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The influencing mechanism of multi-factors on green investments: A hybrid analysis

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ABSTRACT

Given the grimmer ecological environment, green investments have increased influence on the support and acceleration of the environmental improvement. To identify the driving forces of green investments, we examine the direct and spillover effects of political, economic and environmental factors using a hybrid analysis. The results are based on two sets of data, which includes text data (1339 environmental policies) from the official websites of provincial environmental protection departments and statistical data (434 valid samples) from the Chinese Statistical Yearbook (2003–2016). First, LDA topic model is employed to construct political factors, during which the optimal topic number N are determined as 3. As an evaluation index, the average F-score is up to 75.39% and three topics are categorized, namely environmental regulation and protection, pollution prevention and treatment as well as environmental public governance. Then, spatial econometric models are built to test the spatial characteristics of green investments and the spillover effects of the above three factors. The results show that the economic factors and environmental factors play more significant roles than political factors. However, regarding the development of green investments during 2003–2016 in Chinese provinces, the government has gradually strengthened its power in boosting green investments and improving the environment, especially in setting up and monitoring environmental regulation. Tests of policy time-lag effects and robustness are also carried out in order to confirm the validation of the model. The adjusted R^2 of both tests are highly up to 0.905. Our results have significant implications to both research and practice in green investments and policy-making.

1. Introduction

The increasing urbanization and rapid industrialization have created huge pressures on the ecology system and have led to serious environmental issues (e.g., extreme weather, soil erosion, marine pollution, etc.), producing huge impact on modern societies (Burke et al., 2015). Given this circumstance, environmental protection has become a vital concern to the governments, enterprises and even the publics. In China, governments at all levels have made substantial efforts and have taken measures to improve the environment, such as establishing emission trading scheme (Mo et al., 2016), implementing environmental taxes/charges (Li and Masui, 2019), developing emission treatment programs (Wu et al., 2016), and shutting down inefficient power/industrial facilities (Ding et al., 2018). However, all these actions demand massive green investments. In 2016, more than 900 billion yuan[1] has been invested in environmental treatment projects, accounting for 1.24% of Chinese GDP (National Bureau of Statistics, 2018), though it is still far from enough. Therefore, cultivating the influencing factors and thus enhancing the efficiency utility of green investments are becoming important and timely issues. Regarding green investments research, previous studies primarily consider economic and environmental factors (Martin and Moser, 2016; Drake et al., 2016; Xiao et al., 2019). Yang et al. (2019) find that the cost of green investments negatively impacts the "green" level of environmental supply chain. Dai et al. (2016) indicate that the green investments in renewable energy substantially reduce the emission of CO2 and air pollutants. However, the impact of government has yet been paid less attention. In addition, research is still limited about how to

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[1] These values are in 2016 constant prices, and the exchange rate was approximately US$ 1 = 6.64 yuan.

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quantify environmental policy and explore its effects. Therefore, it is a challenge to quantify environmental policy and explore the influencing mechanism of political factors on green investments, and clarify government's role in leading the development of green investments.

Besides, the developments of green investments among 31 Chinese provinces are quite inequity. China's economic growth has gone through two stages during the past 14 years from 2003 to 2016. The first stage (2003−2011) was a fast-growth period which had an average GDP growth of more than 10.8%. The second stage (2012−2016) was steady-growth period with an average GDP growth of only 7.3%. Fig. 1 displays the average annual growth rate of green investments in two different periods. In the fast-growth stage (2003−2011), the average annual growth rates were much higher in eastern China. The governments of eastern developed provinces were more inclined to develop economy at the cost of environmental damage, which results in the concomitant increase of GI. However, things changed during the steady-growth stage (2012−2016). The average annual growth rates in China's western region were higher than eastern region. The prosperous economy in eastern region led to positive environmental impact and began to cut down the expenditure of GI. Therefore, a distinct spatial characteristic exists in the development of green investments among 31 Chinese provinces, which needs a further spatial analysis for exploration.

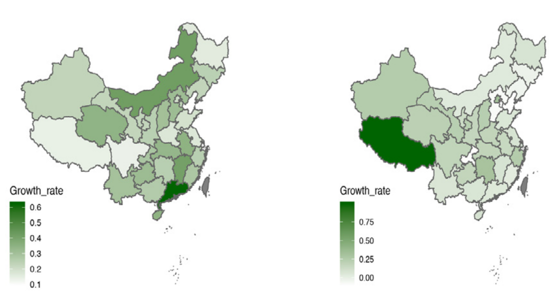
To bridge the research gaps, three research questions are put forward as follows.

RQ1: How to quantify the environmental policies and construct political factors?

RQ2: How do economic, environmental and political factors affect different types of green investments respectively?

RQ3: What are the spatial characteristics of green investments among Chinese provinces and the spillover effects of the above three factors?

In this paper, latent Dirichlet allocation (LDA) topic model is adopted to solve the first research question. Then, OLS and spatial econometric model are used in further analysis to answer research question 2 and 3. There are some contributions that should be pointed out in our study. Firstly, we extract the text features of environmental policies, categorizing different political orientations and quantifying the political factors using LDA model. To the best of our knowledge, there are few studies concentrate on the quantitative analysis of policies clustering using text mining technology. Our study carries out a reasonable and effective categorization of environmental policies, which provides a better illustration of environmental policies' impact on green investments. Secondly, most research ignores the combination impacts of the political, economic and environmental factors on green investments, and consider them separately. Our study takes into consideration of



(a) Average annual growth rate (2003-2011) (b) Average annual growth rate (2012-2016)

Fig. 1. Average annual growth rate of green investments among 31 Chinese provinces.

multi-factors and explores the influencing mechanism of these factors on green investments. Particularly, we explicate the government's different roles in leading the development of different types of green investments. Finally, we analyze the spatial characteristic of green investments and spillover effects of the above factors, which enriches the literature of spatial econometric analysis by exploring the current situation of green investments' development among 31 Chinese provinces.

Following the introduction above, the rest of the article is organized into four sections. Firstly, a literature review of the relationship between green investments and the driving factors is described in section 2. Data and methods are introduced in section 3. Section 4 presents the analytics processes, empirical results as well as some discussions. Finally, section 5 provides the conclusions and implications of this study.

2. Literature review

2.1. Green investments

Green investments (GI), also known as environmental investments (Marinoni et al., 2009), directly refer to social investments used for supporting the environmental improvement. There are different types of GI, like individual environmental donations (Sollberger et al., 2016) or enterprise social-responsible investments (Yang et al., 2019), which cause the difference in definitions of GI. According to Eyraud et al. (2013), “GI refers to the investment necessary to reduce greenhouse gas and air pollutant emissions, without significantly reducing the production and consumption of non-energy goods”. Similarly, Martin and Moser (2016) state that GI is a particular type of corporate social responsibility activity, which can be used to reduce carbon emissions. Based on realistic background and prior literature, GI are mainly used in three fields: urban infrastructure investments, pollution treatment investments as well as environmental facilities investments.

