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The Impact of Energy Consumption Structure on China's Environmental Quality

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Abstract: This paper explores the effects of energy structure on China's environment quality from 2000 to 2014. We set up a composite pollution index covering air, water and land dimension of the environment to represent the environment quality. Greater index means worse environment quality. Based on the extended Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model, we study the elasticities of population, affluence, energy structure and energy efficiency on the pollution index. Results show that energy structure is statistic significant to China's overall environmental quality. Both population and affluence affect positively the pollution index but energy efficiency performs negatively. Measures to lower coal proportion are particularly important to improve environmental quality.

Keywords: energy structure; environmental quality; STIRPAT model; IPAT equation;

1 Introduction

China has became one of the biggest emitter in the world due to its fast growing energy consumption [2].Chinese central government has made its strategic goal of building a two-oriented society, trying to achieve a harmony and united society by integrating energy, environment and development. In the Eleventh Five-Year Plan, it is clearly proposed that energy consumption intensity (ton of standard coal per ten thousand Yuan Dynasty of GDP) should be reduced by 20% and major pollutants emissions should be cut 10%.

Recently, researchers have turned to combine across environmental domains or environmental types to construct one environmental measure. While in early studies, ambient conditions were mostly explored singly (BOD [3], carbon dioxide emissions[4],sulfur dioxide[11]). There have been some composite environmental quality indexes covering three environmental domains, air, water and land. Messer, et al [9] constructed an environmental quality index (EQI) representing multiple domains of the non-residential ambient environment, including the air, water, land, built and sociodemographic domains. Yang, et al [14] proposed a pollution emissions index that could reflect the level of environmental quality. Three pollutants including waste-water, exhaust and solid waste were considered in their index. Yang, et al [13] presented a composite environmental pollution index of China by selecting the total waste water emissions, industrial exhaust emissions and industrial solid waste emissions.

Energy structure plays an important role in environment quality. Li, et al [7] considered total factor energy efficiency, industrial structure and energy structure are the main factors that affect the environmental pollution of China. Xu, et al. [12] showed that the contribution rate of economic development to carbon emissions per capita was exponential growth, however, the contribution rate of energy structure and energy efficiency restraining to carbon emissions per capita were as the inverse U shape. Marrero [8] included energy variables in a dynamic panel data model and suggested how merely

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shifting the energy mix toward renewable sources (and, to a lesser extent, nuclear) would yield significant reductions in per capita emissions. Hong et al.[5, 6] suggested that coal-fired electricity infrastructure needs to be replaced by low-carbon electricity generation options.

As single pollutant can hardly express the situation of environmental quality, we propose a composite pollution index that can reflect the level of environmental quality in China. An expanded STRIPAt model is applied to test the influencing factors of the composite pollution index.

2 Methodology

2.1 Composite pollution index

Three pollutants including waste-water, exhaust and solid waste are selected then consolidated to form a pollution index. Because waste water and exhaust are difficult to be stored, emissions are adopted. Since tremendous amount of solid waste is stored instead of being discharged, production is employed. Considering China is a big developing economy, we pick industrial waste water emissions, industrial exhaust emissions and industrial solid waste production as indictors that influence the comprehensive evaluation index of environmental quality. They are measured at different units of spatial and temporal aggregation.

Measures collected at different scales would need to be meaningfully combined. We turn evaluation indicators into dimensionless data in the first place by range standardization method. Let x_{tj} be the numerical value of indicator j at time t ($j = 1, 2, 3; t = 1, 2 \cdots, T$). The normalized value x^*_{tj} is given as

$$x^*_{tj} = \frac{x_{tj} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{1}$$

where x_j^{min}, x_j^{max} are the minimum and maximum of x_{tj} respectively.

The composite pollution index is defined as the linear combination of the three standardized emissions. Analytic Hierarchy Process (AHP) is applied to find the combination coefficients [15]. The judgement matrix in this study is

$$A = \begin{pmatrix} 1 & \frac{3}{2} & 5 \\ \frac{3}{2} & 1 & 6 \\ \frac{1}{5} & \frac{1}{6} & 1 \end{pmatrix} \tag{2}$$

Followed by the process of AHP, we obtain the composite pollution index as

$$I = 0.8059water + 0.5788gas + 0.1247solid \tag{3}$$

where $water, gas, solid$ represent respectively the amount of waste water emissions, waste gas emissions and industrial solid emissions which have been normalized.

