Impact of Innovative City Construction on Green Growth
Evidence from China's Innovative Pilot Cities

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Abstract- This essay investigates how innovative city policy affect green growth. It employs data from 284 prefecture-level cities in China between 2007 and 2019, green total factor productivity index as a gauge of green growth, innovative city policy as a quasi-natural experiment, and a multi-period DID approach to examine how such policy affects green total factor productivity. The results of the study show that on the average the green total factor productivity of innovative pilot cities is 0.95% higher compared to non-pilot cities, indicating that an innovative city policy has a significant contribution to green growth. This result also survived in robustness tests. In addition, this study finds that in the impact of innovative city policy on green growth is heterogeneous across city scale and resource, with the driving effect being more pronounced in medium-sized cities and non-resource-based cities.

Keywords- innovative city policy; non-resource-based cities; multi-period DID; green total factor productivity

1. Introduction

In 2008, the National Development and Reform Commission and the Ministry of Science and Technology in China approved Shenzhen as the first national pilot innovative city, and since then, the two departments have issued a series of policy documents to set up pilot innovative cities in batches [1]. In 2010, the "Guidance on Further Promoting Pilot Innovative Cities" clarified that the process of building innovative cities should accelerate the transformation of economic development, strengthen the R&D and application of environmental protection technology, and promote the coordinated and sustainable development of economy and society. In 2016, the "Guidelines for Building Innovative Cities" added the principle of "green and low-carbon" to the construction [2]. In 2018, the "Letter on Supporting New Batches of Cities in Building Innovative Cities" proposed to explore innovative development paths with their own characteristics, and build regional pilot cities.

Through technology spillover and industry chain synergy in the process of innovative city pilot construction, the pilot cities play an important role as a model and leader in green growth. Some enterprises are the first to implement advanced technologies with government support, and other enterprises imitate and improve them to achieve independent innovation [3]. In innovative pilot cities, the enterprises strongly supported by the government often become the leading enterprises in the industry chain, and the leading enterprises acquire enterprises in the same industry

BDEIM 2022, December 02-03, Zhengzhou, People's Republic of China

DOI 10.4108/eai.2-12-2022.2328730

or expand upstream and downstream of the industry chain [4], so that the related enterprises can produce together and promote the industry to integrate advantageous resources and reduce production energy consumption, thus promoting green growth [5].

So far, 78 pilot innovative cities have been established in six batches (see Figure 1). Compared with non-pilot cities, innovative pilot cities enjoy policy dividends and are located in different zones [6], creating conditions for constructing quasi-natural experiments to identify the contribution of innovative city pilot policy to green growth using the multi-period DID model.

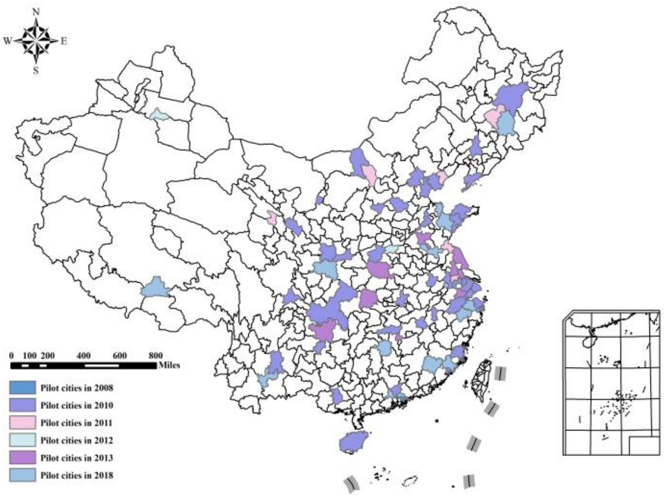

Figure 1. Innovative Pilot Cities Distribution in China

2. Materials and Methods

2.1 Baseline Model Construction

In this study, the influence of innovative city policy on green growth is examined using a DID model by treating it as a quasi-natural experiment that varies among cities and years. The baseline DID model for this study is shown in Equation (1).

