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THE FISCAL EFFECT OF CHINA'S ENVIRONMENTAL PROTECTION TAX REFORM ON CITY-LEVEL GREEN TOTAL FACTOR PRODUCTIVITY

Abstract:
Measuring the green total factor productivity (GTFP) of 288 cities in China, the study found that the environmental protection tax reform significantly promoted green total factor productivity in the short term, and also had a significant fiscal effect in the short to medium term.

Keywords:
Green Total Factor Productivity, Environmental Protection Tax Reform, Fiscal Effect.

1. Introduction

This paper takes the implementation of China's environmental protection tax in 2018 as a policy impact[1,2], uses panel data from 288 cities in China, and uses a dynamic double difference model to study the fiscal effect of environmental protection tax on city-level green total factor production efficiency. Therefore, the research questions are raised here: Does the environmental protection tax reform policy have a long-term effect on improving green total factor production efficiency, or is the policy impact only significant in the short term? Based on the research questions, the research hypothesis is put forward. The implementation of environmental protection tax has a significant positive impact on green total factor production efficiency, especially in the short term after the implementation of the policy. This study will conduct an empirical analysis of the research hypotheses, and the research results will provide empirical basis and policy inspiration for the implementation of environmental tax policies in China and other developing countries.

2. Data and Methodology

2.1 Data Source

The research scope of this paper is 288 cities at prefecture level and above from 2013 to 2022. City-level data mainly comes from the China City Statistical Yearbook, most of the missing values come from local statistical yearbooks or bulletins, and missing values less than 50 are supplemented by linear interpolation and moving average methods. City-level energy consumption data comes from the China Energy Statistical Yearbook.

2.2 Green Total Factor Productivity

The green total factor productivity index is an indicator that comprehensively reflects the economic efficiency and environmental benefits of a city. It can simultaneously consider economic input, economic output and carbon dioxide(CO_2) emissions[3], so it can better evaluate the level of China's environmental protection tax on the green transformation of cities. Green total factor productivity is calculated using the super-slack measure (Super-SBM) model of non-expected output[4]. By solving a linear programming problem and calculating the Super-SBM efficiency score of each DMU, the decision-making units (DMUs) with efficiency values greater than 1 can be evaluated, and the results are more accurate than the SBM model. The model assumes that the production system consists of N decision-making units, each of which has Xi inputs, expected outputs and unexpected outputs [5]. The equation is expressed as follows:

$$\rho^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m} \overline{x}_i / x_{ik}}{\frac{1}{q+w}\left(\sum_{r=1}^{q} \overline{y}_r^{g} / y_{rk}^{g} + \sum_{u=1}^{w} \overline{y}_u^{b} / y_{uk}^{b}\right)} \quad (1)$$

$$s.t.\begin{cases} \overline{x} \geq \sum_{i=1,\neq k}^{n} \lambda_i x_i + s_i^- & i = 1,\dots,m \\ \overline{y}_u^b \geq \sum_{u=1,\neq 0}^{n} \lambda_u y_u^b - s_u^b & u = 1,\dots,w \\ \overline{y}_r^g \geq \sum_{r=1,\neq 0}^{n} \lambda_r y_r^g - s_r^g & r = 1,\dots,q \\ \overline{x}_i \geq x_{ik},\ \overline{y}_r^g \leq y_{rk}^g,\ \overline{y}_u^b \geq y_{uk}^b,\ \lambda \geq 0 \\ \sum_{i=1,\neq k}^{n} \lambda_i = 1,\ \sum_{i=1,\neq k}^{n} \lambda_r = 1,\ \sum_{u=1,\neq k}^{n} \lambda_u = 1 \end{cases} \quad (2)$$

ρ^* represents the efficiency value, s_i^-, s_u^b, s_r^g are the slack of input, expected output and undesired output, λ is a column vector, and a horizontal line is added above the letter to represent the projection value of the corresponding input or output, and the subscript k represents DMU.

Labor and capital inputs are represented by the number of employees and capital stock at the end of each city, respectively. The capital stock is obtained by deflating the total fixed asset formation by the fixed asset investment price index. Due to the lack of energy consumption data for prefecture-level cities, this paper decomposes the total energy consumption of the province (10,000 tons of standard coal) into prefecture-level cities according to the city's GDP contribution. The actual GDP of each city is taken as the expected output, 2013 is taken as the base year, and the city's consumer price index is used for deflation. The CO_2 emissions of prefecture-level cities are taken as undesirable output. The city-level CO_2 emissions data are from CEADs-Carbon Emission Accounts and Datasets for emerging economies (www.ceads.net) for free download, which provides city-level CO_2 emissions data from 1997 to 2019[6], and CO_2 emissions data from 2020 to 2022 are supplemented by the CEICdata database. Table 1 shows the descriptive statistics of the variables, and the maximum and minimum values of each variable are quite different.