2.1.1. Investments in urban infrastructures

The improvement of urban infrastructures is the foundation of urbanization, reflecting the prosperity of a province to some degree. Hence, GI in urban infrastructure construction are always being paid highly attention, particularly for green infrastructure investments. Vandermeulen et al. (2011) describe a model to value the usefulness of green infrastructure investments, which facilitate the construction of green spaces that provide positive effect on people living. Hung and Hobbs (2019) identify four categories of green infrastructure investment strategies and quantify their benefits and costs. As an important part of GI, urban infrastructure investments devote to improve people's living environment and ameliorate the insanitary place in urban.

2.1.2. Investments in industrial pollution treatment

Industrial pollution has become an unavoidable environmental issue with the development of industrialization. The most common industrial pollution include waste water discharge, waste gas (e.g., CO2, SO2, etc.) emission and solid waste discharge (Shahbaz et al., 2013; Wu et al., 2016; Li and Masui, 2019), all of which require lots of investments and great efforts in pollution treatment. Researchers have put forward a number of solutions in order for raising the pollution treatment investments (Chen et al., 2018; Miao et al., 2018; Yu and Gao, 2016).

2.1.3. Investments in environmental facilities of projects

Investments in environmental facilities of projects refer to GI in environmental protection facilities of the acceptance project in a certain year. In China, three simultaneous principles of environmental management system have been set since 2015, which demands that the environmental facilities should be put into use simultaneously with the design, construction, and utilization of the main projects. Even if there is little literature that concentrates on this kind of investment, yet it is still an indispensable part of GI regarding the Chinese context.

In short, the total GI contains urban infrastructure investments, industrial pollution treatment investments and environmental facilities of projects investments, which bring great environmental benefits in dealing with different environmental issues. Most previous studies are limited to a single perspective of GI. In our study, we define GI in a more comprehensive way combined the Chinese current context, trying to find out the influencing mechanism of multi-factors on GI.

2.2. Economic, environmental and political factors of GI

The relationship between economic growth and environmental pollution has been frequently discussed in prior literature (Cole et al., 1997; Dai et al., 2016; Grossman and Krueger, 1995). For example, the Environmental Kuznets Curve reveals an inverted-U-shaped relationship between economic growth and environmental degradation (Cole et al., 1997; Dinda, 2004). Besides, evidence shows that environmental policies also play roles in the development of GI in some cases (Dafermos et al., 2018; Dalby et al., 2018; Liao, 2018). Hence, we review the influencing factors of GI from political, economic and environmental perspectives.

2.2.1. Political factors

Political factors have a high relationship with GI and reflect the government's emphasis on environmental improvement. The political factors usually have twofold effects. On one hand, the stronger effect of political factors leads to the greater GI invested by the government and better promotion of pro-environmental behaviors. Iyer et al. (2015) find that policy facilitates the deployment of low-carbon technologies, which lowers the costs of emissions abatement. Fullerton and Kim (2008) discover that tighter environmental policy positively effects on environmental degradation. On the other hand, the increasing carbon tax rate will cause the decrease of firms' R&D investments in non-carbon energy technologies (Baker and Shittu, 2006).

Particularly, the environmental policy provides a guidance and intervention for both economic growth (Fullerton and Muehlegger. 2019; Wu et al., 2019) and environmental improvement (Xiao et al., 2019; Drake et al., 2016). For example, the environmental policy is setting up by different means (e.g., green subsidies, consumer rebates, environmental taxes, pollution fines) to reward pro-environmental behaviors or regulate environmental damage behaviors. Gadenne et al. (2009) indicate that legislations raise public's environmental awareness and make organizations be more willing to change their business processes and environmental strategies. Krass et al. (2013) test the regulator's incentives and find that environmental taxes motivate the firm's reaction on the choice of green technology. Regarding the political factors, the environmental policy may have different political orientations while many studies mainly concern the regulation aspect (Gadenne et al., 2009; Drake et al., 2016).

2.2.2. Economic factors

Economic factors are powerful driven factors of GI. With an increasing awareness of environmental protection, there has been rising demands for environmental-friendly business practices (Gadenne et al., 2009). Flammer (2013) finds that the investment of environmental corporate social responsibility (CSR) helps to pull up company's stock price significantly. Vandermeulen et al. (2011) assess the direct and indirect economic values and performance of GI. Shahbaz et al. (2013) examine the relationship between CO2 emissions, financial development, energy consumption and economic growth, finding that financial development reduces CO2 emissions.

Specifically, among the economic factors, GDP and GDP per capita undoubtedly play important roles in the development of GI (Zhang et al., 2018; Drake et al., 2016; Shuai et al., 2018). Besides, fixed assets investment should also be regarded as an economic factor since it is highly related to urban infrastructure investments. Both Wang et al. (2017) and Shuai et al. (2018) find that fixed assets investment dominantly contributes to carbon emissions increments.

2.2.3. Environmental factors

The purpose of promoting GI is to reduce environmental degradation, to avoid ecology crisis, and to achieve the goal of low-carbon economy (Shahbaz et al., 2013). To pursue this, the Chinese government has put substantial efforts on pollutants treatment, attracting more and more GI to develop green technologies (Zhao et al., 2019) and green industries (Zhang et al., 2019). Fortunately, the progress in purification and recycling technology turns waste into resource. For instance, membrane bioreactor can be applied to water reuse applications in wastewater treatment (Sepehri and Sarrafzadeh, 2018). Chemical scrubber can be used as a low-cost alternative for oxidative catalysts as a waste gas treatment system (Dobslaw et al., 2019). Even though current green technologies mitigate the environmental degradation, it's still necessary to clarify the environmental factors' impact on GI. The efficient allocation and utility of GI facilitates the development of green technologies and environmental protection (Kök et al., 2016; Linnerud et al., 2014).

Thus, we are focusing on the three main source of pollutants, which are waste gas (Martin and Moser, 2016; Zhang et al., 2018), industrial waste water and solid wastes (Cui et al., 2019; Kerstens et al., 2015; Liu et al., 2018a). It's quite important to unravel the relationship between environmental factors and GI, which is beneficial to both GI's further growth and the reduction of pollutant discharge.

3. Data & methods

This research explores the significant relationship between multi-factors and different types of GI. Environmental policy is the primary indicator that reflects the government's attitude on environment protection and the attention to the development of GI. Therefore, the environmental policies can be used for the construction of political factors through text analysis, which extracts and quantifies the text features of environmental policies. Besides, the economic and environmental factors show significant spatial characteristics, which needs to be tested specifically. Hence, we introduce our dataset firstly and propose a hybrid method based on LDA topic model and spatial econometric model then to figure out the influencing mechanism of multi-factors on GI.

3.1. Data collection

Our dataset contains text data (environmental policies) as well as numeric data (interprovincial statistical data). The environmental policies are fetched from the official websites of Chinese provincial department of environmental protection using Python, which provides flexibility for both data mining and text analysis. The websites of data source are shown in Appendix. In this text corpus, we totally obtain 1339 documents of environmental policies. In order for the following model evaluation, 300 documents of environmental policies in the corpus are separated as test set, accounting for 22.40% of the whole dataset. The rest of 1039 documents are used as training set. Among these policies, full text of each document is utilized and trained in the model. Generally, some NLP (Natural Language Processing) research tent to use the titles or synopses of the articles as the input to train the model due to the ambiguity, unstructured features and other problems of the text (Agrawal et al., 2018; Toubia et al., 2019). As far as we are concerned, every environmental policy was exclusively formulated by policy makers. Therefore, the text of policy is more rigor and more standard than other text. Apart from the stop words, every word else in the policy document counts to the government's sentiment and should be taken into consideration in the text analysis. We input the full text of environmental policies after segmenting the text by words and removing words with a standard list of stop words during data preprocessing.

