

Whether green technology innovation is conducive to haze emission reduction: Empirical evidence from China

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2 **Conducive to Haze Emission Reduction: Empirical**
3 **Evidence from China**

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10

11 **Abstract**

12 With the acceleration of industrialization, haze pollution has become a severe
13 environmental pollution problem, and green technology innovation is one feasible way to
14 alleviate it. Based on the PM_{2.5} concentration data of 30 provinces in mainland China from
15 2011 to 2017, we use a spatial panel model to investigate the spatial characteristics of haze
16 pollution and examine the impact of green technology innovation on it. Results show that
17 haze pollution has spatial correlation and a time lag. Its spatial correlation is associated
18 with geographical distance as well as the compound influence of distance and economic
19 development. Green technology innovation and foreign investment have inhibitory and
20 negative spillover effects on haze pollution. Industrial structure and energy consumption
21 structure play a partial intermediary role between green technology innovation and haze
22 pollution, and the former has a significant negative spillover, while the latter has a positive
23 effect. To reduce haze pollution, China should improve the level of green technology
24 innovation, use foreign investment wisely, and enhance policy support and guidance. It
25 should also promote the rationalization of industrial structure, optimize energy structure
26 and implement energy substitution. Finally, it is crucial that it should strengthen regional
27 collaborative governance and build a multi-agent governance system.

28

29 **Key words** Green technology innovation · Haze pollution control · Spatial panel

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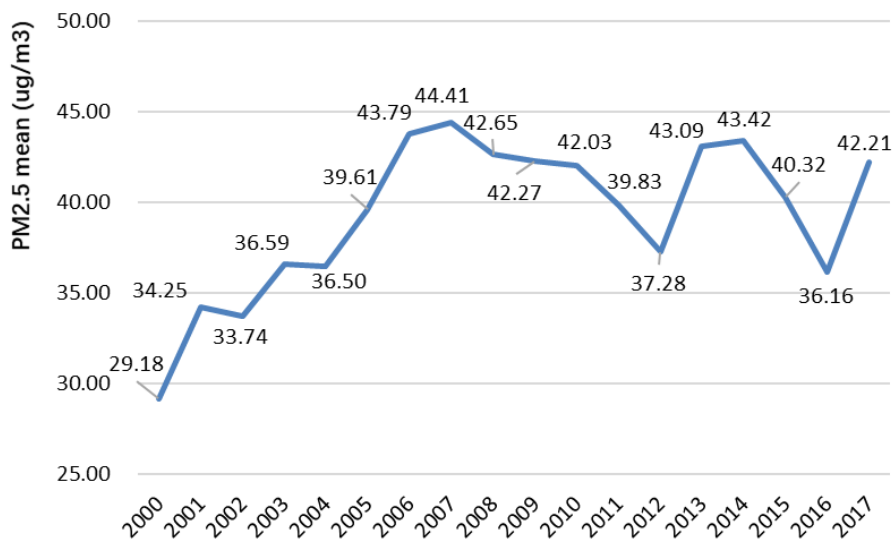
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30 Introduction

31 Due to the acceleration of China's industrialization and urbanization, environmental
32 pollution has gradually become an important issue related to national development and
33 people's life, especially haze pollution (Leeuwen and Mohen, 2013). Haze pollution mainly
34 consists of PM_{2.5}, PM₁₀ and other particles. Among them, PM_{2.5}, which is more subtle,
35 can enter the human lungs and cause more harm to the human body. Therefore, the
36 research on haze pollution mainly focuses on PM_{2.5}. Before 2007, the concentration of
37 PM_{2.5} emission in China increased rapidly, and since then it has basically stabilized in the
38 range of 36ug/m³-45ug/m³, but with large annual fluctuations (Fig. 1). Unlike developed
39 countries, the intensity and scope of environmental management in China is still relatively
40 small, making haze pollution present the characteristics of wide range, high frequency,
41 heavy pollution and serious harm. To some extent, the high level of pollutant emission
42 caused by China's rapid economic development is the fundamental reason for the high
43 incidence of haze (Xie et al., 2017), and the unreasonable economic development mode,
44 such as unbalanced industrial structure, unreasonable energy structure, insufficient
45 technological investment and inefficient environmental governance are also important
46 reasons. Solving haze pollution and winning the battle against air pollution is one of the
47 main tasks of China's economic and social development at this stage (Song, Fisher and
48 Kwoh, 2019).

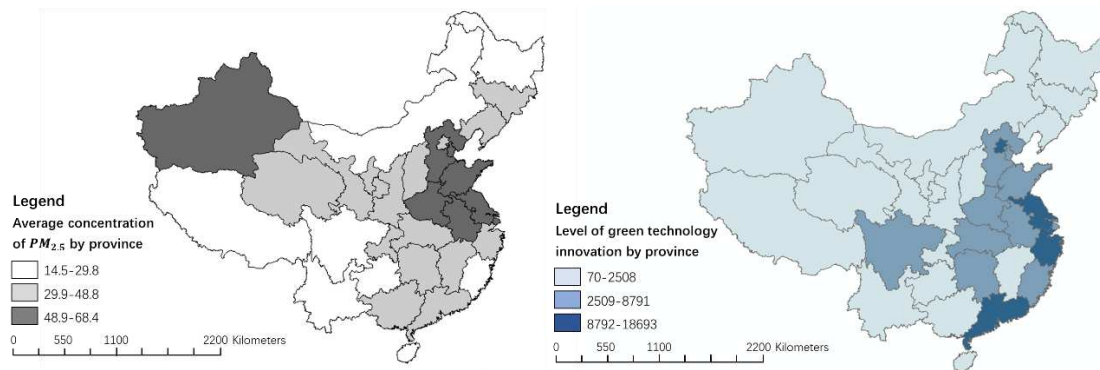


49

50 Fig.1 2000-2017 PM_{2.5} concentration changes in 30 provinces of China (except Tibet)

51 Green technology innovation taking the realization of green development as the core
52 pursuit, and focusing on providing new products, processes, services and market solutions
53 through innovations, reducing natural resource consumption, reducing ecological
54 environmental damage, improving resource allocation efficiency, which could provide

55 power for China to achieve high-quality economic development. Based on the rapid
 56 development of green technology innovation and the above environmentally friendly
 57 characteristics of green technology innovation, combined with the affirmation of the
 58 existing research results on the haze reduction effect of green technology innovation, we
 59 focus on the study of green technology innovation on haze reduction to explore whether
 60 China's green technology innovation can indeed alleviate haze pollution? The research will
 61 enrich China's haze control methods and provide the necessary decision -- making basis
 62 for the formulation of haze control policies.



63

64 Fig.2 Distribution of average $PM_{2.5}$ concentrations and green technology innovation
 65 levels by province in mainland China in 2017

66 Fig.2 shows the distribution of $PM_{2.5}$ and green technology innovation levels by
 67 province in mainland China in 2017, from which it can be seen that haze pollution in China
 68 is mainly concentrated in eight regions -- Hebei, Tianjin, Shandong, Henan, Anhui, Jiangsu,
 69 Shanghai and Xinjiang. And southwest China is less polluted. The regions with higher
 70 levels of green technology innovation are Beijing, Jiangsu, Zhejiang and Guangdong.
 71 Therefore, the relationship between green technology innovation and haze pollution is not
 72 obvious intuitively, and a spatial econometric model needs to be constructed to investigate
 73 this issue.

74 The main contributions of this paper are as follow: First, based on three commonly
 75 used spatial measurement models, the spatial correlation effect of haze pollution at the
 76 provincial level in China is studied. Second, the haze abatement effect of green technology
 77 innovation in China is analyzed based on the weight matrix of geographical distance,
 78 economic weight matrix and nested weight matrix of geographical and economic distance.
 79 Third, the green technology innovation of each province is measured by the number of
 80 green patent applications and $PM_{2.5}$ refers to haze pollution, which is innovative.