Table 1 – Descriptive statistics of variables.

Variable	Obs	Mean	Std. dev.	Min	Max
Labor Input	2880	611747.80	966069.90	39509.00	11591400.00
Capital Input	2880	16270.61	16220.25	1010.13	154212.10
Energy Consumption	2880	1496.54	1658.57	35.59	11859.00
Real GDP	2880	2654.34	3816.98	33.23	36824.49
CO_2 Emissions	2880	37395.05	40242.91	1329.86	457756.70

2.3 Sample selection and variables

The control variables used in this paper are: (1) City scale(LnPop), measured by the total population at the end of the year. Large cities can use the population quantity and quality dividend to improve the core competitiveness of enterprises, use economies of scale to create advantages, and improve production efficiency and energy conservation and emission reduction levels [6]. (2) Economic quality level(LnPer), measured by GDP per capita. Cities with high GDP per capita can achieve consumption upgrades, investment transformation, and energy optimization to improve production efficiency and environmental benefits [7]. (3) Economic development level(GDPR), measured by GDP growth rate. Cities with high GDP growth rates are usually accompanied by investment growth. Governments and enterprises will increase investment in green technologies, such as clean energy, environmental governance, and circular economy, which will improve green total factor productivity [8]. Table 2 shows the descriptive statistics of the variables. The GTFP variable is calculated using the Super-SBM model, GDPR is the GDP growth rate of the city percentage, and other variables are all processed by natural logarithms.

Table 2 – Descriptive statistics of variables.

Variables	Obs	Mean	Std. Dev.	Min	Max
GTFP	2592	0.0278	0.171	-0.988	1.305
LnPop	2592	5.8910	0.708	3.008	8.136
LnPer	2592	10.900	0.529	9.227	12.46
GDPR	2592	6.3710	3.299	-20.63	19.80

3. Empirical analysis results

3.1 Model construction

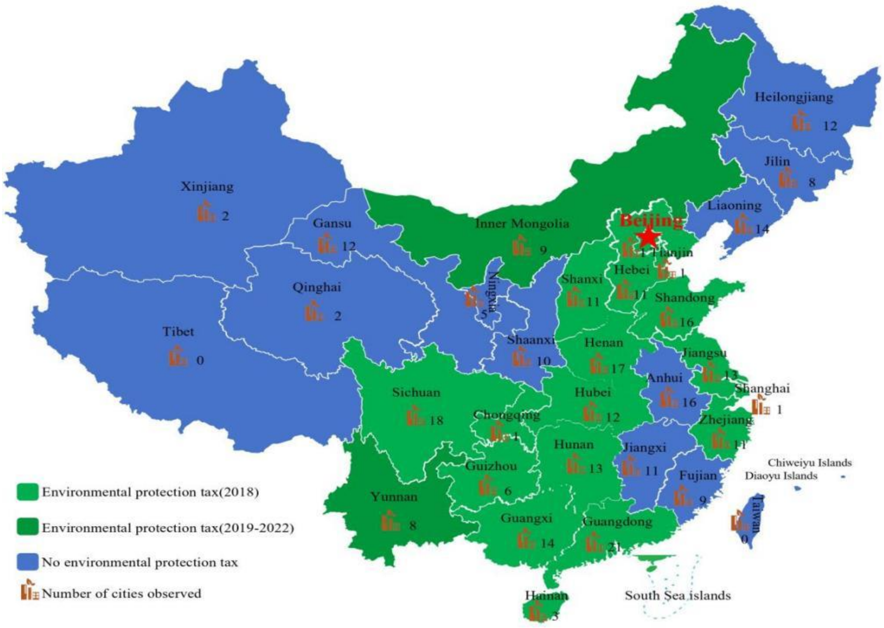

Figure 1 – Distribution of the implementation of environmental protection tax from 2018 to 2022

