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Dynamics of green productivity growth for major Chinese urban agglomerations

Feng Tao [a], Huiqin Zhang [a], Jun Hu [a], X.H. Xia [b,c,*]

[a] Institute of Industrial Economics, Jinan University, Guangzhou 510632, China
[b] School of Economics, Renmin University of China, Beijing 100872, China
[c] Institute of China's Economic Reform & Development, Renmin University of China, Beijing 100872, China

HIGHLIGHTS

- Green productivity growth was measured in major urban agglomerations of China.
- Technical progress is the main contributor to green productivity growth.
- Green and yellow cities were categorized by the criterion of eco-friendliness.
- Green innovators were identified from the sample cities.
- Determinants driving green productivity growth vary across urban agglomerations.

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ABSTRACT

This paper employs the global Malmquist–Luenberger productivity index to measure and decompose green productivity growth for three major urban agglomerations in China over the period 2003–2013. As the first study known to focus on the green productivity of emerging cities in developing countries, the results show that technical progress, rather than efficiency improvements, is the main contributor to green productivity growth. Using the criterion of eco-friendliness, we categorize the cities into 'green' and 'yellow' city groups and identify 10 green innovators for the sample cities. The analysis also discusses the determinants of the drivers of green productivity growth and provides some useful policy implications.

1. Introduction

The emergence of urban agglomerations is an important phenomenon in the development of Chinese regional economies. Of these, three major urban agglomerations in China—the Yangtze River Delta, the Pearl River Delta, and the Beijing–Tianjin–Hebei region—all on the east coast, have become main drivers of industrialization and urbanization across the whole country and are key regions supporting the emergence of China as a 'world factory.' Although the geographic territory of these urban agglomerations, comprising some 51 cities in total, only accounts for 5.31% of China's land area, they accommodate 20.85% of the total population and account for 41.60% of the country's gross domestic products (GDP) in 2014 [1]. However, China has paid a high cost in energy consumption and pollution emissions for its dramatic growth in economic prosperity over the last few decades.

For the most part, we deem the traditional mode of industrialization and urbanization, characterized by incredibly large amounts of inputs, energy consumption, and pollution emissions, but low production efficiency, as unsustainable. In 2014, total electricity consumption of the three urban agglomerations accounted for 45.29% of all cities across China. At the same time, their shares of wastewater, sulfur dioxide (SO_2) and soot (dust) emissions accounted for 34.97%, 21.64%, and 26.10% of emissions throughout China, respectively [1]. As highlighted in the National New-Type Urbanization Plan (2014–2020) issued by the State Council of China, these three urban agglomerations will therefore play an important role in finalizing the pending task of energy savings and emission reductions in China in the future.

* Corresponding author at: School of Economics, Renmin University of China, Beijing 100872, China.
E-mail address: xiaxh.email@gmail.com (X.H. Xia).

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As energy and the environment represent ‘hard’ constraints for economic growth, we cannot precisely evaluate economic quality until we fully incorporate the negative effects of environmentally harmful by-products into conventional measures of productivity. Based on the directional distance functions (DDF) proposed by Chambers et al. [2], Chung et al. [3] inventively introduced a Malmquist–Luenberger (ML) productivity index to calculate environmentally sensitive productivity growth, or green productivity growth [4], by incorporating undesirable outputs. The ML index has been widely used in previous studies [4–11].

However, a ML index derived from a contemporaneous production possibility set (PPS) may face problems of spurious technical regress and also encounters noncircularity and linear programming infeasibility when measuring cross-period DDFs [7,12]. To overcome this weakness of the ML index, Oh [7] proposed the global Malmquist–Luenberger (GML) productivity index as an alternative to the ML index by integrating the DDF and the concept of the global technology set [13]. The slack-based ML index developed by Arabi et al. [14] may further improve the GML index given its summing of the slacks of desirable and undesirable outputs as the objective function of their models [15]. In recent years, the GML has been widely used to measure productivity growth under energy and environment constraints. For example, Ananda and Hampf [16] applied the GML index including greenhouse gas emissions to evaluate productivity in the Australian urban water sector and found that the conventional index significantly overstated productivity growth.

Wang and Feng [17] and Yang and Zhang [18] utilized the GML index with an improved slacks-based measure (SBM) to analyze the productivity growth of 30 sample provinces in mainland China during the periods 2003–2011 and 2003–2014, respectively. Fan et al. [19] applied the GML index to measure and decompose the total factor carbon dioxide (CO_2) emission performance of 32 industrial subsectors in Shanghai over the period 1994–2011, while Emrouznejad and Yang [15] applied a new range-adjusted measure based GML productivity index to evaluate the reduction in CO_2 emissions in Chinese light manufacturing industries. Wang and Shen [20] used the GML index to calculate China’s industrial productivity by considering environmental factors and examining the nonlinear relationship between environmental regulation and environmental productivity.