81 Literature review

82 Haze is the result of the interaction between specific climatic conditions and human
 83 activities. With the increasing pollution of the atmosphere caused by human activities,

84 haze pollution has become a key issue of social concern. In 1995-1999, the international
85 scientific cooperation project "INDOEX" conducted a comprehensive study on
86 atmospheric brown cloud (ABC) and its impact on climate for the first time. It was found
87 that the haze layer over the Indian Ocean, South Asia, Southeast Asia and East Asia has a
88 high content of soot, which mainly comes from the combustion of fossil fuels and biofuels.
89 Based on this experiment, in August 2002, the United Nations Environment Program
90 officially launched the international ABC research project (Ramanathan et al., 2001). The
91 research results of Chun-Chung and Vernon (2006) show that haze pollution will affect
92 China's economic development by influencing the process of urbanization. Chen and Chen
93 (2018) further found that haze pollution greatly reduces the quality of China's economic
94 development and has a particularly significant impact on large cities. Guan et al. (2014)
95 studied the drivers of haze pollution in China by using structural analysis method, and
96 found that capital formation and export production are important causes of haze pollution.
97 It has also been empirically verified that haze pollution has significant spatial
98 characteristics (Ma and Zhang, 2014). Based on the spatial Durbin model, Ma et al. (2016)
99 found that China's coal-based energy consumption structure is an important factor that
100 affects haze pollution.

101 Green technological innovation is also called ecological technological innovation. It is
102 a technological innovation that promotes the coordinated development of man, nature and
103 society for the purpose of saving resources and energy and protecting the environment. In
104 1994, Braun and Wield first proposed the concept of "green technology innovation" (Braun
105 and Wield, 1994). And then the concept was introduced to China. Chinese scholars Chen
106 and Wang (1998) first investigated the incentive mechanism of green technology
107 innovation. The "Green Economy Initiative" of the United Nations Environment Program
108 in 2008 and the Copenhagen Conference in 2009 and other related events have made green
109 technology innovation a topic of global concern and the relevant literature has also been
110 enriched. Although China's green technology innovation has made great progress in
111 recent years, it is still in a stage of insufficient development and it is far from completely
112 relying on green technology to develop production (Wang et al., 2019); Luo and Liang
113 (2016) calculated the technological innovation efficiency of China's industrial enterprises
114 through principal component analysis and found that there is a significant regional gap
115 between the eastern, central and western regions, and the gap is still widening.

116 There are direct and indirect relationships between green technological innovation
117 and haze pollution. Existing studies by domestic and foreign scholars have directly
118 discussed the effects of technological innovation on haze emission reduction and have also
119 studied technological innovation on carbon emissions and energy efficiency. The
120 intermediary factors of the indirect impact of pollution are used to explore the emission
121 reduction effect of green technological innovation.

122 In the research on the direct relationship between green technological innovation and
123 haze pollution, Liu (2018a) used the nuclear density method to analyze the dynamic
124 evolution and spatial spillover effects of China's technological innovation and haze
125 pollution. The results showed that technological innovation can not only reduce the
126 province's Haze pollution can also indirectly lead to a decrease in the degree of haze
127 pollution in neighboring provinces through knowledge spillover effects. Liu (2018b) used
128 the spatial Dubin model to analyze the impact of technological innovation on China's
129 PM2.5. The empirical results showed that technological innovation could significantly
130 reduce PM2.5 emissions in the region, neighboring regions, and the world. Yi et al. (2020)
131 considered the heterogeneity of technological progress and analyzed the impact of
132 different technological advances on haze pollution and found that due to the cost
133 reduction effect and income effect, neutral technological progress and technological
134 progress that reduce labor input are beneficial to the haze. However, technological
135 progress that reduces resource input has no significant impact on haze pollution. In
136 addition, due to the energy rebound effect, energy-saving technological progress cannot
137 effectively reduce haze pollution.

138 In exploring the indirect impact of green technological innovation on haze pollution,
139 scholars often conduct research on the influence of green technological innovation on
140 intermediary factors such as carbon emissions or energy efficiency. Regarding carbon
141 emissions, Honjo (1996) came to the conclusion that green technology innovation reduced
142 carbon emissions through research. Apergis et al. (2013) believed that through green
143 technology innovation, enterprises obtained green technology and produced green
144 products to reduce carbon emissions. Carbon emissions in the production process, thereby
145 reducing environmental pollution. Du et al. (2019) found that in economies with income
146 levels above the critical value, green technology innovation has a significant effect on
147 carbon emissions reduction. Regarding energy efficiency, Garbaccio et al. (1999) studied
148 the reasons for the sharp decline in China's energy output ratio from 1978 to 1995 and
149 decomposed the reduction in energy consumption into technological changes and various
150 types of structural changes, and found that technological changes were the main reason.
151 The structural changes have increased energy use. Fisher Vanden et al. (2006) also studied
152 the reasons for the increase in energy productivity in China's industrial sector and came
153 to a conclusion similar to Garbaccio that technological progress and industrial structure
154 optimization are both important factors. Wurlod and Noailly (2018) studied green
155 technology innovation in the industrial sector of OECD countries. Results showed that
156 green patent activities in a specific sector increased by 1% and energy intensity decreased
157 by 0.03% and the phenomenon has become more pronounced in recent years. Therefore,
158 existing studies proved that green technological innovation could improve energy
159 efficiency and effectively reduce carbon emissions in production activities. Carbon
160 emission itself has little effect on haze pollution, but its by-products, such as the

161 production of particulate matter in combustion, will aggravate haze pollution. In addition,
162 low energy use efficiency is the root cause of air pollution. It may be possible to improve
163 energy efficiency through technological innovation Effectively improve haze pollution,
164 which also shows to a certain extent that green technological innovation has the effect of
165 mitigating and inhibiting environmental pollution.

166 To sum up, most of the existing literature on green technology innovation and haze
167 pollution researches focus on the indirect impact of green technology innovation on haze
168 pollution and the research literature in this area is relatively abundant. There are relatively
169 few documents that specifically explore the direct relationship between green
170 technological innovation and haze pollution or model the two together to study the haze
171 reduction effect of green technological innovation. Based on the above practical reasons
172 and research background, we take the main "culprit" of haze pollution--PM2.5 and the core
173 indicator of green technology innovation research--the number of green patent
174 applications (Brunnermeier and Cohen, 2003) as the research object. A spatial panel data
175 model is used to empirically test the haze reduction effects of China's inter-provincial
176 green technology innovations to find out the specific effects of green technology
177 innovations on haze pollution, and to find other ways to reduce haze pollution and
178 effectively prevent haze pollution. The research perspective of this paper is relatively
179 innovative, which enriches the empirical research in this field to a certain extent and
180 provides corresponding theoretical reference for China's haze reduction.

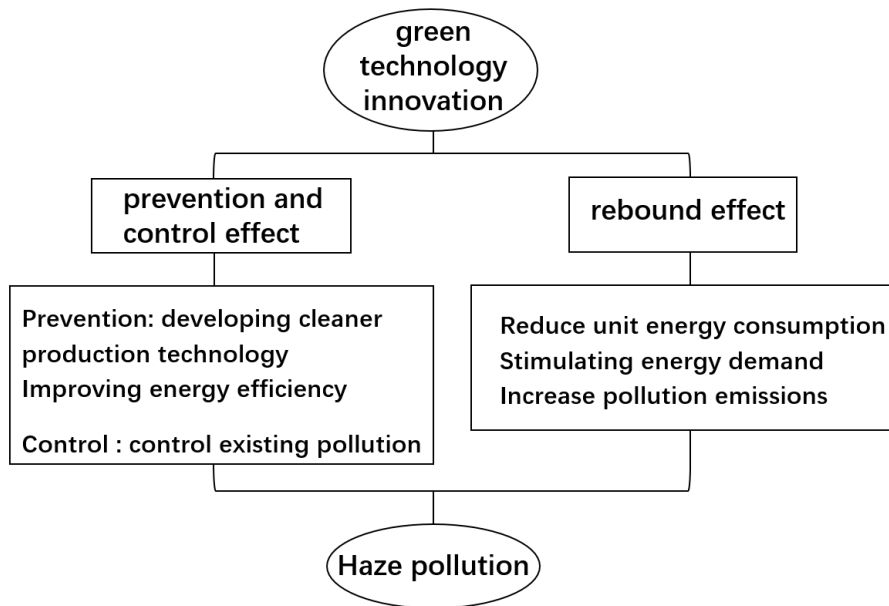
181 Influence mechanism

182 The effect of green technological innovation on the prevention and treatment of
183 environmental pollution is self-evident. From the perspective of product life cycle analysis,
184 green technology innovation follows ecological principles and ecological economic laws,
185 and integrates environmental principles at each stage of the innovation process, which not
186 only pays attention to the production cost of the product, but also pays attention to the
187 social and ecological costs of the product to realize the product .The goal is to minimize
188 the total cost of the entire life cycle, which has the characteristics of saving resources and
189 energy and conforming to sustainable development.