Figure 1 intuitively shows the dynamic situation of the implementation of environmental protection tax from 2018 to 2022. The tax burden changes of 31 provinces (regions and cities excluding Hong Kong, Macao and Taiwan) are divided into tax rate increase areas and transfer areas. If the sample is located in the province (region and city) where the environmental protection tax is increased, and comes from the implementation of environmental protection tax in 2018 and later, then Post*Treat takes 1, otherwise it is 0. The double difference model is a widely used causal inference method in environmental economics. This estimation method accurately identifies the causal effect by comparing the differences between the experimental group and the control group before and after the policy implementation. Therefore, the following benchmark DID model is constructed:

$$Y_{it} = \alpha_0 + \alpha_1 post_i \times treat_t + \sum \beta X_{it} + \lambda_i + \delta_t + \mu_{it} \quad (3)$$

Where: i and t represent the city and year respectively. Yit represents the green total factor productivity of the city in the t-th year of the i-th city, treat is a dummy variable, which is 1 if the city is located in the tax rate increase zone, otherwise it is 0, post is a dummy variable, which is 1 when $t \geq 2018$, otherwise it is 0. Xit is a series of control variables for the city. λi and δt are the individual fixed effect (FE) and time fixed effect (FE), respectively, μit is a random term, and α reflects the effect of GTFP.

3.2 Parallel trend test

The premise of using the DID model is that the experimental group and the control group meet the parallel trend hypothesis, before the implementation of the environmental protection tax, the trend of green total factor productivity changes in the treatment group and the control group is consistent. This paper adopts the event study method to test whether the samples of the treatment group and the control group meet the parallel trend hypothesis before the implementation of GTFP, and conducts a dynamic effect analysis on the policy impact effect. The model is as follows:

$$Y_{it} = \beta_0 + \sum_{t=2014}^{2022} \beta_t Treat_t \times d_t + \sum \beta_1 X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (4)$$

Among them, dt is the year dummy variable (t = 2014, 2015, ..., 2022. 2017 is the base period). If the year is 2014, it is taken as 0, and for the other years, it is taken as 0. In formula (4), we focus on the changes in coefficients. In theory, the condition for the DID model to satisfy the parallel trend hypothesis test is that β_{2014}, β_{2015}, β_{2016}, and β_{2017} are not significant. In addition, by comparing β_{2018} to β_{2022}, the dynamic impact of EPTR on GTFP can also be analyzed.

The parallel trend test results are shown in Figure 2. β_{2014}, β_{2015}, β_{2016}, and β_{2017} are not significant, indicating that there is no difference between the treatment group and the control group before the policy is implemented, and the parallel trend is satisfied. At the same time, the impact of environmental protection tax on GTFP is significantly positive in the year after the policy is implemented.

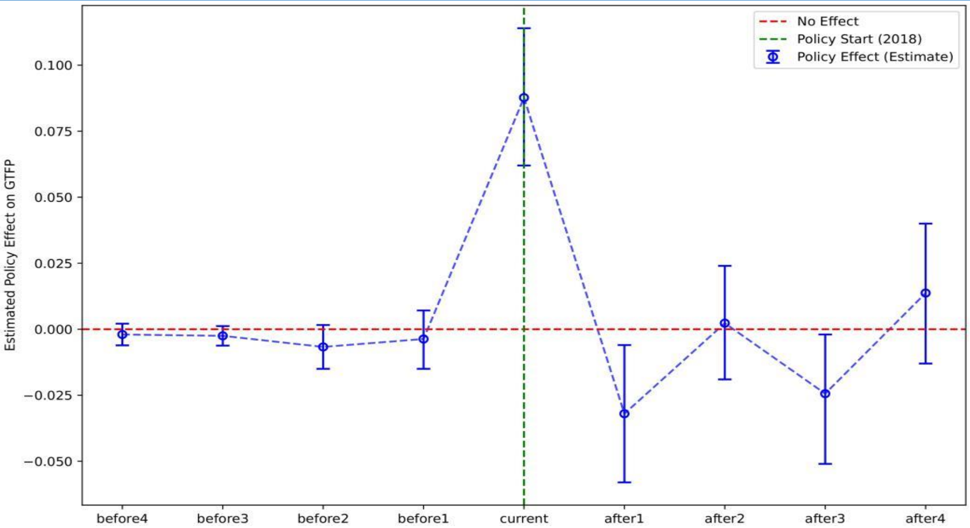

Figure 2 – Parallel Trend Dynamic

3.3 Baseline regression results

Table 3 gives the baseline regression results. Column (1) does not contain any control variables, and columns (2) to (4) gradually add control variables. All regressions cluster standard errors at the individual level and include time and individual fixed effects. The results show that the coefficient of Post*Treat is significantly positive, and the direction of the coefficients of all control variables is consistent with expectations.

