laplace priors. The Bayesian LASSO estimation differs from the ordinary least square (OLS), penalised by the least squares method that minimises the residual sum of squares while controlling the L1 norm of the coefficient vector of regression [19, 20]. The Bayesian LASSO not only can obtain a more stable estimation but can also automatically provide interval estimates for all parameters, including the error variance [19]. The Bayesian LASSO model of the relationship among the EEPT, E_i and influencing factors, x_j (j = 1,..., n) can be expressed:

$$E_i \sim N\left(\mu_i, \sigma_E^2\right) \tag{9}$$

$$\mu_i = \sum_{j=1}^{n} \beta_j x_{j,i} + \xi \tag{10}$$

$$\widehat{\boldsymbol{\beta}} = argmin_{\beta}(\boldsymbol{\mu} - \boldsymbol{\beta X})^T(\boldsymbol{\mu} - \boldsymbol{\beta X}) + \lambda\|\boldsymbol{\beta}\|_1 \tag{11}$$

$$\boldsymbol{\beta}|\lambda, \sigma_E^2 \sim \prod_{j=1}^{n} \frac{\lambda}{2\sigma_E} e^{-\frac{\lambda|\beta_j|}{\sigma_E}} \tag{12}$$

...where μ_i and σ_E^2 represent the mean and variance of the normal likelihood distribution of E_i, β_j is the linear regression parameters of the influence variables $x_{j,i}$, n is the number of the influence variables, ξ represents the intercept and random error, $\hat{\boldsymbol{\beta}}$ represents the estimate of the regression parameters $\boldsymbol{\beta}$ and $\boldsymbol{\mu}$ and $\boldsymbol{X}$ are the matrices of μ_i and $x_{j,i}$, respectively. The coefficient λ is greater than 0 and determines the amount of shrinkage.

All the computations, including data fitting and Bayesian statistics inference, were implemented by a computer programming language, Python 3.6.

Results and Discussion

Results

Estimation and Spatial Trends of the EEPT

As presented in Section 2.2, firstly, the function between the sorted daily $PM_{2.5}$ concentrations and the sorted daily average temperature in the i-th city, $F_{i,2017}(T_{i,(d),2017})$, needs to be fitted. Fig. 1 shows