190 The impact of green technological innovation on haze pollution mainly comes from
191 two aspects (Fig.3). On the one hand, green technological innovation has a "prevention
192 effect" on haze pollution, which can reduce haze pollution and improve environmental
193 quality. First, green technology innovation improves production methods, optimizes
194 corporate production structure, and develops cleaner production technologies to solve the
195 problem of haze pollution at the source and reduce the difficulty of back-end governance.
196 Second, green technology innovation improves Energy utilization in the production
197 process to reduce the use of high-polluting energy so as to improve enterprise production

198 efficiency and reduce enterprise pollution emissions (Cai and Li, 2018). The above two
 199 methods could reduce the main pollutants that form haze from the source emissions, such
 200 as PM_{2.5}. Third, through green technological innovation to improve the efficiency of the
 201 treatment of pollution that has already occurred, alleviate the degree of haze pollution and
 202 achieve the goal of treating haze pollution.

203 On the other hand, technological innovation may also hinder the treatment of haze
 204 pollution to a certain extent. Research by Sun et al. (2012) found that technological progress
 205 has increased haze pollution since the 1990s. Li and Zhou (2006) believed that the
 206 phenomenon was caused by the “rebound effect” of energy caused by technological
 207 progress, that is, on the basis of constant energy prices, green technological innovation has
 208 reduced energy consumption per unit of output. However, it will stimulate enterprises to
 209 increase the use of energy, resulting in an increase in the final consumption of energy,
 210 leading to an increase in pollutant emissions and aggravating haze pollution. Based on the
 211 above discussion, it can be seen that the impact of green technological innovation on haze
 212 pollution has two sides, and its final impact depends on the combined effect of the
 213 "prevention effect" and the “rebound effect”.



214 Fig.3 The double impact of green technology innovation on haze pollution

215 Research model design

216 Based on the above theories, a spatial panel model is constructed to empirically estimate
 217 the impact of green technology innovation on haze pollution. It is noteworthy that haze
 218 pollution is expected to spatially correlate across regions due to atmospheric circulation,
 219 industrial transfer and inter-regional traffic flow. Thus, we should consider the spatial
 220 characteristics of haze pollution. The results of Xiao et al. (2019) show that there is an

221 apparent spatial correlation of green innovation among provinces in China. Moran's I
 222 index is used to test whether haze pollution has spatial correlation, and its calculation
 223 formula is as follows.

$$224 \quad I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{j=1}^n (x_i - \bar{x})^2} \quad (1)$$

225 Where n is the 30 provinces in mainland China except Tibet. w_{ij} is the spatial weight
 226 matrix. x and \bar{x} are $PM_{2.5}$ concentrations and their mean values for each province,
 227 respectively.

228 Construction of spatial weight matrix

229 In this paper, three spatial weight matrices are structured to measure the spatial correlation
 230 of haze pollution (Getis, 2009). Geographic distance weight matrix considers the
 231 geographic distance between provinces, which is the reciprocal square of the distance
 232 between the geographical centers of provinces i and j (Zhang et al., 2020):

$$233 \quad W_1 = w_{ij} = \begin{cases} 1/d_{ij}^2 & i \neq j \\ 0 & i = j \end{cases} \quad (2)$$

234 Where d_{ij} is the distance between the geographic centers of provinces i and j .

235 Economic weight matrix considers the differences in economic development levels
 236 between provinces (Du et al., 2018). The more similar the level of economic development
 237 is, the greater the spatial weight coefficient is. The formula is as follows:

$$238 \quad W_2 = w_{ij} = \frac{1}{|Y_i - Y_j|} \quad (3)$$

239 Where Y represents the economic development level of each province, and it is
 240 usually expressed by GDP per capita.

241 Nested weight matrix of geographical and economic distance considers the radiation
 242 effect of geographic distance and economic factors. The formula is as follows:

$$243 \quad W_3 = \varphi W_1 + (1 - \varphi) W_2 \quad (4)$$

244 Where φ represents the proportion of the geographic distance weight matrix,
 245 between 0-1. In order to simplify the analysis, in this paper, the value of φ is 0.5.

246 Basic model setting

247 In order to better empirically test the impact of green technology innovation on haze
 248 emission reduction, on the basis of the above theoretical model, the following basic panel

249 model is constructed in this paper:

$$\begin{aligned} 250 \quad \ln PM_{it} = & \gamma_0 + \gamma_1 \ln GP_{it} + \gamma_2 \ln PD_{it} + \gamma_3 \ln AFC_{it} + \gamma_4 \ln IS_{it} + \gamma_5 \ln EC_{it} \\ 251 \quad & + \gamma_6 \ln FDI_{it} + \varepsilon_{it} \end{aligned} \quad (5)$$

252 In the above equation, $\ln PM_{i,t}$ is the explained variable, indicating the natural
253 logarithm of haze pollution for province i in year t , which is measured by $PM_{2.5}$
254 concentration in this paper. GP is the core explanatory variable, indicating the degree of
255 green technology innovation, which is measured by the number of green patent
256 applications. The remaining five variables are control variables, respectively: PD is the
257 population density of each province (Liu et al., 2017). AFC represents the air circulation
258 coefficient, which measures the degree of atmospheric circulation between regions. IS
259 represents the industrial structure advanced index, reflecting the level of industrial
260 structure advanced in each province. EC represents energy consumption structure, that is,
261 the proportion of coal consumption in total energy consumption. FDI refers to the
262 proportion of actual use of foreign direct investment in local GDP, which measures the
263 level of regional openness. γ_0 represents the constant term and γ_1 to γ_6 respectively
264 represent the regression coefficient of each variable. ε represents the random disturbance
265 term. The purpose of this paper is to empirically test green technological innovation, that
266 is, whether the core explanatory variable GP can inhibit haze pollution ($PM_{2.5}$).

267 Construction of spatial econometric model

268 Spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM) are
269 commonly used spatial econometric models of panel data. They respectively focus on
270 measuring the spatial effects caused by the spatial correlation of the explained variables,
271 error terms and explanatory variables. Their basic forms are as follows (Elhorst, 2014):

272 (i) Spatial lag model (SLM)

$$273 \quad y = \rho W y + \alpha \tau_N + X \beta + \varepsilon \quad (6)$$

274 (ii) Spatial error model (SEM)

$$275 \quad y = \alpha \tau_N + X \beta + u \quad (7)$$

276 The generating process of the disturbance term u is as follows:

$$277 \quad u = \delta W u + \varepsilon \quad (8)$$

278 (iii) Spatial Durbin model (SDM)

$$279 \quad y = \rho W y + \alpha \tau_N + X \beta + W X \theta + \varepsilon \quad (9)$$

280 In above equations, y is the $N \times 1$ dimensional vector composed of the explanatory
281 variables. W is the spatial weight matrix, and $W y$ is the endogenous interaction effect

282 between dependent variables. X is the independent variable, which is an $N \times K$
 283 dimensional vector. WX is the exogenous interaction effect between independent
 284 variables. ρ is the spatial autoregressive coefficient, represents the degree of spatial
 285 relevance, which measures the impact Wy on y . τ_N represents the order unit matrix,
 286 which is an $N \times 1$ dimensional vector associated with the constant parameter α to be
 287 estimated. θ and β are $K \times 1$ dimensional vectors with fixed parameters to be estimated.
 288 δ is the spatial autocorrelation coefficient, and ε is the random error term.