Clearly, these issues in China have attracted the attention of numerous researchers, not least because of China’s position as the world’s largest developing country in terms of both energy consumption and environmental pollution. However, most existing studies are from the perspective of industrial sectors [4,9,19,20] or large regions [8,10,15,17,18], rather than cities, which especially in China, are the most basic independent decision-making units participating in the national and global economy. More importantly, there is a pronounced neglect of the study of the green productivity of emerging cities in developing countries in the extant productivity benchmarking literature. This is an important omission in that emerging cities during the industrialization process make a tremendous contribution to energy consumption and pollution emissions in developing countries, to the extent that ignoring the negative effects of environmentally harmful by-products may lead to biased measures of productivity and thence suboptimal policy outcomes [16].

In China’s postreform period, the GDP growth rates of emerging cities in the three major urban agglomerations have largely led the country, while also facing heavy pressure via energy needs and pollution outcomes. Therefore, the posited gap between green and conventional productivity may be more significant than even in other regions of China. Moreover, as these agglomerations are now motivated to adopt technologies on energy saving and cleaner production, their green productivity might suggest an even higher growth rate than reflected in conventional measures. Consequently, analysis of the dynamics of green productivity growth for these three major urban agglomerations not only has important policy implications for other cities in China, but also emerging cities in other developing countries.

Here, we apply the GML index to calculate and decompose green productivity growth for the three major urban agglomerations in China. Using the criterion of eco-friendliness based on a comparison of the GML index in Oh [7] and the GM index in Pastor and Lovell [13], we categorize cities into ‘green’ and ‘yellow’ city groups and identify 10 green innovation cities. We also discuss the determinants driving green productivity growth. To our knowledge, this study is the first attempt to examine the green productivity growth of new cities across urban agglomerations in developing countries.

The remainder of the paper is organized as follows. Section 2 introduces the GML productivity index and discusses the data. Section 3 presents the results and provides some discussion. Section 4 concludes.

2. Method and data

2.1. The GML productivity index

Considering a panel of $k = 1,\ldots,K$ cities and $t = 1,\ldots,T$ time periods, for city k at time period t, the inputs and outputs set can be assumed as $(x^{k,t}, y^{k,t}, b^{k,t})$, where the production technology can produce M desirable outputs, $y = (y_1, y_2, \wedge, y_M) \in R_+^M$, and J undesirable outputs, $b = (b_1, b_2, \wedge, b_J) \in R_+^J$, by using N inputs, $x = (x_1, x_2, \wedge, x_N) \in R_+^N$. A contemporaneous benchmark technology is defined as:

$$P^t(x^t) = \left\{(y^t, b^t):\ x^t \text{ can produce } (y^t, b^t)\right\} \tag{1}$$

To incorporate undesirable outputs, Chung et al. [3] introduced the DDF as:

$$\vec{D}_0(x, y, b, g) = \max\{\beta:\ (y, b) + \beta g \in P(x)\}, \tag{2}$$

where $g = (y, b)$ is a direction vector, and β denotes the value of the DDF. Taking the direction vector, g, as the weight, the DDF seeks more outputs that are desirable and fewer that are undesirable [21].

We then express the ML index developed by Chung et al. [3] as:

$$ML^s\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + D^s\left(x^t, y^t, b^t\right)}{1 + D^s(x^{t+1}, y^{t+1}, b^{t+1})}, \tag{3}$$

where the ML index measures the green productivity of cities between time periods t and $t + 1$. When the ML value is greater (smaller) than one, it indicates a green productivity increase (decrease) of a target city, indicating that city’s production activity has enabled more (fewer) desirable outputs and less (more) pollution emissions.

However, Oh [7] notes that the geometric mean form of the ML index has a weakness in that it is not circular or transitive and that a linear programming infeasibility arises in measuring the cross-period DDF. To overcome this limitation, we define a global benchmark technology as $P^G = P^1 \cup P^2 \cup P^3 \cup \ldots \cup P^T$. As depicted in Fig. 1, P^G envelopes the contemporaneous benchmark technologies. Based on the global technology set, Pastor and Lovell [13] develop the global Malmquist productivity growth index (GM index), as follows:

$$GM^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D^G(x^{t+1}, y^{t+1})}{D^G(x^t, y^t)}. \tag{4}$$

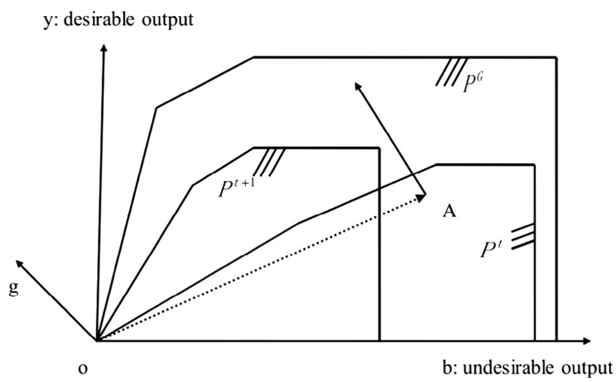


Fig. 1. The global Malmquist–Luenberger productivity index.