Table 3 – Benchmark regression.

Variables	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
Post*Treat	0.0214**	0.0230**	0.0241**	0.0298***
	(0.010)	(0.010)	(0.010)	(0.010)
LnPop		-0.0473*	-0.0515*	-0.0467*
		(0.026)	(0.026)	(0.026)
LnPer			-0.0331*	-0.0407**
			(0.017)	(0.017)
GDPR				0.0059***
				(0.001)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Obs	2592	2592	2592	2592
R-squared	0.550	0.551	0.552	0.557

Note: We report robust standard errors in parentheses and cluster robust standard errors at the individual level. ***, ** and * indicate significance at 1 %, 5 %, and 10 % level, respectively.

3.4 Robustness Test

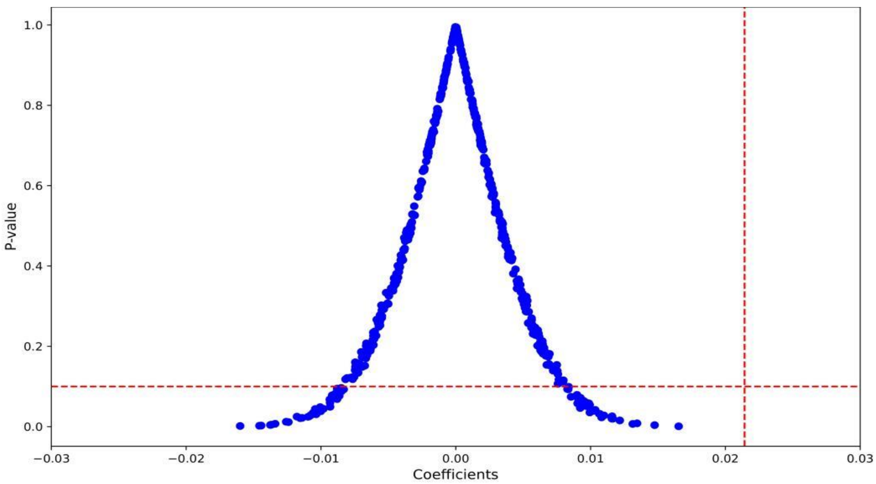

Figure 3 – Placebo test (500 times)

The estimated coefficients in actual DID models differ significantly from estimates under random errors. The horizontal red dashed line represents a significance threshold of 0.10 for evaluating random estimates as non-significant. The distribution is close to a normal distribution and is symmetric around 0. This shows that in the absence of real treatment, the coefficients are mostly concentrated around 0, with no systematic bias. The actual estimated coefficient is on the right, close to 0.02. This indicates that the size of the coefficient is significantly different from the random coefficient in the placebo test. The P value of the actual coefficient is below the significance level, which is considered to be significantly different from 0, indicating that the policy treatment has a real impact. The placebo test result proves that the randomly generated coefficients are distributed around 0, and there is a clear difference between the actual estimated coefficients (red vertical lines) and these random coefficients. This proves that the results of the DID model are not caused by random errors. The identified The policy effect is robust.

5. Conclusion

This paper uses panel data from 288 cities in China from 2013 to 2022 and adopts a dynamic DID model to empirically analyze the fiscal effect of the 2018 environmental protection tax reform on city-level green total factor production efficiency. The study found that the environmental protection tax reform has significantly improved the city's green total factor production efficiency in the short term; it also has a significantly suppressed fiscal effect from the short term to the medium term. The dynamic DID trend shows that in 2020 and 2022, there was a promotion effect, but the promotion effect was not significant, indicating that tax policies may also have some negative impacts while encouraging city-level green development. This inhibitory effect may stem from the increased costs and adaptive adjustments of enterprises in response to tax pressure in the early stages of reform.

In conclusion, this study accepts the hypothesis that the implementation of environmental protection tax has a significant positive impact on green total factor production efficiency, especially in the short term after the policy is implemented, but it is also accompanied by certain effects in the short to medium term adaptability costs. Therefore, when promoting environmental protection tax policies, policymakers should consider the economic characteristics and industrial structure characteristics of different regions, adapt to local conditions, and formulate flexible policy measures to ensure the long-term effect of environmental tax reform and help China achieve its sustainable development goals, the research conclusions of this article also have certain reference value for other developing countries to implement environmental tax policies.

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