2.2 Extended STIRPAT model

The basic Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model [1] is

$$I = aP^bA^cT^de \tag{4}$$

where I represents environmental impact, P population, A affluence and T technology, $a - d$ model parameters and e the error term..

Taking logarithms allows for hypothesis testing and examining ecological elasticities using linear regression. After applying this transformation, the model becomes [10]:

$$lnI = a + b(lnP) + c(lnA) + dlnT + \epsilon \tag{5}$$

where ϵ is the value of e after taking logarithm form. Considering energy structure and energy efficiency as two technology influencing factors, we extend the original STIRPAT model as follows:

$$lnI = a + b(lnP) + c(lnG) + f(lnSE) + g(lnEE) + \epsilon \tag{6}$$

where I is the composite pollution index, P is population (10 thousands persons), G is GDP (One hundred million Yuan, 2000 constant price), SE stands for energy structure, which is reflected by the percent of coal consumption on the total energy consumption, EE is energy efficiency (GDP per ton of standard coal).

2.3 Ridge regression

The multicollinearity refers to a statistical phenomenon that two or more predictor variables in a multiple regression are highly correlated, which can be tested by valuing the variance inflation factors (VIF) of the variables. If the VIF is larger than 10, it indicates that a severe multicollinearity existed. Multicollinearity will result in large standard error among related independent variables. These errors are mainly reflected by regression model parameters large variance, which will significantly reduce the stability of the regression model.

The ridge regression can handle multicollinearity by incorporating a small positive k to the diagonal of the quantity [16]. The ridge estimator is obtained by

$$\hat{\beta} = (X'X + kI)^{(-1)}g \tag{7}$$

where $g = X'Y$,k is the ridge parameter or the biasing parameter that satisfies $k \geq 0$ and I is an identity matrix.

Although ridge regression is a biased estimation, a minimal bias k can significantly improve the estimation and reduce the overall mean squared error. When $k = 0$, the ridge regression is converted back to ordinary least square (OLS) regression. Considering the fact that mean square error is reduced at the cost of a variance in parameter estimation an appropriate ridge regression coefficient k thereby should no only reduce the VIF under acceptable range but also should be a small as possible. Within the econometric literatures, several way to decide the optimal k value have been proposed. The ridge trace plot method is a widely applied method that has been employed in this paper. The $\hat{\beta}$ coefficients are plotted by changing k with a step length of 0.01 within [0,1] and the optimal value for k is chosen a the point where $\hat{\beta}$ appears to stabilize.

3 Results

3.1 Data

Data used in this study are extracted from China Statistical Yearbook and China Statistical Yearbook of Environment in the relevant years. Fig. 1 shows the evolution of coal consumption structure structure and the pollution index from 2000 to 2014. The proportion of coal in total energy consumption fell by 6.5 percentage point from its peak before the Asia Financial Crisis. Oil percentage remained stable. The clean energy, such as natural gas and primary electricity increased fast. Meanwhile the rate of environmental pollution index decreased as well. Thus there may be a positive correlation between the coal proportion and pollution index.

3.2 Ordinary least square regression of the model

OLS regression was performed using SPSS 18.0 package to estimate the coefficients of the model. Table 1 shows the results. The coefficient of determination (R^2) for the model is 0.917, and the F-test is highly significantly with an F-static of 39.504 at 0.1% significant level. However,the variable of P,G and EE cannot pass the t-test even at 10%

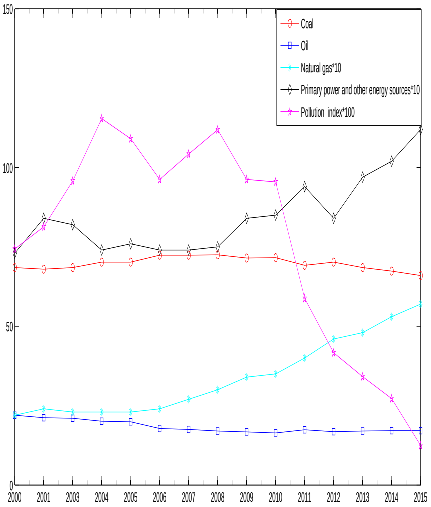

Figure 1: Evolution of energy consumption structure and pollution index. Different vertical scales are taken to ensure a same range.