Unfortunately, the GM index does not consider undesirable outputs, such as pollution emissions. According to Fukuyama and Weber [22], Färe and Grosskopf [23], and Arabi et al. [14], we should define a global directional distance function of a SBM on the global technology set P^G incorporating the undesirable outputs as follows:

$$D^G(x,y,b) = \max\left\{\beta : \ (y+\beta y, b-\beta b) \in P^G(x)\right\}. \quad (5)$$

As developed by Oh [7], we express the GML index as:

$$GML^{t,t+1}\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right) = \frac{1+D^G\left(x^t,y^t,b^t\right)}{1+D^G\left(x^{t+1},y^{t+1},b^{t+1}\right)}, \quad (6)$$

where we use GML to measure the green productivity of cities based on the global production possibility set between periods t and $t+1$. When the value is greater (smaller) than one, GML corresponds to the green productivity increase (decrease) of a target city toward the global technology frontier. Following Pastor and Lovell [13] and Oh [7], we then decompose the GML index into two components:

$$\begin{aligned} & GML^{t,t+1}\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right) \\ & = \frac{1+D^t\left(x^t,y^t,b^t\right)}{1+D^{t+1}\left(x^{t+1},y^{t+1},b^{t+1}\right)} \\ & \times \left[\frac{\left(1+D^G(x^t,y^t,b^t)\right)/\left(1+D^t\left(x^t,y^t,b^t\right)\right)}{\left(1+D^G\left(x^{t+1},y^{t+1},b^{t+1}\right)\right)/1+D^{t+1}\left(x^{t+1},y^{t+1},b^{t+1}\right)}\right], \quad (7) \\ & = \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG^{t,t+1}_{t+1}}{BPG^{t,t+1}_{t}}\right] \\ & = EC^{t,t+1} \times BPC^{t,t+1} \end{aligned}$$

where TE^s is the green technical efficiency at time period s and $EC^{t,t+1}$ is the green efficiency change between two time periods. The latter captures the catch-up effect whereby cities approach the efficiency frontiers more closely and catch up with the relatively advanced cities [24,25], such that there is a green efficiency improvement (deterioration) when its value is greater (smaller) than one. The measure $BPC^{t,t+1}$ denotes the best-practice gap between a contemporaneous technology frontier and a global technology frontier, along the ray from the observation at period s in the direction (y^s, b^s). Hence, in calculating the green technical change during two periods, $BPC^{t,t+1}$ denotes the best-practice gap change during these same two periods [7], reflecting how close a contemporaneous technology frontier shifts toward the global technology frontier in the direction of more desirable outputs and less pollution emissions, whereby a value of $BPC^{t,t+1}$ greater (smaller) than one indicates green technical progress (regress).

2.2. Data

Considering data availability, the sample covers 51 cities at the prefecture level and higher across the three major urban agglomerations in China during the period 2003–2013. Of these 51 cities, 29 are in the Yangtze River Delta, 13 in the Beijing–Tianjin–Hebei region, and nine in the Pearl River Delta. Table 1 details the input and output variables used to measure green productivity using the GML index. All data are from the Chinese City Statistical Yearbook [1] and the China Statistical Yearbook [26]. Table 2 provides selected descriptive statistics of the variables used in this study.

Table 3 reports the average level and growth rate of the input and output variables by agglomeration. As shown, the average real gross regional product (GRP) in our sample is 144.3 billion Chinese renminbi (RMB), with cities in the Pearl River Delta displaying the highest average GRP (227.5 billion RMB). The average annual growth rate in real GRP is 11.7%, with cities in the Beijing–Tian jin–Hebei region having the highest average growth rate of GRP (12.2%).

The average level of wastewater emissions is 156.4 million tons across our sample, led by cities in the Yangtze River Delta (179.2 million tons). The average annual growth rate in wastewater emissions is −0.1% for our sample with only cities in the Pearl River Delta exhibiting negative growth rate in wastewater emissions (2.2%). The average level of SO_2 emissions is 81.4 thousand tons across our sample, led by cities in the Beijing–Tianjin–Hebei region (115.0 thousand tons). The average annual growth rate in SO_2 emissions is −4.5% for our sample, with all three agglomerations demonstrating negative growth rates in SO_2 emissions. The average level of soot (dust) emissions is 31.1 thousand tons and the average growth rate is 5.1%, with cities in the Pearl River Delta displaying the highest growth rate (8.4%).