289 Variable description and data source

290 This paper selects panel data from 30 provinces in mainland China for 2011-2017 to
 291 conduct an empirical study (Tibet has not been included in the study due to lack of data).
 292 Due to the late start of $PM_{2.5}$ monitoring in China, the $PM_{2.5}$ data used in this paper are
 293 from the atmospheric composition analysis group of the United States. Green patent
 294 authorization data are from China patent database. The industrial structure advanced
 295 index is calculated by using the original data of China Statistical Yearbook and referring to
 296 the calculation method proposed by Fu (2010). Other data source from the National Bureau
 297 of Statistics of China (NBS), the China Statistical Yearbook (2011-2017) and the EPS (Easy
 298 Professional Superior) data platform. Table 1 describes these variables. Table 2 presents the
 299 corresponding descriptive statistics of variables.

300 **Table 1** Variable description

Variable	Meaning	Unit
PM	the annual average value of $PM_{2.5}$ emissions, measuring the haze pollution degree	ug/m^3
GP	Green patent authorizations, measuring the level of green technology innovation	term
PD	population density, expressed by the ratio of the number of resident population at the end of the year and the land area of each province	person/km ²
AFC	air flow coefficient, measuring the degree of air flow between different regions	/
ISI	industrial structure advanced index, measuring the advanced level of the industrial structure	/
EC	energy consumption structure, the proportion of coal consumption in total energy consumption, measuring the impact of coal use on haze pollution	%
FDI	the actual use of foreign direct investment as a proportion of local GDP, measuring the region's openness to the outside world.	%

301

302 **Table 2** Descriptive statistics of variables

Variable	Obs	Mean	Std	Max	Min
PM	210	40.33	15.42	82.2	10.2
GP	210	2764.01	3411.77	18693	20.0
PD	210	465.38	693.20	3825.69	8.15
AFC	210	7.35	0.75	8.52	4.4
ISI	210	6.62	0.30	7.61	6.1
EC	210	67.52	30.13	152.93	4.91
FDI	210	2.29	2.05	12.10	0.04

303 **Analysis of empirical results**

304 Based on model (5), combined with the spatial panel data model, the following investigate
 305 the impact of green technology innovation on haze pollution.

306 **Spatial correlation test**

307 Moran's I test is used to check the existence of spatial autocorrelation in $\ln PM$. The
 308 Lagrange Multiplier (LM) test (Anselin, 1988) and the robust LM test (Anselin et al., 1996)
 309 are used to justify whether we select a spatially lagged term of $\ln PM$ or a spatial error
 310 term. Table 3 reports the test results under three weight matrices, i.e., the geographic
 311 distance weight matrix (W_1), the economic weight matrix (W_2), and the nested weight
 312 matrix of geographical and economic distance (W_3). The test results show that the Moran's
 313 I test statistics are significant at the 1% level of significance, indicating that haze pollution
 314 has significant spatial correlation, in relation to geographical space, economic
 315 development level and the comprehensive impact of the two. Under W_1 and W_3 , both
 316 LM and robust LM tests show that the null hypotheses of no spatially lagged $\ln PM$ and
 317 no spatially lagged error term are rejected at the 1% level of significance. Under W_2 , the
 318 LM test results further show that the null hypothesis of no spatially lagged $\ln PM$ cannot
 319 be rejected and no spatially lagged error term must be rejected, justifying that the spatial
 320 error model should be selected.

321 **Table 3** Results of spatial correlation test

	Distance W_1	Economic W_2	Nested W_3
Moran's I	1.4e+05***	175.069***	478.594***
LM test: no spatial error	68.827***	16.174 ***	208.948***
Robust LM test: no spatial error	62.953***	16.679***	205.277***
LM test: no spatial error	9.982***	0.012	9.251***

lag			
Robust LM test:			
no spatial lag	4.108**	0.517	5.580**

322 Note: *, **, *** denote statistical significant at 10%, 5% and 1% confidence levels respectively.

323 Model selection

324 As in the previous analysis, there are mainly three spatial measurement models: SLM, SEM
325 and SDM. In order to choose a more suitable model, a spatial diagnostic test is required.
326 Table 4 shows the parameter estimation results of SLM, SEM and SDM models based on
327 W_1 , W_2 and W_3 , respectively. Take the matrix W_3 as an example. Firstly, the Hausman
328 test is used to determine whether to choose a random effect or a fixed effect. The results
329 show that the SLM model accepts the null hypothesis of random effects, while the SEM
330 model and SDM model significantly reject the null hypothesis of random effects and fixed
331 effects should be selected. Secondly, based on the choice of fixed effects, a joint significance
332 test should also be performed to further determine whether the model should choose
333 individual fixation, time fixation or dual fixation. The null hypothesis of LR test (ind-
334 both/time-both) is that individuals/time fixed effects should be selected. The results of LR
335 test show that SEM model should choose individual fixed effect, while SDM model should
336 choose individual and time double fixed effect. Finally, the LR test is again applied to select
337 the better model. The original hypothesis of LR test (ind-both/ time-both) is that
338 individual/time fixed effects should be selected. The results of LR test show that the SEM
339 model should select individual fixed effects, while the SDM model should select individual
340 and time double fixed effects. Finally, use the LR test again to select a better model. The
341 null hypothesis of this test (SDM-SLM / SDM-SEM) is that the SLM/SEM model should be
342 selected. The test results of SDM model vs. SLM model and SDM model vs. SEM model
343 show that the SDM model has significant advantages, so SDM should be selected. And the
344 results of AIC also support this conclusion. Therefore, under the matrix W_3 , the SDM
345 model is a better model. In the same way, the same test is performed on the spatial
346 measurement model based on the matrix W_1 and W_2 . The results of Hausman test and
347 LR test show that under the matrix W_1 , the double fixed SDM model has better fitting
348 degree (According to relevant research, from the perspective of experience, a negative
349 Hausman test can be seen as a signal to reject the original hypothesis, so we should prefer
350 to choose fixed effect. (Lian et al., 2014). Under the matrix W_2 , the dual-fixed SLM model
351 fits better, which is contrary to the conclusion of the LM test above. Moreover, the value of
352 spatial ρ of the SLM model is not significant. It can be concluded that under the matrix
353 W_2 , the possibility of the spatial correlation of haze pollution is low. Therefore, the
354 subsequent analysis of the SLM model under the matrix W_2 will not be done in the
355 following, but the analysis will be focused on the SDM model under the matrix W_1 and
356 W_3 . Based on the above analysis, regression analysis is performed on models with a higher
357 degree of fit under the matrix W_1 and W_3 respectively to explore the haze reduction

358 effect of green technological innovation.

359 **Table 4** Spatial diagnostic tests

	Distance W_1			Economic W_2			Nested W_3		
	SLM	SEM	SDM	SLM	SEM	SDM	SLM	SEM	SDM
Hausman	5.27	-17.97	24.84 ***	-1.39	6.67	-13.48	0.70	56.88** *	15.59**
	re	fe	fe	fe	re	fe	re	fe	fe
LR test (ind-both)		10.26	37.12** *	62.76** *		38.08** *		9.76	58.30** *
LR test (time-both)		608.77 ***	599.33 ***	589.47 ***		563.89 ***		597.67 ***	598.70 ***
LR test (SLM-SDM)			220.43 ***			8.19			249.17 ***
LR test (SEM-SDM)			39.93 ***			235.97 ***			69.91 ***
ρ	0.8190 ***		0.5257 ***	0.0256		0.0825	0.8467 ***		0.4132 **
δ		0.8359 ***			0.5845 ***			0.8607 ***	0.8359 ***
AIC	- 275.85	- 460.35	- 488.28	- 421.77	- 190.00	- 417.97	- 245.77	- 429.03	- 486.95

360 Note: *, **, *** denote statistical significant at 10%, 5% and 1% confidence levels respectively.

361 **Regression analysis**

362 **Analysis of regression results**

363 Based on the results of the spatial diagnostic test, the SDM model under the matrix
 364 W_1 and the matrix W_2 has batter fitting degree for sample data. Therefore, the regression
 365 results of the SDM model under the matrix W_1 and the matrix W_3 are listed, and
 366 compared with the OLS results. The specific results are shown in Table 5.