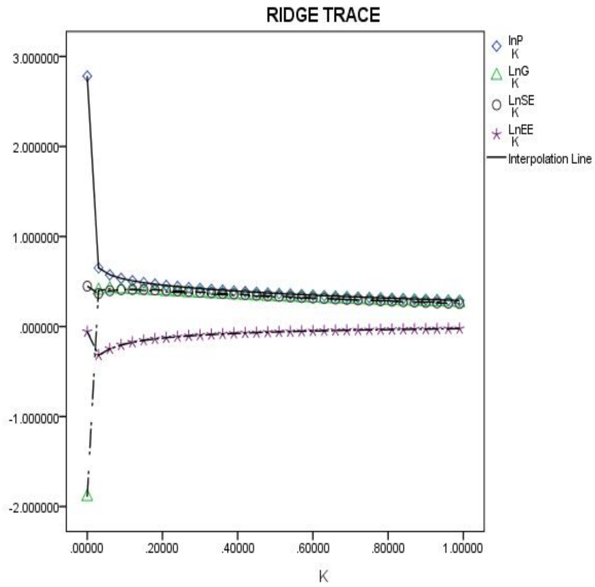

Figure 2: Ridge trace curve

Table 1: Influencing factors of pollution index by OLS

	Unstandardized coefficients	Std.error	t-Statistic	Sig.	VIF.
C	-727.695	393.703	-1.848	0.094	.
LnP	75.605	43.617	1.733	0.114	432.955
LnG	-2.707	2.610	-1.037	0.324	559.208
LnSE	10.103	5.267	1.918	0.084	9.188
LnEE	-0.290	2.204	-0.131	0.898	31.676
R square	0.940	Adjusted R square	0.917		
F	39.504	Sig.	0.000		

significant level. Furthermore, there exists serious multi-collinearity among variables because most VIF values are larger than 10.

3.3 Ridge regression of the model

We carried on ridge regression to eliminate multi-collinearity. As shown in Fig. 2, we obtained a ridge trace curve by plotting the values of the coefficients against the successive values of k with a step length of 0.02. The number 0.1 is selected as the ridge parameter because the coefficients of independent variables tend to be stable at this point. Tab. 2 shows the ridge regression results when $k = 0.1$. The overall fit is very good with a coefficient of determination (R^2) of 0.918. The F-test of the model is highly significant with an F-statistic of 28.06 at the 0.1% significance level. Except for EE, all estimated coefficients passed the significance tests with t-statistic at 1%significance level.There- fore, more reliable parameter estimates were obtained and the STIRPAT model in this study is expressed as follows:

$$lnI = -182.4395 + 14.2561lnP + 0.5900742lnG + 9.2443842lnSE - 0.9847834LnEE \tag{8}$$

Table 2: Ridge regression results(k=0.1)

Items	Non-normalized coefficient	SE(B)	Normalized coefficient	t-Statistic	Sig.t.
LnP	14.2561017	1.8020212	0.5246827	7.9111732	0.0000130
LnG	0.5900742	0.0697940	0.4125244	8.4545128	0.0000072
LnSE	9.2443842	2.1330150	0.4104086	4.3339519	0.0014803
LnEE	-0.9847834	0.5561270	-0.1939851	-1.7707887	0.1070154
C	-182.4395372	17.7958156	0.000000	-10.2518222	0.0000013
R square	0.9181943703	F	28.06024395 Sig.F	0.00002048	

3.4 Discussion

The elasticities for population, GDP and energy structure are statistically significant The elasticity for energy efficiency is not statistically significant but has a negative sign. This means that population, GDP and energy structure promote the pollution index, decrease the environment quality while energy efficiency affect environment quality in the positive way. The contribution of influencing factors varies in a very different scales. Population ranks first (0.524) followed by affluence(0.413), energy structure(0.410) and energy efficiency (-0.193). Holding other factors constant, decreasing the coal percentage by 1, the pollution index is decreased by 9.244 percentage.

The ridge regression results confirm the finding that energy structure is the key factor influencing overall environment quality: smaller coal proportion in the total energy consumption is associated with better environment quality. In terms of policy, the regressions also confirms that measures to lower coal proportion would lead to a substantial improving of quality in air, water and land.

4 Conclusion

Based on the extended STIRPAT model,we explored the effects of population, affluence, energy structure and energy efficiency on China's environment quality from 2000 to 2014. We set up a composite pollution index covering air, water and land dimension of the environment. To address the multi-collinearity among the independent variables,a ridge regression method was employed to give a more reliable estimation for the coefficient under acceptable bias. The results show that energy structure is the largest driving force to leading to increases pollution index. Additionally, population and affluence, shown significant positive effects on pollution index. This comprehensive estimate of environmental quality would improve our understanding of the relationship between energy consumption and environmental quality.

Acknowledgments

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