The average size of the labor force in the three agglomerations is 1141.2 (in thousands) with a growth rate of 8.8%. Cities in the Pearl River Delta have the largest average labor forces (1731.7) and the largest labor force growth rate (10.3%). The average capital stock is 244.8 (in billions) RMB with a growth rate of 2.8%, with cities in the Pearl River Delta having the largest average capital stocks (320.1 RMB) and those in the Yangtze River Delta the highest growth rates (2.6%). The average level of electricity consumption is 1,625,102 tens of megawatt-hours (MW h) with an annual growth rate of 9.5%. Cities in the Pearl River Delta have the highest average level of electricity consumption (2,622,709 tens of MW h) while cities in the Yangtze River Delta have the highest electricity consumption growth rates (10.2%).

Table 1
Input and output variables.

Input/ output	Proxies	Measures
Desirable outputs	Real gross regional product (GRP)	Calculated in 2004 constant prices using the GRP deflator at the province level for the city
Undesirable outputs	Wastewater, SO_2, and soot (dust)	Collected from the Chinese City Statistical Yearbook
Inputs	Capital stock	Estimated by the perpetual inventory method
	Labor force	The total number of urban employed persons at year-end including employed persons in urban state-owned and private enterprises and self-employed individuals in urban areas
	Electricity consumption	Collected from the Chinese City Statistical Yearbook

Table 2
Descriptive statistics of input and output variables.

Variables	Observations	Mean	SD	Max	Min
Real GRP (billion RMB)	561	144.3	230.5	1718.7	5.7
Wastewater (million tons)	561	156.4	150.0	912.6	9.6
SO_2 (thousand tons)	561	81.4	69.6	496.4	1.3
Soot (thousand tons)	561	31.1	42.4	506.5	0.2
Labor (thousands)	561	1,141.2	1,847.2	13,423.3	51.4
Capital (billion RMB)	561	244.8	435.4	2,548.6	19.0
Electricity (tens of MW h)	561	1,625,102	2,213,655	14,106,000	36,332

Table 3
Growth rates of input and output variables.

Urban agglomeration	Real GRP (billion RMB)		Wastewater (million tons)		SO_2 (thousand tons)		Soot (dust) (thousand tons)		Labor (thousands)		Capital (billion RMB)		Electricity (tens of MW h)	
	Level	Growth	Level	Growth	Level	Growth	Level	Growth	Level	Growth	Level	Growth	Level	Growth
Beijing–Tianjin–Hebei	128.7	12.2	115.5	−0.3	115.0	−0.7	57.7	5.3	1256.0	5.7	264.5	2.4	1,633,020	9.0
Yangtze River Delta	125.5	11.2	179.2	−0.8	72.9	−8.8	24.3	4.0	906.5	9.3	212.5	2.6	1,311,950	10.2
Pearl River Delta	227.5	10.9	140.6	2.2	60.4	−4.1	14.4	8.4	1731.7	10.3	320.1	2.4	2,622,709	7.6
Average	144.3	11.7	156.4	−0.1	81.4	−4.5	31.1	5.1	1141.2	8.8	244.8	2.8	1,625,102	9.5

3. Results and discussion

3.1. Distribution of green productivity indices

Figs. 2–4 plot the kernel densities of green productivity and its components in 2004 and 2013. Fig. 2 is for the Beijing–Tianjin–Hebei region. As shown in Fig. 2(a), there is a marked polarization in the distribution for 2004, with a mode located around one with a high probability mass. However, the hump becomes lower and the right tail gains more probability mass in 2013. This widening and flattening of the distribution reveal that green productivity has generally improved and that more cities have gained a higher level of productivity over the period studied. Fig. 2(b) shows that the distribution of efficiency change is more concentrated in 2013. The left tail loses some mass but the right tail obtains some mass. This implies that many cities have improved efficiency over the sample period. As reported in Fig. 2(c), compared with 2004, the hump of technical change is higher in 2013, indicating a rapid increase in technology.