367 **Table 5** Model estimation results

Variable	OLS	SDM model based on	
		distance W_1	distance W_3
lnGP	0.0401	-0.0626	-0.1323***
lnPD	0.2373***	0.3167	0.6443
lnAFC	-1.9802***	0.0739	0.1603
lnISI	0.8033	0.1949	-0.5277
lnEC	0.1886***	0.0881*	0.1484***

lnFDI	-0.0659**	-0.0266*	-0.0489***
L. lnPM		0.3397***	0.3275***
ρ		0.5257***	0.4132**
WlnGP		-0.4436***	-1.9346***
WlnPD		1.8510	6.6474*
WlnAFC		1.0623**	2.2868**
WlnISI		-7.3341***	-22.9147***
WlnEC		0.2680**	1.0582***
WlnFDI		-0.0740	-0.4255***

368 Note: *, **, *** denote statistical significant at 10%, 5% and 1% confidence levels respectively.

369 According to the above regression results, it is found that:

370 First, ignoring the spatially related effects affects the effect of the explanatory variables
371 on the explained variables and the extent of their effect. First of all, on the coefficient signs
372 of the core explanatory variables, the SDM model based on the matrix W_3 has consistent
373 and opposite variable coefficient signs to the OLS model, which shows that when
374 considering the spatial effect, the core explanatory variables will have a completely
375 opposite impact on the explained variables by adding the spatial effect, indicating that the
376 variables and sample data in this study have obvious and non-negligible spatial correlation.
377 And then, on the absolute values of the coefficients of the core explanatory variables, the
378 estimates of the SDM model are greater than those of the OLS model, indicating that the
379 simple non-spatial OLS model underestimates the degree of influence of the core
380 explanatory variables on haze pollution because of ignoring the spatial correlation
381 between the variables.

382 Second, the spatial correlation of China's haze pollution is significant. The spatial ρ
383 is significantly positive, indicating that the haze pollution between regions has significant
384 spatial correlation and strong spillover effects. Geographical distance and the combined
385 factors of geography and economy are both important factors that affect the degree of
386 regional haze pollution: when the two places are geographically close, the exchange of
387 production and other activities between the two places makes them have more similar haze
388 pollution conditions. It is precisely because of the spillover effect of haze pollution that it
389 is impossible for a region to complete haze control work alone, nor can it be deliberately
390 to improve the local atmospheric environment simply by transferring pollution-intensive
391 industries to neighboring regions. Although this method may temporarily improve the
392 local environmental quality, pollution from neighboring areas will inhibit this
393 improvement. Therefore, the management of haze pollution requires the coordinated
394 participation of multiple entities.

395 Third, GP, EC and FDI are all conducive to haze reduction. The core explanatory
396 variable GP has a significant inhibitory effect on haze pollution. The estimated results of

397 the SDM model based on the matrix W_3 show that for every 1% increase in regional green
398 technology innovation, local haze pollution will be reduced by 0.1323%. In addition, EC
399 and FDI also have different effects on haze pollution: the optimization of EC can effectively
400 reduce haze pollution. For every 1% reduction in the proportion of coal consumption in
401 total energy consumption, haze pollution is reduced by 0.1484%. This is the same as the
402 research conclusion of Shao et al. (2016). And every 1% increase in FDI will reduce haze
403 pollution by 0.0489%, which is in line with the "pollution halo" hypothesis: FDI can be
404 achieved by introducing environmentally friendly technologies and products improve the
405 environmental quality of a country. In general, the effect of GP on haze pollution is limited.
406 On the one hand, China's GP is still in the development stage, the level still needs to be
407 improved, and the scale still needs to be expanded. On the other hand, the haze pollution
408 control measures need to be optimized. In the treatment of haze pollution, a multi-pronged
409 approach is needed to coordinately optimize the energy consumption structure and
410 increase the positive spillover of foreign capital to achieve significant results.

411 Fourth, the time lag of the explanatory variables is significantly positive. Considering
412 that the pollutants of air pollution such as haze are often cumulative, there is a certain
413 "time lag" between cause and effect, that is, when the current haze pollution is at a high
414 level, the haze pollution level of next phase may continue to rise, thus showing a "snowball
415 effect" (Shao et al., 2016). Therefore, the time lag term of the explanatory variable haze
416 pollution is added to the SDM model as an explanatory variable. The results show that
417 haze pollution has a significant time lag. At a significance level of 1%, the previous haze
418 pollution significantly affected the current pollution level, which is manifested in that for
419 every 1% increase in the previous haze pollution, the current haze pollution will increase
420 by 0.3397% and 0.3275% respectively.

421 **Analysis of spillover effects**

422 Since the coefficients of the explanatory variables in the spatial panel data model do not
423 reflect the spatial effects, the spatial spillover effects of each variable on haze pollution are
424 listed below. The results are shown in Table 5. As we can see:

425 First, the symbol correspondence of spillover effect of the two models is consistent,
426 which indicates that the spillover effect is relatively stable and the model has good
427 robustness.

428 Second, GP has obvious negative spillover effect. The direct effect of GP on haze
429 pollution is not significant in matrix W_1 . But the spillover effect of it is significant in both
430 matrices, indicating that local GP has a significant inhibitory effect on haze pollution in
431 adjacent regions. GP has the positive externalities of knowledge and technology spillover,
432 and the government should guide it with policies and regulations to give full play to its
433 positive externalities.

434 Third, PD, AFC, ISI, EC, and FDI have significant spillover effects on haze pollution.
435 Firstly, the accumulation of population often aggravates haze pollution through
436 consumption, travel, production and so on. The regression results show that PD has a
437 significant positive spillover effect on haze pollution under W_3 , indicating that population
438 has aggravated haze pollution, which is the same as the research conclusion of Shao et al.
439 (2019). Secondly, AFC promotes similar haze pollution in neighboring areas. Thirdly,
440 Changes in industrial structure has obvious spillover effect on haze pollution. When
441 Zhang et al. (2020) studied the spatial impact of industrial structure on haze pollution, they
442 also came to the conclusion that industrial structure has an inhibitory effect on haze
443 pollution, and further divided industrial structure changes into two major categories:
444 rationalization and upgrading. During the sample period, only the rationalization of the
445 industrial structure played a role in reducing haze. In this paper, due to the rationalization
446 of the industrial structure, every 1% increase in the local ISI will reduce the haze pollution
447 in neighboring areas by 7.3341%, and reduce the haze pollution in neighboring areas with
448 similar economic development levels by 22.9147%, which has a profound impact. We
449 believe that this is due to the differences in the level of economic and technological
450 development between regions, and the transfer of pollution by the industrial echelon will
451 cause transboundary pollution between regions. The development of local green
452 technology innovation has promoted the higher level of local industrial structure, reduced
453 high-polluting industries transferred to neighboring areas, and reduced haze pollution.
454 Fourthly, the spillover effect of EC on haze pollution is significant. The results of SDM
455 model based on W_1 and W_3 respectively show that a 1% decrease in the proportion of
456 coal consumption in total energy consumption will reduce the haze pollution in
457 neighboring areas by 0.2680%, and the decline in neighboring areas with similar economic
458 development levels will be even greater. More, 1.0582%. Currently, coal ranks first in
459 China's energy consumption structure. In the long run, changing the energy consumption
460 structure is the key, but it is difficult to change it in the short term. Then increasing the use
461 of high-quality energy, especially the use of high-quality coal, is the main way to reduce
462 haze in the short term (Ma and Zhang, 2014). Finally, FDI also has a negative spillover
463 effect on haze pollution. For every 1% increase in FDI, haze pollution in neighboring areas
464 with similar economic development levels will be reduced by 0.4255%.

465 **Analysis of mediating effects**

466 Mediating effect means that the influence relationship between variables (X to Y) is
467 not a direct causal chain relationship, but is produced through the indirect influence of one
468 or more variables (M). In this case, we call M as a mediating variable, and through M the
469 indirect influence X on Y called the mediation effect.

470 Based on the regression results of the above spatial panel model, the direct impact of
471 GP on haze pollution is not significant or the degree of impact is not obvious, while the

control variables of ISI, EC and FDI have considerable impact on haze pollution. Can GP influence changes in the ISI, EC, and FDI to promote the development of haze emission reduction? Combining the "prevention and control effect" and "rebound effect" of GP on the impact mechanism of haze pollution -- the "prevention effect" brought by the development of cleaner production technologies, the improvement of energy utilization efficiency and the improvement of pollution control methods can reduce haze pollution. The increase in energy use efficiency leads to a reduction in unit energy consumption and a reduction in costs. On the contrary, it stimulates the "rebound effect" brought about by the increase in energy demand, which will expand haze pollution. The following applies the intermediary effect model, using ISI, EC and FDI as intermediary variables to explore the transmission mechanism between GP and haze pollution, and broaden the ways to prevent haze pollution.