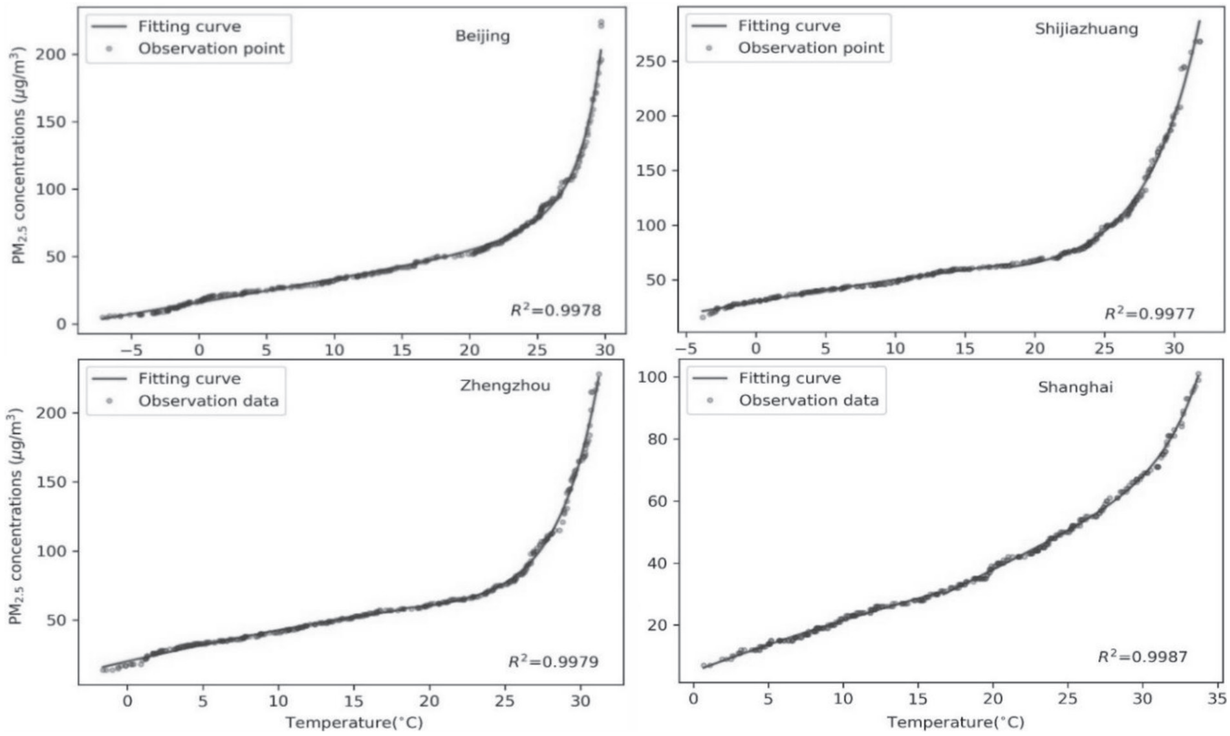

Fig. 2. Points with the y-coordinate of sorted real (observed) daily $PM_{2.5}$ concentrations vs. x-coordinate of the sorted daily average temperature and the corresponding fitted curves in Beijing, Shijiazhuang, Zhengzhou and Shanghai.

four cases of fitted results in Beijing, Shijiazhuang, Zhengzhou and Shanghai; their corresponding goodness of fit R^2 are 0.998, 0.998, 0.998 and 0.999, respectively. The maximum and minimum of the goodness-of-fit functions, $F_{i,2017}(T_{i,(d),2017})$, across the 30 cities were 0.986 and 0.999, respectively. Except for Tianjin (0.986) and Urumchi (0.991), R^2 in the other 28 cities are all greater than 0.995, as listed in Table 1.

Table 1. Estimates of the absolute values and percentages of the EEPT in the 30 cities in 2018 and the goodness of fit (R^2) for predicting the counterfactual daily $PM_{2.5}$ concentrations in the 30 cities in 2018.

City	EEPT (ug/m^3)	Percentage of the EEPT (%)	R^2
Beijing	5.70	11.3%	0.998
Tianjin	10.6	19.3%	0.986
Shijiazhuang	9.94	13.8%	0.998
Taiyuan	7.71	13.2%	0.997
Hohhot	4.76	11.6%	0.996
Shenyang	7.71	17.4%	0.997
Changchun	10.9	26.6%	0.998
Harbin	13.5	28.6%	0.998
Shanghai	2.15	5.9%	0.998
Nanjing	0.92	3.3%	0.998
Hangzhou	3.80	9.7%	0.998
Hefei	7.95	15.1%	0.998
Fuzhou	1.09	4.5%	0.993
Nanchang	12.1	31.5%	0.995
Jinan	9.69	17.8%	0.997

City	EEPT (ug/m^3)	Percentage of the EEPT (%)	R^2
Zhengzhou	5.97	9.9%	0.998
Wuhan	7.42	14.6%	0.998
Changsha	8.08	16.2%	0.998
Guangzhou	0.00	0.0%	0.996
Nanning	1.85	5.5%	0.996
Chongqing	5.56	13.7%	0.996
Chengdu	3.70	7.9%	0.998
Guiyang	0.28	0.9%	0.998
Kunming	-0.88	-3.5%	0.998
Lasha	1.68	10.1%	0.996
Xi’an	9.76	14.9%	0.997
Lanzhou	3.98	8.9%	0.997
Xining	-2.38	-6.4%	0.995
Yinchuan	5.40	13.4%	0.998
Urumchi	10.9	16.9%	0.991