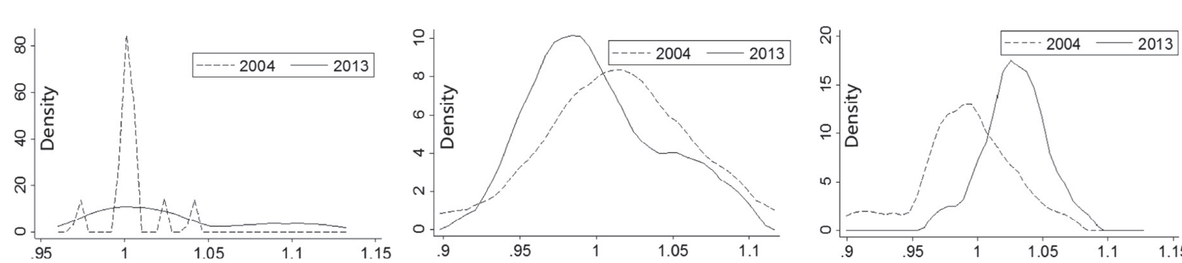
Fig. 3 plots the kernel density of green productivity and its components for the Yangtze River Delta. Similar to Fig. 2(a), the distribution in Fig. 3(a) becomes flatter and wider over time, indicating that while many cities increased their productivity, the productivity gap between cities became larger. As shown in Fig. 3(b), the efficiency change hump flattens and the right tail gains more mass in 2013 compared with 2004. This indicates that efficiency improved greatly and the efficiency of most cities remained above unity over time. As also seen in Figs. 2(c) and 3(c) shows that the technology mode moved significantly to the right in 2013 and gained some mass. This change in distribution implies that many cities in the Yangtze River Delta experienced a gain in technology over the study period.

Fig. 4 plots the density of green productivity and its components for the Pearl River Delta. As shown in Fig. 4(a), the productivity hump becomes lower and the left tail gains mass. This reveals that green productivity increased in the Pearl River Delta over time. The change in distribution in Fig. 4(b) also shows that many cities became progressively less efficient over the sample period. As seen in Fig. 4(c), the largest hump moves to the right, indicating that while technology advanced in many of the cities, others were unable to catch up and fell even further behind.

To summarize, Figs. 2–4 reveal that the sources of green productivity growth include both efficiency and technical change. Figs. 2(b), 3(b) and 4(b) illustrate that the polarization in the green productivity distribution was mainly because of efficiency change in the three urban agglomerations. Figs. 2(c), 3(c) and 4(c) show that green productivity growth benefited most from technical change.

3.2. Temporal trends of green productivity growth

Fig. 5 depicts the annual cumulative growth of green productivity for the three urban agglomerations. In general, the green productivity index for the three urban agglomerations grew slowly over the studied period. In most years, the green productivity growth of the Beijing–Tianjin–Hebei region was higher than the two other agglomerations. However, across the whole sample period, the Yangtze River Delta saw the largest cumulative increase (30.1%) in green productivity, compared with 25.1% and 18.8% in



(a) Productivity growth (b) Efficiency change (c) Technical change

Fig. 2. Kernel density plots of productivity growth, efficiency change, and technical change of GML in the Beijing–Tianjin–Hebei region.

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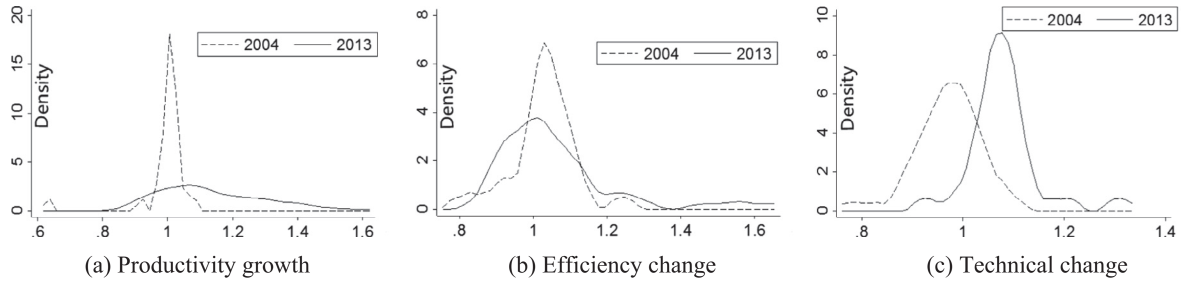

Fig. 3. Kernel density plots of productivity growth, efficiency change, and technical change of GML in the Yangtze River Delta.

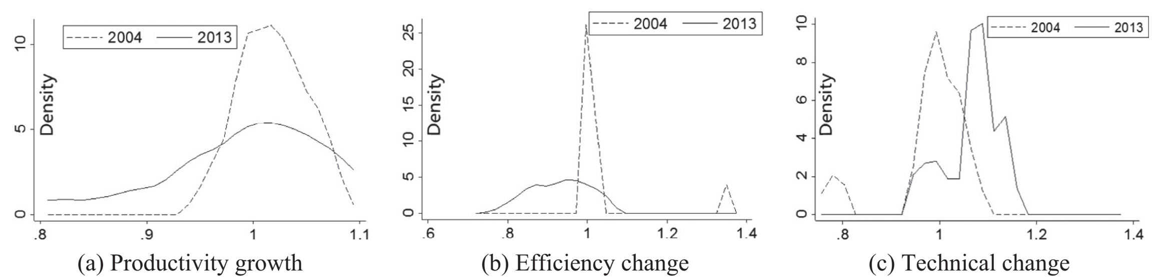

Fig. 4. Kernel density plots of productivity growth, efficiency change, and technical change of GML in the Pearl River Delta.