Simulation study have found that "Bootstrap method" has higher statistical power than other methods of intermediary effect test (Song et al., 2012). Therefore, based on this method, this paper uses Stata14 to test the intermediary effect of sample data. The original hypothesis is that there is no mediating effect. The results are shown in Table 6.

Table 6 Results of the mediating effect test

Intermediary variable	Direct effect	Indirect effect
ISI	0.0014***	-0.0004*
EC	0.0014***	-0.0002**
FDI	0.0014***	-0.0002

Note: *, **, *** denote statistical significant at 10%, 5% and 1% confidence levels respectively.

It can be seen from the results that the direct and indirect effects of I and EC on haze pollution are both significant, indicating that ISI and EC play a part of the mediating role in green technological innovation and haze pollution. The indirect effect of FDI on haze pollution is not significant, but the direct effect is significant, indicating that there is no intermediary effect. The proportion of secondary industry in China's industrial structure and the abnormally high proportion of coal in the energy consumption structure are the important reasons for haze pollution. Therefore, promoting the rationalization of industrial structure, reducing the proportion of pollution-intensive enterprises and increasing energy technology innovation, reducing the use of disposable energy such as coal, realizing energy substitution, and adjusting the energy consumption structure are the keys to achieve haze control (Wei et al., 2015).

Robustness test

Considering the robustness of the model and preventing accidental conclusion, another measurement model, the GMM model, was chosen to re-estimate the model in this paper,

504 and the results are shown in Table 7.

505 **Table 7** Estimation results of robustness test

Variable	GMM model regression and correlation test results
lnGP	-0.4022***
lnPD	1.4262***
lnAFC	-6.5353***
lnISI	-6.2165**
lnEC	0.3430*
lnFDI	-0.3396***
Over-identification	0.1461
Hausman Test	109.25***
DWH test for heteroskedasticity	
Durbin	122.936***
Wu-Hausman	645.03***

506 Note: *, **, *** denote statistical significant at 10%, 5% and 1% confidence levels respectively.

507 The results show that under the GMM model, the coefficient signs and statistical
508 significance of the core explanatory variables are completely consistent with the SDM
509 model under matrix W_3 , and the signs of other control variables are basically the same,
510 meanwhile the significant differences are small. The GMM model passes the over-
511 recognition test, indicating that the instrumental variable PD is appropriate. The Hausman
512 test results indicate that the other explanatory variables are all exogenous, and there is no
513 influence of heteroskedasticity. The results have high reliability. Therefore, the results
514 show that the original model has good robustness and the estimation results have high
515 credibility.

516 Conclusions and policy implications

517 Using the panel data of 30 provinces in mainland China in 2011-2017, we apply spatial
518 models to estimate the impact of GP on haze pollution and its transmission mechanism
519 under alternative spatial weight matrices. Results show that China's haze pollution has a
520 significant spatial correlation. Every 1% increase in local haze pollution increases haze
521 pollution by 0.5257% in adjacent areas and by 0.4132% in the geographically close region
522 with similar economic development. In addition, the time lag of haze pollution will lead
523 to "snowball effect", which means the current haze pollution will have an impact on the
524 next phase of haze pollution. GP is an effective means to prevent and control haze
525 pollution. Every 1% increase in GP can reduce haze pollution by 0.1323%. Its spatial
526 spillover effect is significant. The improvement of local GP has an evident radiation impact
527 on haze pollution in adjacent areas, specifically manifested in a 0.4436% reduction in haze
528 pollution in geographically adjacent areas and a 1.9346% reduction in geographically

529 adjacent areas with similar economic development. The spillover effects of EC, FDI, and IS
530 on haze pollution are negative and significant, indicating that the optimization of EC, the
531 increase of foreign investment and the rationalization of industrial structure contributed
532 to the reduction of haze pollution. ISI and EC play a partially mediating role in green
533 technological innovation and haze pollution. PD and AFC have significant positive spatial
534 spillover effects on haze pollution.

535 The policy implications of this paper are to understand the role of haze pollution
536 inhibition factors, and emphasize the importance of the strengthening of haze pollution
537 contributory factors, which means to better play the role of "prevention and control effect"
538 of green technology innovation and to reduce the negative impact of the "rebound effect".
539 In terms of promoting the enhancement of inhibiting factors: first, vigorously promote
540 green technology innovation. Second, encourage the private sector, such as enterprises, to
541 engage in green technology innovation and give full play to the role of environmental
542 policy tools to the externalities of environmental innovation (Liao, 2018), and to reduce
543 barriers to innovation (Gupta and Barua, 2018). Third, increase support for green
544 technology innovation in public institutions, higher education institutions and other
545 departments. Fourth, introduce high-quality foreign investment and appropriately
546 increase the guidance in the use of foreign capital. Fifth, guide foreign investment in favor
547 of environmentally friendly technologies and high value-added products. Finally, give full
548 play to regional synergies, and undertake joint efforts to prevent and control haze
549 pollution, and build a collaborative governance system with the participation of multiple
550 entities (Yin et al., 2020). With local governments in the leading role, cooperation in haze
551 control among regions should be strengthened. At the same time, the power of enterprises
552 should be connected, the common interest network of all subjects established, and
553 knowledge sharing realized (Arfi et al., 2018). In terms of inhibiting the enhancement of
554 pollution contributory factors: efforts should be directed towards reducing the generation
555 of haze pollution in production and promoting the rational upgrading of industrial
556 structure. Rational upgrading does not constitute blind demand for the reduction of
557 secondary industry and the expansion of tertiary industry, but aims to make secondary
558 industry more environmentally friendly and reduce the damage of industrial pollution to
559 the atmospheric environment. By optimizing the energy structure, reducing the
560 consumption of fossil energy, developing clean energy and increasing the promotion and
561 popularization of clean energy and realizing energy substitution earlier. In addition, the
562 aim should be to reduce the generation of haze pollution in daily life: raising public
563 awareness of energy conservation and environmental protection, improve the utilization
564 rate of public transport, and reduce the pollution of the atmosphere caused by automobile
565 exhaust.

566

567 **Declarations**

568 **Ethics approval and consent to participate** (Not applicable)

569 **Consent for publication** (Not applicable)

570 **Availability of data and materials**

571 The datasets used and/or analysed during the current study are available from the
572 corresponding author on reasonable request.

573 **Competing interests**

574 The authors declare that they have no competing interests

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579 **Authors' contributions**

580 Ming Yi identified the topic and the basic framework of this paper and revised the paper
581 at a later stage; Ying Lu gathered data for the writing, completed the first draft of the entire
582 paper and was responsible for formatting edits; Le Wen made repeated revisions to the
583 empirical part of the paper; Ying Luo proposed revisions to the thesis; Shujing Xu
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589

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725 **Appendix**

726 Raw Data:

	Prov ince	Year	PM _{2.5} (ug /m ³)	GP (term)	PD (person/ km ²)	AFC	ISI	EC (%)	FDI (%)
1	Beiji ng	2011	52.1	3919	1230.06	8.11	7.5293	24.15	2.65
1		2012	45.2	5088	1260.96	7.67	7.5339	22.59	2.67
1		2013	55.2	7588	1288.68	7.27	7.5420	21.45	2.50
1		2014	52.4	9341	1311.11	7.69	7.5612	18.16	2.42
1		2015	51.1	11143	1322.68	7.67	7.5899	12.14	3.27
1		2016	47.4	12094	1323.90	7.89	7.5997	8.70	3.20
1		2017	48.8	11769	1322.68	7.67	7.6096	4.91	5.50
2		2011	71.1	991	1138.66	8.21	6.9463	49.47	10.39