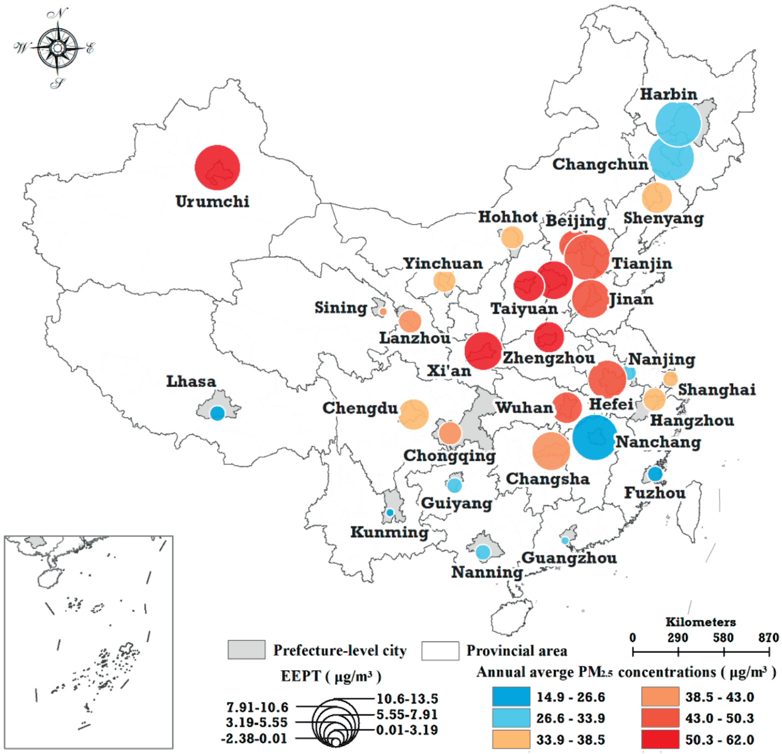

Fig. 3. Spatial distributions of the absolute value of the EEPT and annual average $PM_{2.5}$ concentrations across the 30 provincial capital cities.

The EEPT, E_i and percentage of the EEPT (π_i) of the 30 cities were estimated based on Equations (8) and (9). The corresponding results are listed in Table 1. Except for three cities, namely, Kunming, Xining and Guangzhou, the EEPTs of the other cities were all positive. The minimum of the 27 positive absolute values (0.28 μg/m^3) and percentage of the EEPT (0.9%) were noted in Guiyang. Nevertheless, the maximum of the absolute value and percentage of the EEPT were noted in two cities: Harbin (13.5 μg/m^3) and Nanchang (31.5%). Five cities had EEPT greater than 10.0 μg/m^3, and 13 cities had EEPT less than 5.0 μg/m^3. 18 cities, including Beijing and Tianjin, had a percentage of the EEPT greater than 10.0%, whereas six cities, including Shanghai and Nanjing, had less than 5.0%.

The spatial pattern of the estimated EEPT across the 30 cities showed a distinct geographical clustering feature. As shown in Fig. 2, the EEPT of northern regions represented by three cities, Urumchi (Xinjiang Province), Harbin (Heilongjiang Province) and Changchun (Jilin Province), was at a high level. On the contrary, that of southern regions, including five cities, Kunming (Yunnan Province), Guiyang (Guizhou Province), Nanning (Guangxi Province), Guangzhou (Guangdong Province) and Fuzhou (Fujian Province), was at a low level. Meanwhile, the annual average $PM_{2.5}$ concentrations in the southern regions were low. The western region and Yangtze River Delta region located in East China experienced a low EEPT level, and the corresponding $PM_{2.5}$ level was also low. The EEPT and $PM_{2.5}$ pollution in north and central China jointly belonged to a high value range. Of note, three provincial capital cities, Harbin, Changchun and Nanchang, experienced low $PM_{2.5}$ pollution but has a high EEPT level. As outlined above, the absolute value of EEPT in Harbin is the highest, and the percentage of the EEPT in Nanchang is the maximum. The spatial pattern of the relative percentage of the EEPT in the 30 provincial capital cities (Fig. 3) was generally similar with that of the absolute value of the EEPT, although minor differences occurred in a few regions.