$$GTFP_{it} = \alpha_1 + \beta_1 Treat\_time_{it} + \sum_{k=1}^{K} c_{1k} X_{kit} + \delta_i + \sigma_t + \varepsilon_{it} \quad (1)$$

Where $GTFP_{it}$ is the GTFP for city *i* at time *t*. $Treat\_time_{it}$ is the product of *Treat* and *Time*, *Treat* is the regional dummy variable, *Time* is the time dummy variable for the innovative city policy implementation. X_{kit} is the kth control variable affecting the GTFP for city *i* at time *t*, which includes human resources (HR), economic development (ED), government intervention (GI), infrastructure development (ID), and openness level (OL). δ_i refers to the fixed effect of city *i*. σ_i indicates the fixed effect of year *t*. The error term ε_{it} is assumed to be i.i.d.

2.2 Data and Variables

This study selects data from 284 prefecture-level cities between 2007 and 2019. After completing the missing data using average interpolation, a total of 3,692 sample data were obtained (see Table 1).

Table 1 Descriptive Statistics

Variables	**Obs.**	**Mean**	**Std. dev.**
GTFP	3,692	1.0018720	0.0501449
HR	3,692	34.470540	70.361840
ED	3,692	10600000	23600000
GI	3,692	16.954110	10.700260
ID	3,692	1219.7790	866.8525
OL	3,692	0.0453539	0.0542009

2.2.1 Predicted Variable

In this paper, Green Total Factor Productivity (GTFP) is chosen as a predictor variable because it does not only assess productivity improvement from the perspective of economic growth, but assesses environmental improvements from the perspective of pollution emissions.

The SBM-GML method, which has a wide range of applications, is selected to measure GTFP. Referring to the Oh [7], the GML index is set in Equation (2).

$$\begin{aligned} & GML^{t,t+1}\left(x_t, y_t^g, y_t^b, x_{t+1}, y_{t+1}^g, y_{t+1}^b\right) \\ & = \frac{1+D^G\left(x_t, y_t^g, y_t^b\right)}{1+D^G\left(x_{t+1}, y_{t+1}^g, y_{t+1}^b\right)} \\ & = \frac{1+D^t\left(x_t, y_t^g, y_t^b\right)}{1+D^{t+1}\left(x_{t+1}, y_{t+1}^g, y_{t+1}^b\right)} \\ & \times \left[\frac{\left(1+D^G\left(x_t, y_t^g, y_t^b\right)\right) / \left(1+D^t\left(x_t, y_t^g, y_t^b\right)\right)}{\left(1+D^G\left(x_{t+1}, y_{t+1}^g, y_{t+1}^b\right)\right) / \left(1+D^{t+1}\left(x_{t+1}, y_{t+1}^g, y_{t+1}^b\right)\right)}\right] \\ & = \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}\right] \\ & = EC^{t,t+1} \times BPC^{t,t+1} \end{aligned} \tag{2}$$

The GML index in Equation (2) can be decomposed into green technical efficiency change (EC) and green technical progress (BPC).

2.2.2 Explanatory Variable

As the primary explanatory factor in this study, *Treat_time* is used to measure whether a city is an innovative pilot city. *Treat_time* refers to the interaction of *Treat* and *Time*, where *Treat* is a regional dummy variable and *Time* is a time dummy variable. When *Treat* is equal to 0, it means that the city is not an innovation pilot city. When *Time* is equal to 0, it means that the innovative city policy has not been implemented in this year.

2.2.3 Control Variables.

To investigate the net effect of innovative city policy on green development, some variables that may affect green development were selected as control variables.

a) Human Resources (HR): Measured by the number of people employed.

b) Economic Development (ED): Measured in terms of gross domestic product.

c) Government Intervention (GI): Measured by the ratio of municipal budget expenditures to GDP.

d) Infrastructure Development (ID): Measured by road area per capita.

e) Openness Level (OL): As determined by the FDI to GDP ratio.