Besides, the interprovincial statistical data of different types of GI, economic factors (e.g., GDP, GDP per capita, fixed-assets investment) and environmental factors (e.g., waste water, waste gas, waste solid) are obtained from China Statistics Yearbook (2003–2016) and China Environmental Statistics Yearbook (2003–2016). GI are comprised of urban infrastructure investments (GI_UI), treatment of industrial pollution investments (GI_TP) and environmental protection acceptance projects investments (GI_EP). Fig. 2 displays the development trend of different types of GI during 2013–2016.

Fig. 2 demonstrates the unbalanced development among different types of GI. During the past 14 years, both the GI_UI and GI_EP present fast-growing trends while GI_TP remains steady. To compare the trend of GI and multi-factors and explore their relationships, we also plot the changes of economic and environmental factors during 2003–2016.

The two subgraphs in Fig. 3 shows the development trends of both economic and environmental factors, which are increasing year by year generally. Obviously, it's the difference of growth rates that influences the consistency and results in the diversified relationship between GI and multi-factors.

The economic factors containing GDP, GDP per capita and fixed assets investment are the basis of GI development. The environmental factors, including waste water discharge, emissions of waste gas and solid, measure the aggravation of environmental pollution. The descriptive statistics and correlation matrix of variables are given in Table 1 and Table 2, respectively.

In Table 2, coefficients that are greater than 0.5 in the first column of the correlation matrix show a high relevance between GI and other variables, except for variable Gas.

3.2. LDA topic model

LDA (Latent Dirichlet Allocation) topic model, a general text mining technology based on unsupervised learning, is mainly used for extracting “topics” from document collections and forming clusters according to the “topics” (Blei et al., 2003). As an effective way for dimensionality reduction of text corpus, LDA model has been widely used in many studies to deal with different types of texts, such as online reviews (Dong et al., 2018; Korfiatis et al., 2019; Srinivas and Rajendran, 2019), news (Liu et al., 2018b), blogs and tweets (Saura et al., 2019), etc. Compared to these texts, policies are not only much longer, but also more rigorous and objective, being different in both text style and length. Yet there are few studies that concern on policy's quantification using text mining technology. Therefore, it is a challenge to extract as much text features as possible from environmental policies since they have rich contents and abundant connotations.

Assume that each document in a corpus D is composed of a mix of multiple topics, then the document d can be generated in the following process (Blei et al., 2003; Srinivas and Rajendran, 2019).

1. Choose document length N from Dirichlet distribution $N \sim Dir(\beta)$.
2. Choose θ from Dirichlet distribution $\theta \sim Dir(\alpha)$.
3. For each word in the document, choose $z_n \sim Multinomial(\theta)$, choose w_n from a multinomial distribution $p(w_n|z_n, \beta)$ conditioned on the topic z_n.

where, α and β are the hyper-parameter of the Dirichlet prior determined based on the topic distribution and word distribution, respectively. The K-dimensional Dirichlet random variable θ is the probabilistic distribution of document-topic matrix. w_n denotes the nth word and z_n indicates the latent topic assigned to w_n.

Fig. 4 displays LDA model with a probabilistic graphics. In order to infer the topic distribution for each document and the content of each topic, we use EM algorithm to estimate the topic distribution (latent variable z). As a result, the LDA model outputs a list of words with different probabilities categorized by topics. We name these topics according to top words ordered in decreasing probability in each topic.

Topic number's deciding is a prerequisite before we use LDA model. Perplexity is an appropriate index to determine the topic number and evaluate the performance of the topic categorization. Theoretically, a lower perplexity score demonstrates better generalization performance of the model, which also indicates that the topics are better representation of the text. The perplexity is calculated as:

$$perplexity(D) = exp\left\{\frac{\sum_{d=1}^{M}\log p(w_d)}{\sum_{d=1}^{M}N_d}\right\} \quad (1)$$

$F1$-score is another measure to assess the accuracy and validity of

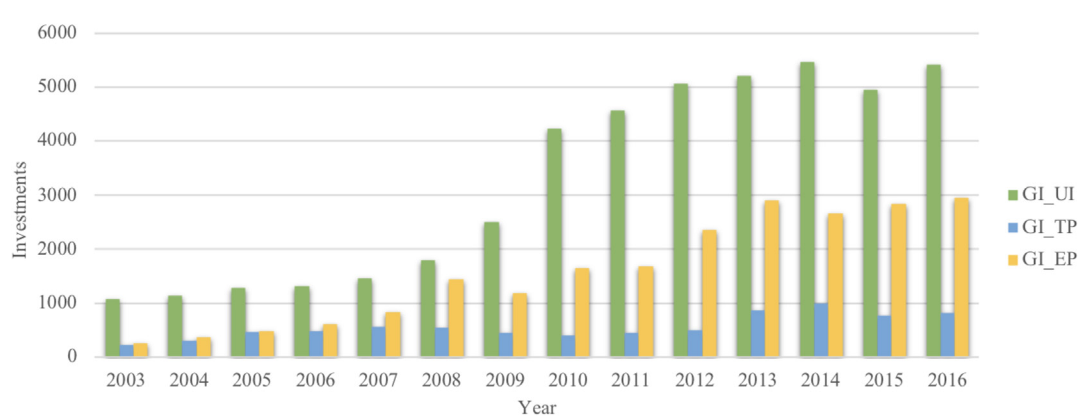


Fig. 2. The development trend of different types of GI.

the model based on the *Precision* and *Recall* of training set and test set. The formula of $F1$-score for each topic is shown below:

$$F1_k = \frac{2.precision_k \cdot Recall_k}{Precision_k + Recall_k} \quad (2)$$

where k means the kth topic. Specifically, for topic k, $Precision_k = tp_k/(tp_k + fp_k)$ and $Recall_k = tp_k/(tp_k + fn_k)$. By convention, true positive samples (tp) represent the samples predicted as true in training set that are actually true in test set. False positive samples (tp) are the samples predicted as true in training set while they are actually false in test set. False negative samples (fn) are the samples predicted as false in training set while they are actually true in test set. True negative samples (tn) are the samples that are regarded as false both in training set and test set. Finally, the average F-score are computed according to $F1_k$ of each topic:

$$F = \frac{1}{K}\sum_{k=1}^{K} F1_k \quad (3)$$

3.3. Spatial econometric model

Both economic and environmental factors have a spatial heterogeneity (Jiang et al., 2018; Liu et al., 2018a; Pistocchi et al., 2019).