Influencing Factors

Considering the small sample capacity, the Bayesian LASSO multiple linear regression model was employed in this study. The diagram of the influencing factors is shown in Fig. 4. The outcome variable is the absolute value of the EEPT (μg/m^3), and the influencing factors cover four categories of variables, economic, social, EPT's and natural. The economic variable is represented by four proxy variables: gross domestic product (GDP) (hundred billion Chinese yuan), proportion of the secondary industry (PSI) (%), tourism output value (TOV) (10 billion Chinese yuan) and output value of the secondary industry (OVSI) (10 billion Chinese yuan). The social variable is represented by three proxy variables: urbanisation rate (UR) (%), resident unemployment rate (RUR) (%) and resident average

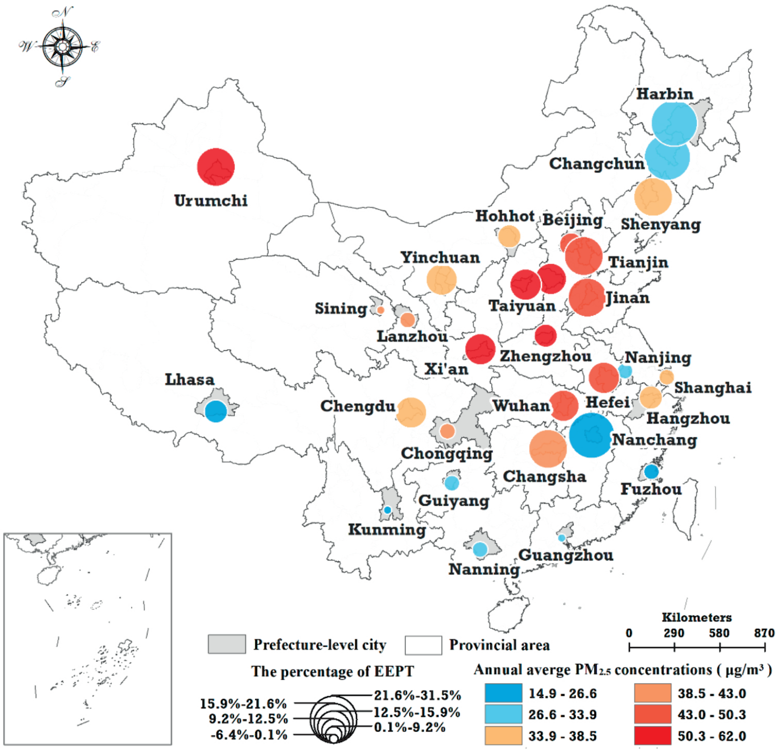

Fig. 4. Spatial distributions of the relative percentage of the EEPT and annual average $PM_{2.5}$ concentrations across the 30 provincial capital cities

schooling years (RASY) (Year). The EPT's variable is represented by two proxy variables, environmental protection tax rate (EPTR) (Chinese yuan per pollutional equivalent) and waste gas treatment input (WGTI) (hundred million Chinese yuan). The natural variable is represented by two proxy variables: relief amplitude (RA) (%) and heterogeneity of vegetation (HV) (%).

Firstly, all the 11 influencing factors were inputted into the Bayesian LASSO regression model, and the initial regression results are listed in Table S1. The results show that the posterior probabilities of four regression parameters, $\beta_k(k = 3,4,8,11)$, greater than 0 or less than 0, were less than 70%. The corresponding four variables were TOV ($P(\beta_8<0|data) = 65.9\%$), OVSI ($P(\beta_4<0|data) = 53.1\%$), EPTR ($P(\beta_8<0|data) = 63.7\%$) and HV ($P(\beta_{11}<0|data) = 51.9\%$). Then, these four variables were excluded, and the other seven variables (i.e. GDP, PSI, UR, RUR, RASY, WGTI and RA) were inputted into the Bayesian LASSO model.

Table S1. The Bayesian LASSO regression results for EEPT in 2018.