3. Results

3.1 Baseline Regression Analysis

Stepwise regression is used to estimate the baseline model, and the results are shown in Table 2. Column (1) shows that without adding any control variables, the estimated coefficient of *Treat_time* is 0.0068, which is significantly positive at the 10% level, indicating that innovative city policy can significantly contribute to green growth. The significance of the estimated coefficient of *Treat_time* increases when each control variable is added gradually. The estimation results in column (6) show that the GTFP of innovative pilot cities increases by 0.95% on average compared to non-pilot cities. From the results, it can be found that the estimated results of *Treat_time* are significant with or without the inclusion of control variables, and the estimated results of *Treat_time* are significant at the 5% level when control variables are included, indicating that innovative city policy can promote green growth.

Table 2 Baseline Regression Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Treat_time	0.0068*	0.0104***	0.0097**	0.0096**	0.0094**	0.0095**
	(1.73)	(2.65)	(2.52)	(2.48)	(2.43)	(2.45)
HR		-0.0319***	-0.0476***	-0.0473***	-0.0476***	-0.0476***
		(-8.19)	(-11.43)	(-11.36)	(-11.41)	(-11.40)
ED			0.0469***	0.0458***	0.0450***	0.0453***
			(9.84)	(9.26)	(9.02)	(9.04)
GI				-0.0026	-0.0027	-0.0027
				(-0.85)	(-0.87)	(-0.88)
ID					-0.0042	-0.0043
					(-1.18)	(-1.21)
OL						0.0007
						(0.67)
Constant	0.9879***	1.0709***	0.4257***	0.4477***	0.4874***	0.4858***
	(352.46)	(101.87)	(6.41)	(6.28)	(6.18)	(6.15)
City FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	3,692	3,692	3,692	3,692	3,692	3,692
R-squared	0.1190	0.1361	0.1600	0.1602	0.1605	0.1606

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t*-value is reported in parenthesis.

3.2 Heterogeneity Analysis

3.2.1 Scale Heterogeneity in Cities

For cities of different scales, the role of innovative city policy in promoting green development may be different [8]. In this paper, with reference to the urban classifications in China, the sample of prefecture-level cities is divided into three subsamples of small cities, medium cities and large cities according to the population size for the city, and the regression results are shown in Table 3.

As can be seen from Table 3, innovative city policy has the most significant contribution to green growth in medium cities. The effect is not significant in small and large cities. This may be due to the fact that for small cities, with their low level of technology and inadequate infrastructure, the investment required for green growth is greater than the benefits it brings, while for large cities, "urban diseases" caused by excessive city size and concentration of various populations can lead to a decrease in the efficiency of urban governance, thus affecting green growth [9].

Table 3 Results of Scale Heterogeneity Test

Variables	(1)	(2)	(3)
Treat_time	-0.0049	0.0062*	0.0312
	(-0.16)	(1.66)	(0.37)
Constant	0.7568***	0.3534***	3.0518**
	(4.82)	(3.94)	(2.33)
City FE	Y	Y	Y

Year FE	Y	Y	Y
Control	Y	Y	Y
Obs.	608	2,922	162
R-squared	0.1200	0.1941	0.1367

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t*-value is reported in parenthesis. Columns (1), (2), and (3) show the regression results for small cities, medium cities, and large cities, respectively.

3.2.2 Resources Heterogeneity in Cities

Unlike non-resource-based cities, the industrial structure of resource-based cities is mostly oriented to their rich resources, and their industrial development mainly revolves around resource-related industries [10]. Therefore, the role of innovative city policy in promoting green growth may be different in these two different types of cities. In this paper, the resource heterogeneity of cities is investigated by dividing the sample into two subsamples, non-resource-based cities and resource-based cities, based on their resource endowments.

The findings in Table 4 demonstrate that while innovative city policy have no substantial influence in resource-based cities, they have a considerable impact on green growth in non-resource-based cities. This may be due to the fact that for resource-based cities, the existence of resource path dependency leads to a preference for developing resource-related industries with high pollution and emissions, making their green growth difficult, and thus innovative city policy cannot play the expected role in promoting green growth in resource-based cities [11].