2	Tianjin	2012	60.3	1477	1187.52	7.70	6.9644	46.11	10.48
2		2013	82.2	2026	1237.15	7.21	6.9879	47.84	10.48
2		2014	76.9	2259	1274.79	7.56	7.0173	44.09	10.89
2		2015	69.8	3062	1300.00	7.65	7.0700	39.25	12.10
2		2016	67.3	3960	1312.61	7.87	7.1598	36.65	5.85
2		2017	68.4	4120	1308.40	7.62	7.1601	34.56	5.75
3	Hebei	2011	51.0	739	400.03	7.65	6.3658	74.56	1.41
3		2012	47.9	1192	402.62	7.51	6.3757	74.05	1.59
3		2013	58.6	1581	405.12	7.14	6.3653	76.24	1.65
3		2014	54.4	1657	407.94	7.34	6.4226	72.20	1.55
3		2015	52.2	2298	410.21	7.33	6.4866	70.33	1.46
3		2016	49.7	2818	412.69	7.64	6.5332	67.38	1.72
3		2017	51.5	3260	415.46	7.23	6.5148	64.45	1.87
4	Shanxi	2011	40.0	421	230.32	7.02	6.5862	130.57	1.23
4		2012	37.5	531	231.46	7.38	6.6490	127.64	1.35
4		2013	43.7	742	232.69	7.24	6.6638	132.43	1.45
4		2014	37.6	828	233.85	7.48	6.7517	135.17	1.50
4		2015	36.5	864	234.87	7.42	6.9401	136.77	1.51
4		2016	33.8	1004	236.03	7.46	6.9928	131.15	1.30
4		2017	36.7	1142	237.31	7.41	6.9490	152.93	0.79
5	Neimenggu	2011	20.6	154	20.98	7.08	6.4649	132.22	2.62
5		2012	20.0	194	21.05	7.40	6.4743	132.20	2.38
5		2013	23.4	270	21.12	6.63	6.4810	141.06	2.52
5		2014	23.2	347	21.17	7.35	6.5492	142.27	2.01
5		2015	24.9	499	21.22	7.37	6.5720	137.75	1.62
5		2016	21.2	559	21.30	7.55	6.6442	134.64	1.91
5		2017	27.1	649	21.38	7.54	6.6296	138.43	1.43
6		2011	32.8	1294	296.15	7.80	6.5152	56.78	9.58

6	Liao ning	2012	27.8	1707	296.55	7.65	6.5388	55.32	9.48
6		2013	36.1	1910	296.62	7.36	6.5536	59.63	9.36
6		2014	40.9	1714	296.72	8.14	6.6358	58.98	8.41
6		2015	43.4	2086	296.11	7.94	6.7184	57.15	1.60
6		2016	33.5	2292	295.84	8.06	6.7887	57.55	0.98
6		2017	36.8	2487	295.23	8.04	6.7689	58.28	1.66
7	Jilin	2011	24.4	374	147.03	6.91	6.3628	86.59	1.24
7		2012	21.6	425	147.08	7.23	6.3711	83.84	1.20
7		2013	29.3	499	147.13	7.06	6.3924	86.04	1.20
7		2014	35.4	493	147.17	7.64	6.4251	86.61	1.21
7		2015	38.2	705	147.22	7.42	6.4618	86.02	1.32
7		2016	28.6	781	146.15	7.54	6.5805	83.93	1.45
7		2017	34.8	873	145.29	7.62	6.5192	83.37	1.38
8	Heil ongji ang	2011	14.7	715	84.45	6.99	6.3423	77.80	2.11
8		2012	14.2	916	84.45	7.28	6.3649	78.19	2.23
8		2013	18.9	1183	84.47	7.06	6.3216	79.95	2.41
8		2014	26.5	1100	84.43	7.58	6.4277	81.23	2.57
8		2015	25.0	1387	83.96	7.23	6.5515	79.13	2.90
8		2016	20.2	1533	83.68	7.72	6.6429	81.63	3.25
8		2017	28.1	1568	83.46	7.59	6.5665	82.44	3.21
9	Shan ghai	2011	47.4	2841	3702.33	8.49	7.2058	38.93	4.07
9		2012	41.3	3455	3754.33	8.40	7.2556	35.85	4.50
9		2013	52.1	3891	3809.08	7.99	7.2902	35.77	4.48
9		2014	51.3	3732	3825.69	8.24	7.3420	31.55	4.42
9		2015	53.7	4632	3808.35	8.22	7.3994	29.66	4.28
9		2016	44.8	5537	3816.23	8.27	7.4347	28.21	4.11
9		2017	57.6	6039	3813.08	8.14	7.4545	27.57	3.49
10		2011	58.7	5175	766.87	8.14	6.7092	70.85	4.25

10	Jiangsu	2012	49.6	7447	768.93	8.16	6.7270	68.74	4.20
10		2013	61.3	10641	770.82	7.56	6.7551	68.35	3.47
10		2014	63.5	10132	772.82	7.81	6.8238	64.37	2.67
10		2015	61.8	13554	774.37	7.76	6.8543	64.28	2.12
10		2016	54.7	15575	776.61	8.10	6.8969	64.52	2.11
10		2017	63.5	16615	779.52	7.83	6.9229	60.50	1.98
11	Zhejiang	2011	34.2	4150	535.59	7.83	6.7828	59.20	2.37
11		2012	34.2	6024	536.96	7.73	6.8131	56.80	2.40
11		2013	37.2	8165	539.02	7.22	6.8314	54.27	2.35
11		2014	38.5	7546	540.00	7.52	6.8808	52.45	2.42
11		2015	34.1	10566	543.04	7.42	6.9241	50.36	2.43
11		2016	28.0	12103	548.04	7.59	6.9524	49.14	2.47
11	2017	36.2	11933	554.61	7.35	6.9674	48.44	2.31	
12	Anhui	2011	52.5	1137	429.35	8.07	6.2866	95.44	2.63
12		2012	47.7	1814	430.79	8.02	6.3078	92.47	2.97
12		2013	55.5	2537	433.80	7.44	6.3248	95.67	3.22
12		2014	60.9	2762	437.63	7.69	6.3936	93.89	3.37
12		2015	53.7	3657	442.01	7.65	6.4744	90.77	3.56
12		2016	48.1	4408	445.76	7.96	6.5366	88.50	3.73
12	2017	59.6	4356	450.00	7.75	6.5037	88.03	3.62	
13	Fujian	2011	20.4	1171	306.43	7.12	6.5432	58.43	2.24
13		2012	20.3	1567	308.73	6.83	6.5507	54.19	1.98
13		2013	20.5	1991	310.87	7.05	6.5513	51.57	1.84
13		2014	22.3	1890	313.51	7.39	6.5781	48.36	1.75
13		2015	20.0	3141	316.23	7.19	6.6245	44.92	1.78
13		2016	18.3	4671	319.11	7.06	6.6518	39.46	1.84
13	2017	22.9	4298	322.16	7.11	6.6398	41.80	1.71	
14		2011	35.2	351	268.77	7.99	6.3464	72.05	3.38

14	Jiang xi	2012	35.9	487	269.70	7.76	6.3719	67.17	3.36
14		2013	36.2	655	270.79	7.28	6.3915	68.34	3.27
14		2014	40.2	693	271.99	7.48	6.4464	66.31	3.31
14		2015	33.9	1173	273.43	7.45	6.4943	65.15	3.52
14		2016	32.5	1665	274.98	7.53	6.5634	62.21	3.77
14		2017	40.0	1771	276.78	7.41	6.5888	61.63	3.83
15	Shan dong	2011	64.7	3028	613.82	8.04	6.5390	74.87	1.85
15		2012	62.3	4009	616.88	7.88	6.5802	73.88	1.82
15		2013	72.4	5042	619.96	7.24	6.6001	76.13	1.84
15		2014	70.3	4991	623.53	7.93	6.6676	77.40	1.84
15		2015	69.2	7022	627.23	7.90	6.7122	77.04	1.84
15		2016	62.9	8774	633.59	7.90	6.7650	75.52	1.90
15	2017	62.8	8791	637.35	7.84	6.7963	70.47	1.91	
16	Hena n	2011	66.6	1376	562.16	7.68	6.2487	87.88	2.47
16		2012	61.9	1727	563.23	7.50	6.2764	76.24	2.64
16		2013	74.7	2197	563.65	7.05	6.2980	81.70	2.63
16		2014	66.7	2250	565.03	7.46	6.4121	75.67	2.65
16		2015	66.0	3061	567.66	7.57	6.4899	73.15	2.70
16		2016	58.5	3498	570.78	7.80	6.5494	71.77	2.80
16	2017	63.3	3917	572.40	7.44	6.5500	70.58	2.59	
17	Hub ei	2011	53.0	1262	309.54	8.07	6.3686	68.10	1.51
17		2012	47.2	1557	310.70	7.88	6.3782	63.85	1.58
17		2013	52.7	2196	311.77	7.37	6.4083	55.34	1.68
17		2014	54.6	2261	312.69	7.68	6.5102	52.03	1.72
17		2015	50.7	2917	314.62	7.57	6.5572	51.23	1.84
17		2016	42.9	3524	316.40	7.76	6.5744	49.54	2.02
17	2017	46.8	3945	317.31	7.57	6.5745	49.05	1.99	
18		2011	46.0	1181	311.41	8.10	6.3632	57.48	2.10