Variables	Posterior median of regression parameters (95%CI)	Posterior probability of regression parameters
Gross domestic product (GDP) (x1)	-0.1508(-0.6833,0.3397)	$P(\beta_{x1}<0 \mid data) = 70.4\%$
Proportion of secondary industry (PSI) (x2)	0.0718(-0.1910,0.3421)	$P(\beta_{x2}<0 \mid data) = 70.0\%$
Tourism output value (TOV) (x3)	-0.0429(-0.2664,0.1708)	$P(\beta_{x3}<0 \mid data) = 65.9\%$
Output value of secondary industry (OVSI)(x4)	0.0078(-0.1412,0.1438)	$P(\beta_{x4}<0 \mid data) = 53.1\%$
Urbanization rate (UR) (x5)	-0.0519(-0.2395,0.1161)	$P(\beta_{x5}<0 \mid data) = 70.6\%$
Resident unemployment rate (RUR) (x6)	2.5005(-0.3642,5.2979)	$P(\beta_{x6}<0 \mid data) = 95.7\%$
Resident average schooling years (RASY) (x7)	1.2781(-1.0922,4.0053)	$P(\beta_{x7}<0 \mid data) = 83.9\%$
Environmental protection tax rate (EPTR) (x8)	-0.1098(-0.6942,0.4670)	$P(\beta_{x8}<0 \mid data) = 63.7\%$
Waste gas treatment input (WGTI) (x9)	0.0523(-0.0463,0.1532)	$P(\beta_{x9}<0 \mid data) = 85.1\%$
Relief amplitude (RA) (x10)	0.2444(-0.0443,0.5310)	$P(\beta_{x10}<0 \mid data) = 95.1\%$
Heterogeneity of vegetation (HV) (x11)	0.0028(-0.1229,0.1377)	$P(\beta_{x11}<0 \mid data) = 51.9\%$

Table 2. Bayesian LASSO standardised regression coefficients of the seven variables for the EEPT.

Variables	Posterior mean of the regression parameters (95% HPD)	Posterior probability of the regression parameters
Gross domestic product (GDP) (x1)	-0.363 (-0.844,0.092)	$P(\beta_{x1}<0 \mid data) = 93.2\%$
Proportion of the secondary industry (PSI) (x2)	0.149 (-0.220,0.568)	$P(\beta_{x2}>0 \mid data) = 77.4\%$
Urbanisation rate (UR) (x5)	-0.127 (-0.576,0.332)	$P(\beta_{x5}<0 \mid data) = 70.9\%$
Resident unemployment rate (RUR) (x6)	0.392 (-0.061,0.811)	$P(\beta_{x6}>0 \mid data) = 99.9\%$
Resident average schooling years (RASY) (x7)	0.332 (-0.296,1.061)	$P(\beta_{x7}>0 \mid data) = 82.9\%$
Waste gas treatment input (WGTI) (x9)	0.218 (-0.157,0.586)	$P(\beta_{x9}>0 \mid data) = 87.2\%$
Relief amplitude (RA) (x10)	0.313 (-0.080,0.710)	$P(\beta_{x10}>0 \mid data) = 94.2\%$

Table 3. Influencing contributions and direction of the seven variables for the EEPT.

Variables	Influencing contributions	Influencing direction
Gross domestic product (GDP) (x1)	19.2%	-
Proportion of secondary industry (PSI) (x2)	7.9%	+
Urbanisation rate (UR) (x5)	6.7%	-
Resident unemployment rate (RUR) (x6)	20.7%	+
Resident average schooling years (RASY) (x7)	17.6%	+
Waste gas treatment input (WGTI) (x9)	11.5%	+
Relief amplitude (RA) (x10)	16.5%	+

The corresponding posterior mean and 95% highest posterior density (HPD) of the standardised regression coefficients and influencing contributions are listed in Tables 2 and 3. The posterior probabilities of the seven regression parameters were all greater than 70.0%. RUR and GDP were the top two influencing factors, whose influencing contributions were 20.7% and 19.2%, respectively. PSI and UR were the bottom two influencing factors, whose influencing contributions were 7.9% and 6.7%, respectively. The middle influencing factors were RASY (17.6%), RA (16.5%) and WGTI (11.5%).

Table 4 lists the non-standardised regression coefficients of the seven variables for the EEPT. The results show that GDP and UR associated negatively with the EEPT. Considering the invariability of the other variables, the EEPT would decrease to 0.15 $\mu g/m^3$ when the GDP increases to 100 billion Chinese yuan and 0.052 $\mu g/m^3$ when the UR increases by 1.0%. The other five variables (i.e. PSI, RUR, RASY, WGTI and RA) associated positively with the EEPT. Thus, the EEPT would increase when one variable increases. Furthermore, the EEPT would increase to 2.50 $\mu g/m^3$ when the RUR increases by 1.0%, 1.28 $\mu g/m^3$ when the RASY increases to 1.0 year, 0.072 $\mu g/m^3$ when the PSI increases by 1.0% and 0.052 $\mu g/m^3$ when the WGTI increases to 100 billion Chinese yuan.