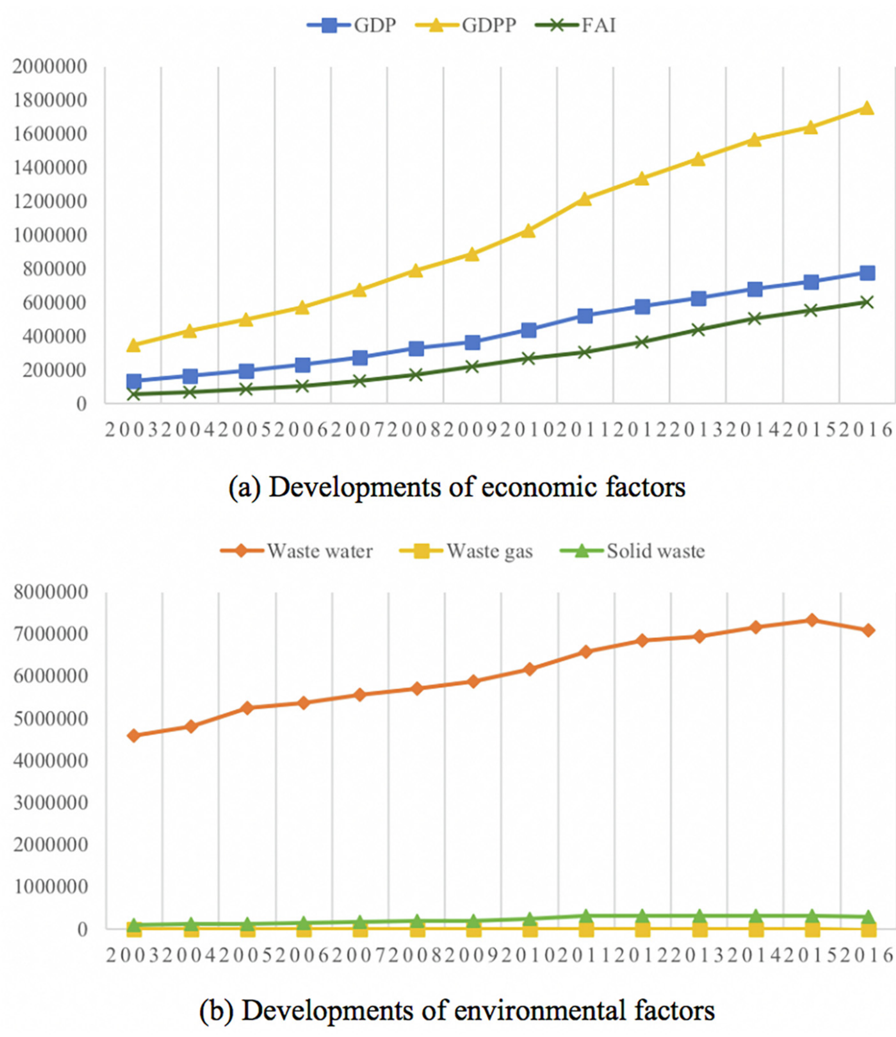


Fig. 3. The development trend of economic and environmental factors.

Table 1
Descriptive statistics.

Variable	Definition	Unit	Mean	S. D.	Min	Max
GI	Total green investments, which includes GI_UI, GI_TP, GI_UB	10^8 yuan	174.05	180.47	0.20	1416.20
GI_UI	Investments in urban infrastructure facilities	10^8 yuan	104.79	122.33	0.20	1262.70
GI_TP	Investments in treatment of industrial pollution	10^8 yuan	17.99	18.20	0.10	141.60
GI_EP	Investments in environmental protection acceptance projects	10^8 yuan	51.27	63.75	0.10	438.20
GDP	Gross domestic product	10^8 yuan	13944.11	13906.00	184.50	80854.91
GDPP	GDP per capita	yuan	32722.97	22705.97	3504.47	118127.6
FAI	Investment in fixed assets	10^8 yuan	8966.50	9175.17	133.96	53322.90
Water	Waste water discharged	10^4 tons	196771.29	164285.01	1079.00	938261.0
Gas	Volume of waste gas emission	10^4 tons	119.68	78.61	0.30	333.30
Solid	Industrial solid wastes generated	10^4 tons	7508.12	7500.32	5.50	45576.00

Table 2
Correlations matrix.

	GI	GI_UI	GI_TP	GI_EP	GDP	GDPP	FAI	Water	Gas	Solid
GI	1									
GI_UI	0.946**	1								
GI_TP	0.681**	0.550**	1							
GI_EP	0.821**	0.603**	0.588**	1						
GDP	0.798**	0.673**	0.684**	0.772**	1					
GDPP	0.584**	0.537**	0.358**	0.522**	0.598**	1				
FAI	0.801**	0.687**	0.702**	0.748**	0.898**	0.529**	1			
Water	0.597**	0.485**	0.554**	0.602**	0.862**	0.311**	0.670**	1		
Gas	0.253**	0.215**	0.475**	0.167**	0.213**	−0.243**	0.221**	0.347**	1	
Solid	0.501**	0.452**	0.492**	0.409**	0.355**	0.119*	0.506**	0.225**	0.587**	1

Note: * Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

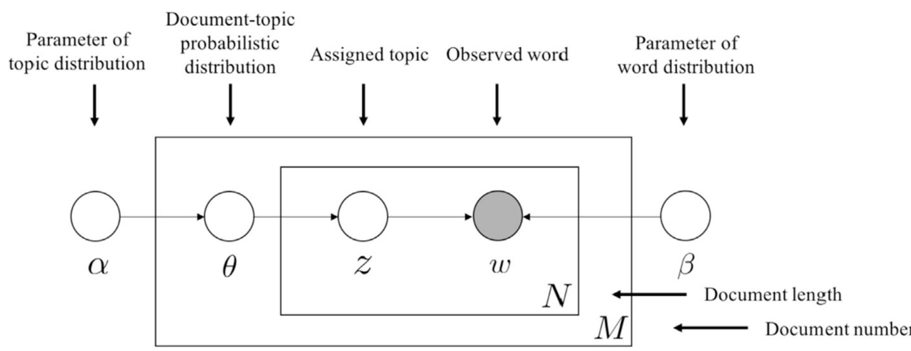


Fig. 4. Probabilistic graphics of LDA topic model.

However, whether political factors have spillover effects remain unknown. Therefore, it's necessary to apply spatial analysis to find out the spatial characteristics and test the spillover effects of multi-factors on Chinese development of GI.

Firstly, spatial correlation analysis is conducted to clarify the spatial autocorrelation of GI using Moran's index (Song et al., 2018), which is calculated as:

$$moran's\ I = \frac{n\sum_i \sum_{i \neq j} s_{ij}(y_i - \bar{y})\left(y_j - \bar{y}\right)}{\left(\sum_i \sum_{i \neq j} s_{ij}\right)\sum_i (y_i - \bar{y})^2} \tag{4}$$

where n is the number of provinces, y_i is the GI volume of the ith province, s_{ij} is the spatial weights between the ith and the jth province. Specifically, there are 31 provinces and municipalities in total in China, except for Hong Kong and Macao regions. Thus, the spatial weights matrix S is a 31×31 dimensional connectivity matrix and constituted by typical elements s_{ij}, which has a value of 1 if the province i and j are neighbor, otherwise is 0. (Beck et al., 2006). A positive value of Moran's index implies that the GI in one province are positively related to that of neighboring provinces while a negative value of Moran's index indicates negative correlation among one province and neighboring provinces, and 0 means no spatial correlation.