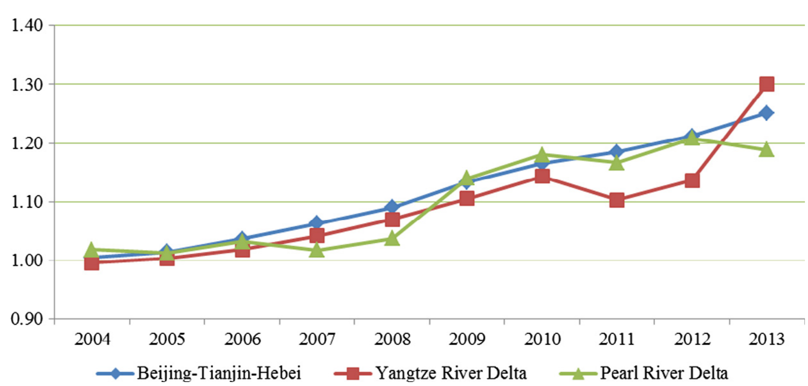

Fig. 5. Cumulative growth of green productivity for the three major urban agglomerations in China. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the Beijing–Tianjin–Hebei region and the Pearl River Delta, respectively.

It is worth noting that during the period 2006–2010, corresponding with China's 11th Five-Year Plan, green productivity increased markedly across all three urban agglomerations. This is possibly because the 11th Five-Year Plan issued by the Chinese central government in 2006 put forward the goal of building a resource-saving and environmentally friendly society. The plan notably involved quantitative reductions in energy and emissions, for example, a reduction in energy consumption and the main pollutant emissions per unit of GDP by 20% and 10%, respectively, by 2010. Central and local governments then subsequently issued a series of policies aimed at achieving the national policy goal.

In the studied period, the Beijing–Tianjin–Hebei region achieved a stable growth trend of green productivity. However, for both the Yangtze River Delta and the Pearl River Delta, the cumulative index fell sharply in 2011. The most likely reason is that the global financial crisis and domestic economic downturn accounted for a major shock to these two export-oriented agglomerations. To stabilize urban employment and exports, the production of energy or pollution-intensive sectors in these two agglomerations may need to remain at this level or even expand. However, urban growth in the Beijing–Tianjin–Hebei region is not as dependent on these exports as the two delta regions.

3.3. City heterogeneity

Table 4 details the average (geometric mean) green productivity growth of the 51 sample cities. As shown, green productivity growth varies across the individual cities. Only Suqian (−17.2%) and Lishui (−3.9%) have a negative growth rate of green productivity while the other 49 cities have positive growth rates, with Xuzhou (6.0%), Changzhou (5.9%), Tianjin (5.4%), Shanghai (5.2%), and Maanshan (5.2%) making up the top-five cities.

For a better comparison of green productivity and conventional productivity, we calculate the corresponding measures for the GM index (Table 4). Note that the three environmentally harmful by-products (wastewater, SO_2, and soot) are not included when measuring the GM index. As shown in the last row of Table 4, overall green productivity growth calculated by the GML index (2.3%) in all three agglomerations is less than the conventional productivity growth calculated by the GM index (2.9%). This implies an

Table 4
Productivity growth, efficiency change, and technical change of cities in three urban agglomerations of China (2003–2013): GML and GM indices.