Discussion

The manner by which air pollution can be effectively controlled has always been a social issue of great concern to governments. Considering years of sewage charges, China has brought the Environmental Protection Tax Law into force in 2018. However, can environmental protection tax reduce $PM_{2.5}$ pollution? Are there some differences in the EEPT in various regions? What are the influencing factors that cause the difference? This study has focused on the three above-mentioned problems.

On the basis of the monitoring $PM_{2.5}$ concentrations and meteorological data, this study firstly estimated the counterfactual daily average $PM_{2.5}$ concentrations under the condition of the non-implementation of the environmental protection tax, and then the EEPTs on the annual average $PM_{2.5}$ concentrations in the 30 provincial capital cities of China in 2018 were quantified. The results reveal that China's environmental protection tax can reduce the annual average $PM_{2.5}$ concentrations in most cities in 2018.

The estimates of the EEPT on the annual average $PM_{2.5}$ concentrations showed distinct differences in various cities. The spatial distribution of the estimated EEPTs across the 30 cities formed an obvious geographical clustering. Moreover, the spatial pattern of the absolute EEPT was similar with that of the relative percentage of the EEPT. The EEPTs in the

Table 4. Bayesian LASSO regression non-standardised coefficients of the seven variables for the EEPT.

Variables	Posterior median of the regression parameters (95% HPD)	Posterior probability of the regression parameters
Gross domestic product (GDP) (x1)	-0.15 (-0.683,0.340)	P(β_{x1}<0|data) = 93.2%
Proportion of secondary industry (PSI) (x2)	0.072 (-0.191,0.342)	P(β_{x2}>0|data) = 77.4%
Urbanisation rate (UR) (x5)	-0.052 (-0.240,0.116)	P(β_{x5}<0|data) = 70.9%
Resident unemployment rate (RUR) (x6)	2.50 (-0.364,5.298)	P(β_{x6}>0|data) = 99.9%
Resident average schooling years (RASY) (x7)	1.25 (-1.09,4.01)	P(β_{x7}>0|data) = 82.9%
Waste gas treatment input (WGTI) (x9)	0.052 (-0.046,0.153)	P(β_{x9}>0|data) = 87.2%
Relief amplitude (RA) (x10)	0.003 (-0.123,0.138)	P(β_{x10}>0|data) = 94.2%

high-$PM_{2.5}$-polluted regions, namely, Urumchi (Xinjiang Province) and the North China Plain, were also high. Except for three low-$PM_{2.5}$ -polluted areas, Harbin, Changchun and Nanchang, the EEPTs in the low- or middle-$PM_{2.5}$ -polluted cities were also correspondingly low and middle.

The influencing factors and corresponding magnitudes to the EEPT were investigated by employing the Bayesian LASSO regression model, advantaging over the usual multivariable regression based on the OLS. Among the eleven influencing factors, seven were recognised and selected. Specifically, two factors, GDP and UR, associated negatively with the EEPT, whereas the other five factors, RUR, RASY, RA, WGTI and PSI, associated positively with the EEPT. Furthermore, the influencing magnitudes or contributions of the seven influencing factors were quantified, and the descending ranks were as follows: RUR (20.7%), GDP (19.2%), RASY (17.6%), RA (16.5%), WGTI (11.5%), PSI (7.9%) and UR (6.7%).

GDP and UR are regarded as the important indicators for recognising regional economic development. Therefore, the economy generally develops better in areas with high GDP and UR. Considering the experience on air pollution control at home and abroad, inhabitants in the developed areas pay more attention to air pollution control. Compared with the underdeveloped regions, the governments of developed regions have more urgent requirements for air pollution control. Therefore, before the implementation of the environmental protection tax law, the governments of the developed areas may strictly implement the sewage charges policy and have achieved certain effects in air pollution control. Consequently, the EEPTs in the regions with high GDP and UR are lower than those in the regions with low GDP and UR when the environmental protection tax law with higher law enforcement intensity than the previous sewage charges policy begins to be implemented nationwide. In addition, the developed regions have taken the lead