We use spatial Durbin models (SDM), taking into accounts the spatial interaction terms of dependent variable and independent variables. The model is built as follows:

$$\ln\ GI = a + \rho S\ \ln\ GI + X\Theta_1 + SX\Theta_2 + \varepsilon \tag{5}$$

where $\ln GI$ denotes natural logarithm of GI, Θ_1 and Θ_2 are parameter vectors of a series of independent variables and their spatial interaction terms, respectively. ρ refers to the spatial autocorrelation coefficient. a is the constant and ε is the error term. The interaction terms of spatial weights matrix and variables are used to capture spatial spillover effect of each variable.

Besides, environmental policies may drive the GI with a time lag. Usually, political factors need a period of time to take into effect (Song et al., 2015). Therefore, it's also essential to test out the time lag effect of political factors. More detailed analysis is conducted and the results are presented in our empirical study.

4. Results and discussion

4.1. Quantitative analysis of environmental policies

4.1.1. Two methods of choosing topic number

4.1.1.1. Artificial classification. Choosing a topic number for LDA model determines the model performance. To ensure that the model results are closer to human performance, an artificial classification from the environmental policy perspective is carried out before LDA model's training. We classify the whole dataset manually according to the contents of the policies, and thus determining the number of topics. As a result, three topics of policies are categorized based on the orientations of environmental policies. The first topic concerns about environmental regulation and protection. Most environmental policies in this category are the government's laws and regulations in relation to the environmental protection, which help to promote individual's pro-environmental behaviors and simultaneously restrict and regulate environmental damage behaviors. The second topic concentrates on prevention and treatment of pollution. The policies in this category mainly deal with problems of pollutant abatement. The last topic focus on environmental public governance. The policies in this category present the rules and legislations for the urban construction and management.

Through artificial classification, the cluster number is set and the classification results to some degree provide a guidance for the training process of LDA model.

4.1.1.2. Perplexity calculation. Apart from artificial classification, the perplexity is also calculated to confirm the topic number, see equation (1). Fig. 5 displays the perplexity with different topic number, which ranges from 1 to 10.

As is shown in Fig. 5, the perplexity fluctuates ups and downs with different topic number, reaching its lowest point when the topics number equals 4. It indicates that LDA model performs better in generating documents with 4 topics.

4.1.2. Model evaluation

As for the results of artificial classification and perplexity, we test them both in the training and evaluation of LDA model. Among the whole corpus with 1339 environmental policies, 300 of them are separated into test set, while others remained as training set. To begin with, we input the training set in the preprocessed text corpus to LDA topic model. The Dirichlet and conditional multinomial parameters for the LDA model are inferred and estimated based on EM algorithm. Then, we use the trained model to predict the samples in test set and obtain the probability of each document of policy distributed in 4 topics. The evaluation metrics, including *Precision*, *Recall* and $F1$-score of each topic are computed respectively and the general F-score is averaged by the $F1$-scores of all topics.

Average F-score is used to evaluate the model's validity and accuracy. We use two methods to determine the topic numbers in the training of LDA model, while the comparison results of average F-score are shown in Table 3. Apparently, it reaches a better performance when we choose topic number as 3 by artificial classification, whose average F-score is 75.39% and increases by nearly 3% compared to choosing topic number as 4 by perplexity.

Besides, the $F1$-score of topic 1 is the lowest compared to that of other topics. Topic 1 are more difficult to identify for the model. However, the $F1$-scores of other topics are higher, especially for topic 2 and topic 3. As for the average F-score, it is not high enough. Nevertheless, it is also acceptable, given the small sample size of the text corpus in model training. Therefore, the environmental policies of each topic indeed have some distinct characteristics and can be categorized with a reasonable name, which can provide a more intelligible and clearer explanation for next econometric models.

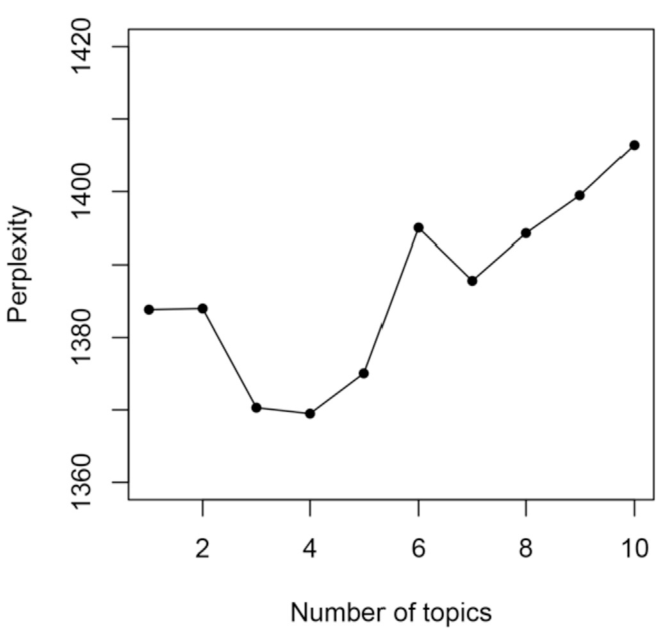


Fig. 5. Perplexity with different topic number.

4.1.3. Model outputs and political factors' construction

The results of model's training with 3 topics outperform that with 4 topics. Hence, we mainly discuss the results of model that trained with topic number 3. Table 4 presents the top words list of each topic as well as the probabilistic distribution of the top words $p(w|z)$. As we can see in the first row of Table 3, there are 59 environmental policies that have the highest probability in topic 1, 467 for topic 2 and 498 for topic 3. The categorization seems uneven as nearly 90% of policies dropped on topic 2 and topic 3. Therefore, we review environmental policies based on these top words of each topic to check out whether the categorization is reasonable.

We find that the top words of each topic correspond to aforementioned environmental orientations that drew by artificial classification, see the last row of Table 3. Therefore, the LDA model captures some underlying features of environmental policies, whose performance to a certain extent is consistent with human subjective classification.

Besides, LDA model outputs the probabilistic distribution of each policy on these four topics. Here, we take Guangdong province as an example, calculating political factors based on different topics in 2015.

Guangdong provincial government published 4 environmental policies in the year of 2015. As we can see in Table 5, we obtain the probabilities of each policy on the 3 topics. Apparently, the sum of the probabilities of each policy is 1. We set the political factors according to the topics, which are regulation factor p^1, prevention factor p^2 and governance factor p^3. Next, we sum over all policies' probabilities by topics and assign the summations to each political factor, respectively. As a result, Guangdong provincial government had the political strengths of 0.00115 for environmental regulation, 1.45072 for pollution prevention and 2.54813 for public governance. Besides, the aggregate political factor $P = p^1 + p^2 + p^3$ is the total number of policies that Guangdong province published in the whole year of 2015. From this example, among these 4 policies that published in Guangdong in 2015, one belongs to topic 2 while the other three policies are categorized in topic 3 according to the maximum probability.

4.2. Spatial econometric analysis

4.2.1. Spatial autocorrelation analysis

Clarifying whether there has spatial autocorrelation in GI is in important prerequisite of spatial econometric model. Therefore, spatial autocorrelation analysis is conducted using Moran's index.

Table 3
Evaluation of LDA model training based on two methods.