Code	City	GML and its components			GM and its components			GML/GM
		GML	EC	BPC	GM	EC	TC	
1	Beijing	1.042	1.025	1.017	1.049	1.010	1.038	0.993
2	Tianjin	1.054	1.032	1.022	1.084	1.021	1.062	0.972
3	Shijiazhuang	1.024	1.012	1.012	1.083	1.023	1.059	0.946
4	Tangshan	1.050	1.000	1.050	1.085	0.989	1.096	0.968
5	Qinhuangdao	1.019	0.995	1.025	1.094	1.018	1.074	0.931
6	Handan	1.013	1.003	1.010	1.074	0.983	1.092	0.943
7	Xingtai	1.002	0.998	1.004	1.064	0.991	1.073	0.942
8	Baoding	1.008	0.997	1.011	1.046	0.981	1.067	0.964
9	Zhangjiakou	1.034	1.018	1.015	1.089	1.024	1.063	0.949
10	Chengde	1.017	1.001	1.016	1.017	0.970	1.049	1.000
11	Cangzhou	1.002	0.999	1.003	1.043	0.995	1.048	0.961
12	Langfang	1.006	0.994	1.012	1.008	0.958	1.052	0.998
13	Hengshui	1.005	1.003	1.002	1.063	1.016	1.046	0.945
–	**Beijing–Tianjin–Hebei**	**1.021**	**1.006**	**1.015**	**1.061**	**0.998**	**1.063**	**0.962**
14	Shanghai	1.052	1.023	1.028	1.055	1.009	1.046	0.997
15	Nanjing	1.037	1.010	1.027	1.030	0.985	1.046	1.007
16	Wuxi	1.049	1.000	1.049	1.038	0.980	1.059	1.011
17	Xuzhou	1.060	1.033	1.026	1.013	0.961	1.054	1.046
18	Changzhou	1.059	1.012	1.046	1.021	0.947	1.078	1.037
19	Suzhou	1.041	0.994	1.048	0.972	0.917	1.060	1.071
20	Nantong	1.019	1.002	1.017	0.993	0.936	1.060	1.026
21	Lianyungang	1.021	1.005	1.016	1.034	1.021	1.013	0.987
22	Huai'an	1.029	1.003	1.026	1.023	0.969	1.056	1.006
23	Yancheng	1.045	0.998	1.047	1.008	0.957	1.054	1.037
24	Yangzhou	1.035	1.004	1.032	0.996	0.944	1.056	1.039
25	Zhenjiang	1.035	1.004	1.031	1.035	0.973	1.064	1.000
26	Taizhou	1.023	0.994	1.029	0.971	0.920	1.055	1.054
27	Suqian	0.981	0.971	1.011	0.900	0.877	1.027	1.090
28	Hangzhou	1.024	0.985	1.039	1.012	0.966	1.047	1.012
29	Ningbo	1.018	0.975	1.045	1.003	0.954	1.051	1.015
30	Wenzhou	1.049	1.023	1.026	1.112	1.055	1.054	0.943
31	Jiaxing	1.005	0.990	1.015	1.016	0.974	1.043	0.989
32	Huzhou	1.010	0.974	1.037	0.997	0.942	1.059	1.013
33	Shaoxing	1.004	0.989	1.015	0.939	0.889	1.056	1.069
34	Jinhua	1.003	0.978	1.025	1.001	0.970	1.032	1.002
35	Quzhou	1.002	0.991	1.011	1.027	0.964	1.065	0.976
36	Zhoushan	1.014	0.984	1.030	1.032	0.982	1.051	0.983
37	Taizhou	1.018	0.975	1.043	1.013	0.959	1.056	1.005
38	Lishui	0.996	0.980	1.016	1.013	0.989	1.024	0.983
39	Hefei	1.027	0.995	1.033	1.030	0.966	1.066	0.997
40	Wuhu	1.004	0.979	1.025	0.996	0.954	1.044	1.008
41	Maanshan	1.052	1.044	1.008	1.122	1.061	1.057	0.938
42	Tongling	1.012	1.003	1.010	1.075	1.001	1.074	0.941
–	**Yangtze River Delta**	**1.025**	**0.997**	**1.028**	**1.016**	**0.966**	**1.052**	**1.008**
43	Guangzhou	1.038	1.000	1.038	1.043	1.001	1.042	0.995
44	Shenzhen	1.008	1.000	1.008	1.018	0.966	1.054	0.990
45	Zhuhai	1.020	0.992	1.027	1.043	0.994	1.050	0.978
46	Foshan	1.030	0.992	1.038	1.053	0.972	1.084	0.978
47	Jiangmen	1.031	0.997	1.034	1.038	0.962	1.078	0.993
48	Zhaoqing	1.004	0.987	1.018	1.020	0.964	1.058	0.984
49	Huizhou	1.001	0.990	1.011	1.025	0.946	1.083	0.977
50	Dongguan	1.007	0.975	1.033	0.956	0.897	1.066	1.053
51	Zhongshan	1.011	0.996	1.016	1.025	0.973	1.053	0.986
–	**Pearl River Delta**	**1.017**	**0.992**	**1.025**	**1.025**	**0.964**	**1.063**	**0.992**
–	**Agglomeration average**	**1.023**	**0.998**	**1.024**	**1.029**	**0.974**	**1.057**	**0.994**

Each of them is the average value.

overestimate of the rate of conventional productivity growth due to the omission of energy consumption and environmentally harmful by-products, as pointed out by Oh [7]. In this sense, the green productivity growth measured by the GML index is more suitable for calculating productivity when highlighting urban sustainable development, suggesting that we should replace the traditional mode of urban growth by a new mode, characterized by more desirable outputs with less pollution emissions.