18	Hunan	2012	47.5	1531	313.45	7.90	6.3951	51.55	2.18
18		2013	45.3	2024	315.89	7.30	6.4530	53.74	2.29
18		2014	49.9	1984	318.09	7.68	6.5250	50.83	2.44
18		2015	42.1	2666	320.26	7.57	6.5697	51.45	2.52
18		2016	37.5	2834	322.11	7.75	6.6264	51.72	2.77
18		2017	41.4	3247	323.90	7.59	6.6450	54.79	2.89
19	Guangdong	2011	28.6	4890	583.60	7.93	6.8082	46.25	2.65
19		2012	28.4	6333	588.56	7.48	6.8328	43.22	2.61
19		2013	28.3	8268	591.33	7.52	6.8635	42.91	2.47
19		2014	31.5	8415	595.78	7.78	6.8952	41.07	2.42
19		2015	26.4	11660	602.72	7.68	6.9321	39.30	2.24
19		2016	25.0	13982	611.06	7.47	6.9616	36.89	1.89
19	2017	33.8	18693	620.50	7.47	6.9731	37.93	1.69	
20	Guangxi	2011	34.9	268	195.99	7.98	6.1754	58.47	0.64
20		2012	36.7	374	197.55	7.41	6.2253	56.68	0.42
20		2013	35.1	594	199.11	7.62	6.2479	57.65	0.35
20		2014	35.8	791	200.59	8.07	6.3133	51.02	0.45
20		2015	30.7	1016	202.36	8.02	6.3346	44.25	0.72
20		2016	27.7	1245	204.14	7.48	6.3507	46.13	0.37
20	2017	37.4	1219	206.12	7.55	6.3693	45.17	0.31	
21	Hainan	2011	15.2	41	250.67	8.41	6.2069	36.39	3.99
21		2012	10.2	83	253.30	8.05	6.2725	39.40	3.71
21		2013	15.0	175	255.79	8.36	6.3333	41.89	3.60
21		2014	13.1	143	258.14	8.51	6.4612	39.97	3.36
21		2015	13.7	180	260.42	8.52	6.5037	39.51	3.35
21		2016	12.9	249	262.14	7.99	6.5303	36.15	3.46
21	2017	22.8	257	264.71	8.40	6.6171	37.34	3.46	
22		2011	45.4	850	355.98	7.58	6.5125	58.41	3.70

22	Chongqing	2012	45.7	1229	359.15	7.48	6.5794	51.97	1.92
22		2013	45.7	1382	362.20	6.81	6.6283	51.42	1.97
22		2014	41.9	1316	364.80	6.58	6.7606	50.67	1.78
22		2015	40.0	2080	367.98	6.72	6.7831	48.35	1.46
22		2016	37.2	2599	371.76	7.26	6.7926	44.04	1.03
22		2017	39.6	2439	375.05	6.98	6.8341	42.26	0.75
23	Sichuan	2011	23.8	1486	165.98	7.20	6.2691	41.54	2.91
23		2012	22.8	1914	166.52	7.02	6.3015	41.22	2.59
23		2013	23.5	3032	167.15	6.84	6.3405	43.42	2.40
23		2014	21.4	2660	167.84	6.66	6.4267	39.69	2.19
23		2015	19.3	3665	169.16	6.61	6.5379	33.36	2.05
23		2016	18.9	4712	170.35	6.90	6.6264	31.11	1.60
23	2017	23.5	4874	171.18	6.81	6.6116	26.88	1.44	
24	Guizhou	2011	33.3	235	197.09	7.36	6.6384	95.20	0.59
24		2012	34.1	319	197.96	7.10	6.6079	96.37	0.46
24		2013	30.6	493	198.99	7.49	6.5810	104.86	0.45
24		2014	30.6	549	199.32	7.63	6.5074	96.51	0.31
24		2015	28.3	791	200.57	7.49	6.4593	92.15	0.25
24		2016	24.5	750	201.99	7.29	6.4510	95.29	0.54
24	2017	29.8	899	203.41	7.42	6.5142	91.38	0.41	
25	Yunnan	2011	16.4	368	117.53	8.25	6.3750	72.36	1.18
25		2012	13.9	470	118.25	8.41	6.3591	67.43	1.25
25		2013	16.7	641	118.95	7.98	6.3701	69.38	1.21
25		2014	13.5	774	119.64	7.50	6.4254	59.27	1.18
25		2015	13.1	950	120.36	7.19	6.4791	53.19	1.25
25		2016	13.0	1273	121.09	8.02	6.5258	50.01	0.35
25	2017	16.7	1427	121.85	7.76	6.5259	46.44	0.35	
26		2011	42.0	938	181.68	7.46	6.4396	97.46	1.25

26	Shan xi	2012	39.2	1150	182.19	7.27	6.4478	106.04	1.31
26		2013	46.1	2011	182.70	6.89	6.4518	116.12	1.43
26		2014	39.9	2093	183.26	7.14	6.5145	116.96	1.47
26		2015	40.6	2326	184.13	7.01	6.5833	112.02	1.61
26		2016	37.7	2524	185.10	7.42	6.6233	115.93	1.75
26		2017	41.6	2508	186.17	7.19	6.6019	114.35	1.85
27	Gans u	2011	42.4	209	56.48	6.36	6.3987	69.31	0.09
27		2012	40.6	321	56.77	6.44	6.4105	66.85	0.07
27		2013	51.1	392	56.88	5.98	6.4219	64.12	0.07
27		2014	50.6	397	57.07	6.46	6.5127	63.78	0.09
27		2015	43.9	474	57.26	6.75	6.6066	62.26	0.10
27		2016	37.9	640	57.48	6.63	6.6718	62.11	0.11
27		2017	48.7	802	57.84	6.54	6.6466	60.27	0.04
28	Qing hai	2011	38.5	20	8.15	6.30	6.4124	33.78	0.80
28		2012	36.7	41	8.22	5.61	6.4225	37.68	0.85
28		2013	41.6	55	8.29	5.31	6.4009	39.30	0.34
28		2014	52.6	38	8.37	5.38	6.4938	32.50	0.17
28		2015	35.3	124	8.44	5.98	6.6081	26.06	0.17
28		2016	34.7	145	8.51	6.64	6.6364	34.10	0.04
28		2017	48.4	155	8.59	5.91	6.6003	29.70	0.05
29	Ning xia	2011	37.8	69	96.89	6.23	6.5927	131.51	0.68
29		2012	36.6	70	98.06	5.75	6.6219	126.11	0.65
29		2013	46.9	126	99.12	5.84	6.6165	127.49	0.39
29		2014	41.5	193	100.30	6.02	6.6722	127.91	0.23
29		2015	37.2	202	101.21	6.24	6.7255	117.72	0.45
29		2016	34.5	304	102.27	6.53	6.7242	110.68	0.61
29		2017	39.6	385	103.33	6.17	6.7668	121.73	0.66
30		2011	51.3	194	13.27	#REF!	6.1831	70.12	0.33

30	Xinji ang	2012	51.2	244	13.41	4.62	6.2073	72.62	0.35
30		2013	56.9	405	13.60	4.66	6.2339	74.44	0.35
30		2014	64.6	396	13.80	4.60	6.3358	76.99	0.28
30		2015	54.7	576	14.17	4.99	6.4219	79.23	0.30
30		2016	51.0	662	14.40	4.45	6.4198	83.19	0.28
30		2017	58.2	813	14.68	4.40	6.4248	83.66	0.12

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