Based on artificial classification	Topic 1	Topic 2	Topic 3	
precision	90.00%	78.10%	96.73%	
Recall	30.00%	96.40%	93.08%	
$F1$-score	45.00%	86.29%	94.87%	
Average F-score		75.39%		
Based on artificial classification	**Topic 1**	**Topic 2**	**Topic 3**	**Topic 4**
precision	90.91%	74.42%	91.72%	100%
Recall	29.41%	89.66%	95.00%	55.56%
$F1$-score	44.44%	81.33%	93.33%	71.43%
Average F-score		72.63%		

Table 4
Top words in different topics.

Topics (policy quantity)	Topic 1 (59)	Topic 2 (467)	Topic 3 (498)
The probabilistic distribution of the top words	protection (0.1375)	pollution (0.2157)	management (0.0658)
	supervision (0.0576)	environment (0.1062)	illegal (0.0513)
	inspection (0.0457)	prevention (0.0804)	renovation (0.0449)
	nature (0.0412)	governance (0.0721)	approval (0.0375)
	regulation (0.0375)	punishment (0.0535)	enforcement (0.0306)
	criterion (0.0368)	resource (0.0274)	implementation (0.0247)
	monitoring (0.0298)	emission (0.0109)	construction (0.0135)
	environment (0.0095)	regulation (0.0082)	administration (0.0106)
	norm (0.0083)	disposal (0.0053)	investigation (0.0079)
	detection (0.0057)	permission (0.031)	examination (0.0023)
Environmental orientations	Environmental regulation & protection	Prevention & treatment of pollution	Environmental public governance

Table 5
An example: Political factors of Guangdong province in 2015.

Policy	Probabilities of policies on each topic			Sum of Topics
	Topic 1	Topic 2	Topic 3	
policy 1	0.00006	0.95006	0.04988	1
policy 2	0.00045	0.00048	0.99907	1
policy 3	0.00058	0.16600	0.83342	1
policy 4	0.00006	0.33417	0.66577	1
Political factors (Sum of Policies)	0.00115	1.45072	2.54813	4

According to Eq. (4), we compute the Moran's index from 2003 to 2016 and plot it in Fig. 6.

In Fig. 6, we plot Moran's index of different types of GI. Obviously, the Moran's index of the total GI fluctuates around 0 during 2003–2016, which implies that there has no great changes in total GI. However, the Moran's index of urban infrastructure investments (GI_UI) has a significant downward trend, which is negative in most years during 2003–2016. It implies that around the provinces with high GI_UI has little neighboring provinces that also invest a lot in urban infrastructure. On the contrary, the Moran' s index of treatment of pollution investments (GI_TP) and environmental protection investments (GI_EP) are greater that 0 and rapidly increase during 2012–2016, which indicates that provinces with high GI_TP and GI_EP are surrounded by provinces that also invest a lot in pollution treatment and in environmental protection. Hence, we can conclude that for most provinces, pollution treatment and environmental protection are much more urgent than urban infrastructure improvement. Provinces with high GI_TP and GI_EP have positive agglomeration effects on neighboring provinces while provinces with high GI_UI have inverse effects on neighboring provinces.

4.2.2. Test of time-lag effect of political factor

Regarding the time-lag effect of political factors, we take into consideration the environmental policies that published in previous year. We mainly consider the time-lag within two order, keeping an appropriate period of time to ensure the fully exertion of the policies' utility and prevent the obsolescence. Therefore, we build up 6 OLS model to test the time-lag effect of different order successively. We set P_t as the number of environmental policies that provincial government published in year t. We can also regard it as the aggregation of political strengths on different environmental orientations. Therefore, P_{t-1} and P_{t-2} are the number of environmental policies published in year $t-1$ and $t-2$, respectively. Other variables are shown clearly in Table 1. The OLS regression results are presented in Table 6.

As we can see, in these six models, we mainly take ln GI as dependent variable along with political, economic and

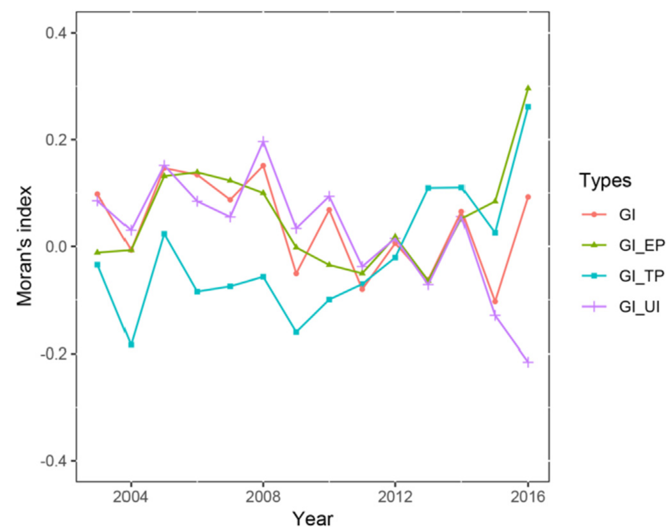


Fig. 6. Global Moran's index.

environmental factors as independent variables. Specifically, the first three model concerns only one political factor with different time-lag P_{t-2}, P_{t-1} and P_t, respectively. Model 4 and model 5 take the weighted sum of consecutive two terms of political factors while model 6 considers the aggregation of different time-lag political factors. Surprisingly, we find that the coefficients of the term P_{t-1} are significant in all models while the coefficients of P_{t-2} and P_t fail to pass the significant test in contrast. This implies that the environmental policy most likely comes into its strongest effect one year after promulgation. Besides, environmental policy is strictly time limited, which may gradually lose its effect after promulgating for over two years. Therefore, we can infer that the political factors have one-year time-lag effect.

Apart from political factors, nearly most other variables have greatly significant and positive influence on GI, except for GDP. Among these variables, GDP per capita ($GDPP$) plays the most important role in GI since it has the biggest and positive coefficients. On the other side, a positive relationship also exists between GI and environmental factors.

In all, economic and environmental factors have powerful drive capability, which grease the wheels of GI development profoundly. In this part, we mainly test the time-lag effect of the political factors. However, according to previous model, policies are categorized into four environmental orientations, yet the influencing mechanism of different political orientations and the spillover effects among these factors on different types on GI remains confusing. Therefore, spatial Durbin model are conducted in further analysis.

Table 6
Test of policy time-lag effect.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
P_{t-2}	0.001 (0.217)			−0.002 (−0.291)		−0.002 (−0.326)
P_{t-1}		0.013** (2.086)		0.014** (2.093)	0.012* (1.752)	0.012* (1.779)
p_t			0.009 (1.527)		0.007 (1.030)	0.007 (1.040)
ln *GDP*	0.059 (0.520)	0.055 (0.480)	0.058 (0.511)	0.056 (0.489)	0.054 (0.474)	0.055 (0.484)
ln *GDPP*	0.733*** (12.351)	0.721*** (12.195)	0.722*** (12.132)	0.722*** (12.163)	0.713*** (11.986)	0.715*** (11.961)
ln *FAI*	0.195*** (2.721)	0.204*** (2.864)	0.199*** (2.788)	0.202*** (2.831)	0.206*** (2.893)	0.204*** (2.858)
ln *Water*	0.267*** (3.689)	0.255*** (3.543)	0.261*** (3.628)	0.256*** (3.550)	0.252*** (3.498)	0.254*** (3.508)
ln *Gas*	0.191*** (4.086)	0.199*** (4.298)	0.191*** (4.137)	0.198*** (4.242)	0.199*** (4.297)	0.198*** (4.238)
ln *Solid*	0.183*** (4.494)	0.180*** (4.458)	0.185*** (4.575)	0.181*** (4.463)	0.181*** (4.495)	0.182*** (4.502)
F value	585.9***	592.443***	589.376***	517.285***	518.595***	460.016***
adjusted R^2	0.904	0.905	0.905	0.905	0.905	0.905

Note: The number in parentheses are t statistics.
*p < 0.1; **p < 0.05; ***p < 0.01.