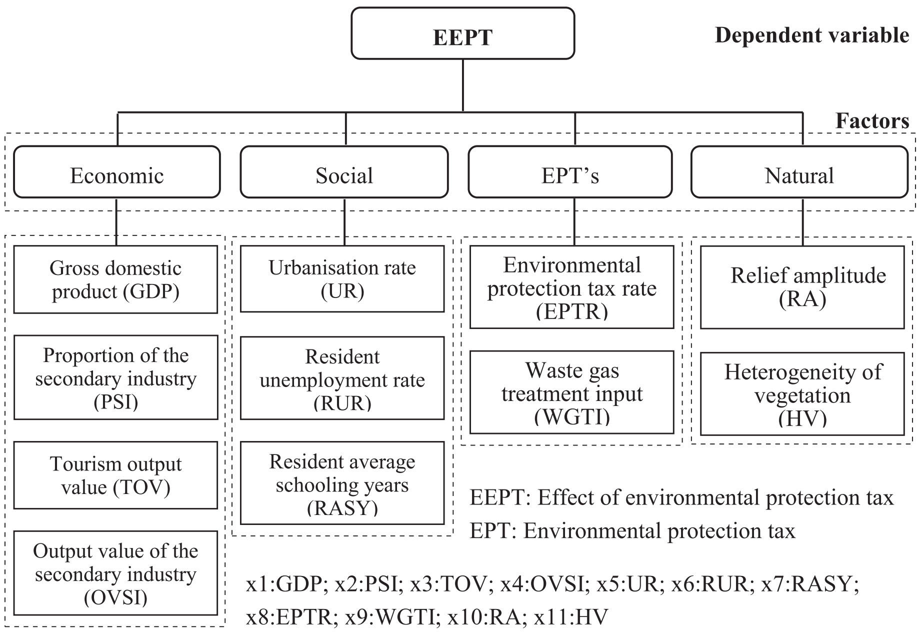

Fig. 5. Diagram of the influencing factors covering four categories of variables represented by 11 proxy variables.

in realising the transformation of industrial structure, from focusing on the development of the secondary industry to giving priority to the development of the tertiary industry, which has greatly reduced local $PM_{2.5}$ pollution. Therefore, the EEPT is not as good as that of the economically underdeveloped regions that are still vigorously developing the secondary industry.

Conversely, the RUR, RASY, RA, WGTI and PSI associated positively with the EEPT. The RUR is the main positive influencing factor of the EEPT, with an influencing contribution of 20.69%. On the one hand, before 2018, the local government in China levied sewage charges from polluting enterprises to curb pollution. As the levy authority was owned by the local government, the intensity of collection and management in different regions varied with the needs of the local economic and social development. Due to the poor economic development in the regions with high unemployment rate, local governments were eager to develop the economy, so the pollution behaviour of enterprises is relatively tolerant. However, since 2018, China has implemented the environmental protection tax law with national coercive force, which levies taxes on air pollution emissions with stricter standards than the previous sewage charges policy. For the underdeveloped areas with high unemployment rates, the implementation of the environmental protection tax law is more powerful than the previous sewage charges policy. Then, the EEPT became more significant than ever. On the contrary, $PM_{2.5}$ pollutant emission is negative externality generated during the production process. By levying environmental protection taxes, the social costs of environmental pollution and ecological damage can be internalised into the production costs of polluting enterprises, and the production costs of polluting enterprises can be increased. Therefore, for economically underdeveloped areas with high unemployment rates, imposing a stricter environmental protection tax than previous sewage charges will undoubtedly increase the cost of polluting enterprises, resulting in a further increase in the unemployment rate.

The RASY is an important indicator to measure the educational level of inhabitants in a certain region. According to the existing research [21], people with a high level of education have a relatively better understanding on environmental science and environmental protection, so the awareness of environmental protection and the degree of concern for environmental issues are high. Meanwhile, those with a high level of education have a higher level of understanding and compliance with the environmental protection tax law and thus might put more pressure on the government to implement environmental protection tax. As a result, the regions possessing inhabitants with a high level of education have a high EEPT. The other main influencing factor is the RA with an influencing contribution of 16.5%. As one of the important natural environmental factors that affect the human environment, the RA has an important impact on the diffusion of atmospheric pollutants. Specifically, when the airflow flows along the surface, friction will occur with various terrain features and the wind speed will change at the same time. The magnitude of influence to the EEPT is closely related to the shape, height and volume of the terrain, among others. For instance, the retardation of mountains has a great influence on the wind speed, especially in a closed valley basin. Due to the influence of the surrounding mountain barrier, the wind speed will rapidly drop, which is not conducive to the diffusion of atmospheric pollutants.