Table 4 Results of Resources Heterogeneity Test

Variables	**(1)**	**(2)**
Treat_time	0.0082*	0.0110
	(1.68)	(1.53)
Constant	0.8777***	0.4149***
	(7.75)	(3.90)
City FE	Y	Y
Year FE	Y	Y
Control	Y	Y
Obs.	2,197	1,495
R-squared	0.1436	0.1789

Notes: * and *** indicate significance at the 10% and 1% levels, respectively. The *t*-value is reported in parenthesis. Columns (1) and (2) show the regression results for non-resource-based cities and resource-based cities, respectively.

4. Robustness Test

4.1 Eliminating Potential Outlier Interference

In this paper, the tailing method is used to exclude the possible outliers in the data. After the 2% tailoring, the results highlighted in Table 5 column (1) show that the coefficient of *Treat_time* is still significant at the 5% level. This indicates that the results of this paper are robust.

Table 5 Robustness Test Results I

Variables	**(1)**	**(2)**
Treat_time	0.0090**	
	(2.30)	
L. Treat_time		0.0142***
		(3.42)
Constant	0.6505***	0.4417***
	(8.28)	(5.08)
City FE	Y	Y
Year FE	Y	Y
Control	Y	Y
Obs.	3,692	3,408
R-squared	0.1492	0.1687

Notes: ** and *** indicate significance at the 5% and 1% levels, respectively. The *t*-value is reported in parenthesis.

4.2 Eliminating Potential Lagged Effects Interference

Any management tools, including innovative city policy, are based on certain institutions and systems as the background, and the management effects occur and are transmitted with the help of the corresponding operational mechanisms, and there are lagged effects. In this paper, the coefficient of *Treat_time* is still significantly positive after lagging the (see Table 5 column (2)), which indicates that the results of this paper are robust.

4.3 Eliminating Potential Other Policy Interference

In the time period selected for this paper, in addition to the innovative city policy, other policies also have been implemented, such as the healthy city policy, the new energy city policy, and the low carbon city policy [12]. They are included in the regression model as dummy variables to avoid any potential interference from these policies on the paper's findings.

Table 6 Robustness Test Results II

Variables	**(1)**	**(2)**	**(3)**
Treat_time	0.0066*	0.0090**	0.0085**
	(1.70)	(2.31)	(2.19)
Healthy	0.0261***		
	(4.90)		

New_Energy		0.0043	
		(1.15)	
Low_Carbon			0.0066**
			(2.02)
Constant	0.4735***	0.4864***	0.4770***
	(6.02)	(6.16)	(6.04)
City FE	Y	Y	Y
Year FE	Y	Y	Y
Control	Y	Y	Y
Obs.	3,692	3,692	3,692
R-squared	0.1666	0.1610	0.1617

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t*-value is reported in parenthesis. Columns (1), (2), and (3) show the regression results for healthy city policy, new energy city policy, and low carbon city policy, respectively.

As shown in Table 6, the coefficient on *Treat_time* remains significant at the 5% level after including each of the three policies as a dummy variable in the regression. This indicates that the results of this paper are robust.

5. Conclusion

This paper conducts an empirical study on the impact of innovative city construction on green growth in prefecture-level cities of China. Based on the findings, the following policy recommendations are proposed: First, this paper finds that abundant human resources can significantly inhibit the green growth of cities, probably because human resources are more concentrated in labor-intensive industries with high energy consumption and low output, and the growth of such industries is not conducive to green growth. Therefore, the government should pay attention to industrial upgrading and promote the transformation of labor-intensive industries with high energy consumption and low output to modern industries with low energy consumption and high output. Second, this paper finds that the promotion of policy on urban green growth varies with city scale and resource. Therefore, governments should choose their own development paths according to local conditions and take into account the actual situation. For large cities, governments should pay attention to the agglomeration effect and improve government efficiency to avoid the "big city disease". For resource-based cities, governments should promote the synergistic development of various industries while taking advantage of resources.

Acknowledgment

The authors acknowledge financial support from the Xiamen University Malaysia Research Fund (Grant No: XMUMRF/2021-C8/ISEM/0033). The usual disclaimer applies.

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