4.2.3. Results of spatial Durbin model (SDM)

In this part, four spatial Durbin model in terms of different types of GI are built to test the spillover effect of multi-factors. Moreover, we focus on political factors more detailed, using four political orientations p^1_{t-1}, p^2_{t-1} and p^3_{t-1} as independent variables with consideration of time-lag effects of environmental policy.

The results of SDM are shown in Table 7. We provide our discussions and explanations mainly from two perspectives: direct effect and indirect effect.

4.2.3.1. Direct effect. Direct effect indicates the main effects of independent variables in one province that act upon its own. For instance, in Table 7, the environmental regulation factor p^1_{t-1} has significant and positive effect on ln *GI* and ln *GI_UI*. It means that total GI has a tremendous increase under the government's environmental regulation, especially for the part of ln *GI_UI*. Besides, p^1_{t-1} also performs a negative impact on ln *GI_EP*, causing the reduce of environmental facilities investments. In contrast, the pollution treatment factor p^2_{t-1} has negative effect on ln *GI_UI* while having positive effect on ln *GI_EP* instead. We can infer that there have mutual controlling and balancing effect between p^1_{t-1} and p^2_{t-1}. The environmental public governance factor p^3_{t-1} positively associates to ln *GI*, but having no relationship with the other types of GI. Different political factors may exert different effects on GI. Obviously, the government plays different roles in leading the development of GI, performing its macro-control function through environmental policies.

As for economic factors, GDP per capita significantly influences all three types of GI. Basically, economic growth is the foundation of GI. An economically developed province will be more capable of boosting GI and improving environment. Fixed assets investment (ln *FAI*), as the name suggests, is investment of assets that cannot directly sold, such as urban infrastructure, lands buildings and so on. Therefore, ln *FAI* shows significant in urban construction investments.

Considering environmental factors, the pollutants of waste water, waste gas and solid waste are mostly related to different types of GI. It shows that the severer of the environmental deterioration, the higher GI the government will invest, not only for pollution treatments, but also for the development of green technology, which provides an access to cope with waste and turn it into treasure.

Compared to economic and environmental factors, political factors show less significant terms. Therefore, we suggest that the government should strengthen its power of environmental policy for guiding the balanced development of different types of GI.

4.2.3.2. Indirect effect. Next, the interaction terms of spatial weights matrix with multiple factors are also considered and analyzed. Indirect effect, also known as spillover effect, indicates the factors' influence of one province on its neighboring provinces. As we can see, political factors exert stronger indirect effects than direct effect. Concretely, the regulation factor p^1_{t-1} is significant in ln *GI*, ln *GI_UI*, ln *GI_TP* and ln *GI_EP*. However, the parameters of ln *GI*, ln *GI_UI* and ln *GI_EP* are negative while that of ln *GI_TP* is positive, which can be inferred that the environmental policy has strong pertinency. The same policy may produce different effects on different types of GI of neighboring provinces. As for ln *GI_TP*, we find that most provinces with strong regulation political factor are economically developed provinces, such as Beijing, Jiangsu and so on. Around these provinces are powerful industrial provinces (e.g., Henan, Shandong, Zhejiang). Therefore, to prevent the pollution diffusion, neighboring provinces are always required to invest more ln *GI_TP* for pollution treatments.

Regarding pollution treatment factor (p^2_{t-1}), it has negative spillover effect on ln *GI_TP*. Public governance factor (p^3_{t-1}) does not have significant effect on any types of GI. Apparently, these political factors have their exclusive effects on a certain type of G I, which means that it's possible for government to adjust the political orientations and make policy more pertinent to different environmental issues.

The spillover effects of most economic and environmental factors play an opposite influence on different types of GI compared to the direct effect. For instance, fixed assets investment ln *FAI* in one province have negative impact on neighboring province, which completely oppose to the impact on its own province. So is ln *Water* and ln *Gas*. The GI show great difference between one province and its neighboring provinces under the influence of the same factors. This also verifies the existence of spatial characteristic in economic and environmental factors.

4.3. Robustness test

In order to confirm the influence of political factors on GI, a robustness test is conducted. In previous OLS model (see Table 6), we test the time-lag effect of environmental policy and set the number of policies as political factor, which reflects the political strengths on environmental protection. Here, we reset the political factor and use a dummy variable as a substitute. The dummy variable $\tilde{P}_{t-1}$ indicates whether the provincial government publishes environmental policy in year $t-1$. The results of robustness test are presented in Table 8.

In Table 8, the political factor in model 1 remains as the number of environmental policies P_{t-1} while it is changed as dummy variable $\tilde{P}_{t-1}$ in model 2. However, the significances of all variables stay consistent between two models even if the coefficients

Table 7
Test of spatial econometric model with 3 classes.

Variables	ln *GI*	ln *GI_UI*	ln *GI_TP*	ln *GI_EP*
p_{t-1}^{1}	**0.089*** (3.004)**	**0.180*** (4.493)**	−0.024 (−0.555)	**−0.083* (-1.676)**
p_{t-1}^{2}	−0.017 (−1.361)	**−0.034** (-2.022)**	0.011 (0.582)	**0.035* (1.669)**
p_{t-1}^{3}	**0.021* (1.672)**	0.015 (0.880)	0.000 (0.018)	0.031 (1.509)
ln *GDP*	0.035 (0.303)	−0.207 (−1.325)	**0.566*** (3.340)**	−0.189 (−0.981)
ln *GDPP*	**0.673*** (9.586)**	**0.550*** (5.792)**	**0.427*** (4.149)**	**0.754*** (6.450)**
ln *FAI*	**0.194** (2.319)**	**0.649*** (5.736)**	−0.021 (−0.174)	0.131 (0.941)
ln *Water*	**0.332*** (4.229)**	**0.369*** (3.480)**	**−0.222* (-1.932)**	**0.491*** (3.747)**
ln *Gas*	**0.228*** (4.222)**	**0.313*** (4.314)**	**0.573*** (7.243)**	**0.214** (2.377)**
ln *Solid*	**0.149*** (3.533)**	−0.024 (−0.415)	0.093 (1.502)	**0.204*** (2.904)**
$W\times\ p_{t-1}^{1}$	**−0.111* (-1.952)**	**−0.141* (-1.823)**	**0.219*** (2.620)**	**−0.302*** (-3.153)**
$W\times\ p_{t-1}^{2}$	0.010 (0.410)	0.005 (0.142)	**−0.084** (-2.279)**	0.027 (0.634)
$W\times\ p_{t-1}^{3}$	0.008 (0.330)	0.027 (0.829)	0.041 (1.157)	0.025 (0.612)
W×ln *GDP*	0.286 (1.308)	**0.466* (1.658)**	**−0.503* (-1.658)**	0.496 (1.435)
W×ln *GDPP*	0.033 (0.444)	**0.371*** (3.713)**	−0.016 (−0.143)	−0.137 (−1.093)
W×ln *FAI*	**−0.291* (-1.950)**	**−0.689*** (-3.418)**	0.020 (0.092)	−0.115 (−0.461)
W×ln *Water*	**−0.181* (-1.860)**	**−0.322** (-2.541)**	**0.331** (2.420)**	**−0.255* (-1.654)**
W×ln *Gas*	−0.164 (−1.625)	0.128 (0.923)	−0.030 (−0.197)	**−0.428*** (-2.583)**
W×ln *Solid*	**0.259*** (3.032)**	0.030 (0.264)	0.003 (0.025)	**0.321** (2.250)**
W×*dep.var.*	0.003 (0.045)	**0.128** (1.991)**	**0.234*** (3.746)**	−0.012 (−0.176)
Adjusted R^2	0.915	0.865	0.815	0.815
$Sigma^2$	0.144	0.262	0.312	0.401
Log-likelihood	−192.948	−325.497	−365.230	−417.305