The WGTI is an important indicator of regional attention to air pollution control. The more the investments in waste gas treatments, the more attention to air quality is paid by the local government. Hence, the areas with a high WGTI will strengthen the collection and management of environmental taxes and strictly enforce the law when the environmental protection tax law is implemented nationwide, thereby strengthening the corresponding EEPT. The PSI is the least positive influencing factor. Generally, the secondary industry belongs to industries with high energy consumption and pollution emissions. $PM_{2.5}$ pollution is serious in areas with a high proportion of the secondary industry. According to the environmental protection tax law of China, the main object of collection for the environmental protection tax is polluting enterprises. Therefore, the EEPT in areas with a high proportion of the secondary industry is high.

According to the results, the EPTR, an important EPT's variable, is not yet a significant influencing factor to the EEPT. We argued that the setting of the EPTR should match the heterogeneity of the $PM_{2.5}$ pollution in various regions. However, most provincial regions in China have continued the regulations on sewage charges in setting the EPTR to achieve a smooth transition from sewage charges to environmental protection taxes. The present implemented EPTR is unreasonable and too rough to response to the differences of $PM_{2.5}$ pollution in different areas, not combining the requirements of local economic and social development and environmental carrying capacity. The governments of provinces, autonomous regions and municipalities in China should consider the EPTR within the scope of the tax law in light of the requirements for environmental carrying capacity, pollutant discharge status and economic and social ecological development targets in the region.

The results of this study can provide important references for the further improvement of China's environmental protection tax law and related institutional arrangements in other countries. Firstly, the local government should set the EPTR in accordance with the local economic and social development and the characteristics of the natural environment as the EPTR is an effective lever for the EEPT. Secondly, the local government should further improve the efficiency of environmental protection tax collection and management. Environmental protection tax is difficult to monitor because of its professional, so it is difficult to collect and manage. Therefore, on the one hand, the government should strengthen the collection and management of environmental protection tax, especially in areas with a high proportion of secondary industries or large relief amplitude, and strengthen the cooperation between departments and improve the efficiency of environmental protection tax collection and management. On the other hand, the government should strengthen the propaganda of environmental protection tax, increasing the compliance of the public and polluting enterprises on environmental protection tax. Thirdly, the incentive effect of environmental protection tax should be further improved. The environmental protection tax internalises the external costs of environmental pollution into the production costs of the enterprises and increases the burden on the enterprises. Hence, under the global economic downturn, the government should reduce the negative impact of environmental tax through tax incentives or subsidies to polluting enterprises and encourage polluting enterprises to actively improve technology, adjust industrial structure and promote green production. This study not only has a certain reference significance for the further improvement of China's environmental protection tax implementation and the strengthening of the collection and management but also has a certain implication for other high $PM_{2.5}$ polluted countries, such as India.

Nonetheless, this study also has limitations. Firstly, China's environmental protection tax law has not been implemented for a long time, so the term EEPT should be further studied. Secondly, due to the availability of related data and calculated quantity, our study selected the 30 provincial capital cities as the research units. Larger samples will be absorbed in future studies.

Conclusions

This paper has drawn the following conclusions. Firstly, environmental protection tax can generally reduce $PM_{2.5}$ pollution. EEPTs in the different regions of China vary. Secondly, the spatial distribution of the EEPT across the 30 cities showed a distinct geographical clustering feature, and the spatial distributions of the absolute EEPT was generally similar with that of the relative percentage of the EEPT in China, although minor differences were noted in a few regions. Thirdly, the RUR (20.7%) and GDP (19.2%) were the top two influencing factors, and the PSI (7.9%) and UR (6.7%) were the bottom two influencing factors. The median influencing factors were the RASY (17.6%), RA (16.5%) and WGTI (11.5%). Fourthly, the GDP and UR associated negatively with EEPT, and the PSI, RUR, RASY, WGTI and RA associated positively with the EEPT.

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Conflict of Interest

The authors declare no conflict of interest.

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