Note: The number in parentheses are *t* statistics.
*p < 0.1; **p < 0.05; ***p < 0.01.

inevitably change a little. This test not only verifies the robustness of political factor, but also confirms that the environmental policy indeed exerts a positive effect on GI.

5. Conclusions and policy implications

In this paper, we address the problems of GI and its influencing factors using LDA topics model and spatial econometric model. Three key issues are analyzed and solved. With respect to the first issue, there is little literature concentrates on environmental policy's quantification. Our study spares no effort in mining text of policy. A series of data processing steps are conducted and policies are quantified as political factors, which included three orientations: environmental regulation & protection, pollution prevention & treatment and public governance. Our model has cultivated deeper characteristics of environmental policies, which makes the political factor more objective and reliable.

As for the second and third issues, we first conduct a spatial autocorrelation analysis to clear the spatial features of different types of GI. Then, we use OLS regression and discover that political factor exists one-year time-lag effect. Finally, spatial Durbin models in terms of different types of GI are built to test the direct effects and spillover effects of three factors. The influencing mechanism of multi-factors on GI manifests that: (1) the government plays different roles, especially in setting up and monitoring environmental regulation. (2) different political factors control and balance each other mutually. (3) The spillover effects of political factors are more salient than direct effects. (4) Most factors' spillover effects are completely opposite to direct effects, particularly for economic and environmental factors.

Table 8
Robustness test of political factors.

	Model 1	Model 2
P_{t-1}	0.013** (2.086)	
$\tilde{P}_{t-1}$		0.089** (2.090)
ln *GDP*	0.055 (0.480)	0.077 (0.673)
ln *GDPP*	0.721*** (12.195)	0.714*** (11.996)
ln *FAI*	0.204*** (2.864)	0.192*** (2.708)
ln *Water*	0.255*** (3.543)	0.251*** (3.474)
ln *Gas*	0.199*** (4.298)	0.195*** (4.226)
ln *Solid*	0.180*** (4.458)	0.177*** (4.385)
F value	592.443***	592.463***
Adjusted R^2	0.905	0.905

Note: The number in parentheses are *t* statistics.
*p < 0.1; **p < 0.05; ***p < 0.01.

Based on the findings above, we put forward the following policy implications.

(1) The significance of political factors reflects the enforcement intensity of the environmental policies. However, as is shown in Table 7, few political factors are salient, which indicates that environmental policies need more effective implementation. Therefore, the government should reinforce the execution of environmental policies.
(2) The provincial government should more concentrates on the development of self-province, strengthening the direct effects and reducing the spillover effects of political factors. This contributes to promote the GI of self-province instead of causing extra needless influences on neighboring province.
(3) The regulation factor exerts quite significant effects on different types of GI, implying that the government pays most attention and makes great efforts on environmental regulation compared to other political factors. As we know, different political factors impact on different types of GI, which are used to address different environmental issues. In order to achieve the overall environmental improvement, the government should consider equally on different political factors and lead the balanced development of GI.

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Appendix

Table A.1
The text data source of environmental policies from the official websites of Chinese provincial departments of environmental protection.

Province	Quantity	Sources	Province	Quantity	Sources
Beijing	87	http://www.bjepb.gov.cn/	Hubei	69	http://hbt.hubei.gov.cn/xwzx/
Tianjin	51	http://hjbh.tj.gov.cn/	Hunan	25	http://hnhbt.hunan.gov.cn/
Hebei	12	http://www.hebhb.gov.cn/	Guangdong	74	http://www.gdep.gov.cn/
Shanxi	27	http://www.sxhb.gov.cn/	Guangxi	33	http://www.gxepb.gov.cn/
Inner-Mongo	26	http://hbt.nmg.gov.cn/	Hainan	48	http://hnsthb.hainan.gov.cn/
Liaoning	51	http://hbt.ln.gov.cn/	Chongqing	38	http://www.cepb.gov.cn/
Jilin	15	http://hbj.jl.gov.cn/	Sichuan	22	http://www.schj.gov.cn/
Heilongjiang	42	http://www.hljdep.gov.cn/	Guizhou	36	http://www.gzhjbh.gov.cn/
Shanghai	92	http://www.sepb.gov.cn/	Yunnan	63	http://www.ynepb.gov.cn/
Jiangsu	74	http://hbt.jiangsu.gov.cn/	Tibet	9	http://www.xzep.gov.cn/
Zhejiang	81	http://www.zjepb.gov.cn/	Shaanxi	35	www.snepb.gov.cn/
Anhui	54	http://www.aepb.gov.cn/	Gansu	39	http://www.gsep.gansu.gov.cn
Fujian	19	http://hbt.fujian.gov.cn/	Qinghai	39	http://www.qhepb.gov.cn/
Jiangxi	45	http://www.jxepb.gov.cn/	Ningxia	37	http://www.nxep.gov.cn/
Shandong	14	http://www.sdein.gov.cn/	Xinjiang	28	http://www.xjepb.gov.cn/
Henan	14	http://www.hnep.gov.cn/	Total	1339	

Table A.2
The Chinese version of Table 4.

Topics (policy number)	Topic 1 (59)	Topic 2 (467)	Topic 3 (498)
The probabilistic distribution of the top words $p(w\|z)$	保护 (0.1375)	污染 (0.2157)	管理 (0.0658)
	监管 (0.0576)	环境 (0.1062)	违法 (0.0513)
	检查 (0.0483)	防治 (0.0804)	整治 (0.0449)
	自然 (0.0398)	治理 (0.0721)	审批 (0.0375)
	规定 (0.0219)	处罚 (0.0535)	执法 (0.0306)
	标准 (0.0174)	资源 (0.0274)	实施 (0.0247)
	监测 (0.0136)	排放 (0.0109)	建设 (0.0135)
	环保 (0.0095)	条例 (0.0082)	行政 (0.0106)
	规范 (0.0083)	排污 (0.0053)	查处 (0.0079)
	检测 (0.0057)	许可 (0.0031)	调查 (0.0023)
Environmental orientations	Environmental regulation & protection	Prevention & treatment of pollution	Environmental public governance

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