As shown in Table 4, the relationship between the GML and GM indices is very different between the various cities. For example, the average annual growth of Qinhuangdao from the GML index (1.9%) is much lower than by the GM index (9.4%). In contrast, the average annual growth of Suzhou by the GML index (4.1%) is much higher than by the GM index (−2.8%). For some cities, for example, Chengde (GML 1.7%, GM 1.7%) and Zhenjiang (GML 3.5%, GM 3.5%), the gap between the green and conventional productivity growth indices is negligible. It is also noteworthy that only one city's green productivity growth index exceeds the conventional productivity index in the Beijing–Tianjin–Hebei region and the Pearl River Delta. In stark contrast, in the Yangtze River Delta, green productivity growth indices for most cities are larger than the conventional productivity indices.

According to the criterion provided by Oh [7], if a city has a green productivity index significantly higher than the conventional productivity index, we consider that the city has successfully harmonized economic growth with a reduction in its pollution emissions. However, if a city's green productivity index is significantly lower than its conventional productivity index, there is less emphasis on the reduction of pollution and more on the increase in GRP. Using this distinction, we can categorize the cities into two groups, with the former referred to as 'green' cities and the latter as 'yellow' cities. Table 5 lists the green and yellow cities categorized by the GML/GM criterion, and Fig. 6 depicts their geographic location. Altogether, we identify 14 green cities, of which 13 are in the Yangtze River Delta and one in the Pearl River Delta. We also identify 24 yellow cities, with eight cities in the Yangtze River Delta, 10 in the Beijing–Tianjin–Hebei region, and six in the Pearl River Delta. This result coincides with our discussion of Table 3. For example, in the Yangtze River Delta, the average annual rate of real GRP growth is 11.2%, with wastewater and SO_2 emissions decreasing faster and soot (dust) emissions increasing more slowly than the two other agglomerations. The implication here is that the Yangtze River Delta is generally better able to harmonize economic growth with pollution emission reduction than the two other agglomerations. It is also worth noting that the core city in each agglomeration (Beijing, Shanghai, and Guangzhou, respectively) is neither green nor yellow because, as shown in Table 4, the gap for these three cities between their green productivity growth (GML index) and conventional productivity growth (GM index) is negligible.

3.4. Decomposed sources of green productivity growth

Table 4 also lists the decomposed components of productivity growth calculated by the GML and GM indices. The results show that the rates of technical and efficiency change between the GML and GM indices differ considerably. Overall, the green technical change index in each agglomeration exceeds the conventional technical change index. However, the overall green efficiency change index in each agglomeration is much less than the conventional efficiency change index. Oh [7] argued that this difference arises from the incorporation of environmentally harmful by-products into the GML index.

The decomposed components identify the sources of green and conventional productivity growth. As shown in the last row of Table 4, both overall green and conventional productivity growth is mainly from technical change rather than efficiency change. The average value of BPC is 1.024, indicating green technical progress. In the sample period, a contemporaneous technology frontier is able to shift closely toward the global technology frontier in the direction of more desirable outputs and less pollution emissions. However, the average change of green efficiency is 0.998, thereby indicating a green efficiency loss. That is, the sample cities lag behind the contemporaneous benchmark technology frontier during the study period. This result coincides with the discussion in Section 3.1.

Table 5
Green cities and yellow cities categorized by the GML/GM criterion.

City heterogeneity	GML/GM	Cities
Green cities	⩾1.01	Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Taizhou, Suqian, Hangzhou, Ningbo, Huzhou, Shaoxing, Dongguan
Yellow cities	⩽0.99	Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Cangzhou, Hengshui, Lianyungang, Wenzhou, Jiaxing, Quzhou, Zhoushan, Lishui, Maanshan, Tongling, Shenzhen, Zhuhai, Foshan, Zhaoqing, Huizhou, Zhongshan

Note: We omit 13 cities where the values of GML/GM lie in the interval 0.99–1.01.

Of the three agglomerations, green productivity growth in the Yangtze River Delta most benefits from technical change with an average annual rate 2.8%. In contrast, for conventional productivity, the Beijing–Tianjin–Hebei region and the Pearl River Delta benefit most from technical change (6.3%). Only the Beijing–Tianjin–Hebei region benefits from a green efficiency improvement, whereas the two other agglomerations experience a marked deterioration in green efficiency. The decomposed sources of green productivity growth also vary across the individual cities. The technical changes in all cities are positive; Tangshan benefits most from technical change (5%). Table 4 also shows that most cities experience efficiency deterioration, supporting our argument that deteriorating efficiency is an important reason for the decline in the growth rates of both green and conventional productivity.

3.5. Green innovators

Although we calculated the technical change index for each city in Table 4, we are unable to use this to determine which cities exactly shift the frontier in the direction of more desirable and fewer undesirable outputs. To determine which cities are China's 'green innovators', we require the following three conditions to be met [5–7]:

$$BPC^{t,t+1} > 1, \tag{8}$$

$$D^t\left(x^{t+1}, y^{t+1}, b^{t+1}\right) < 0, \tag{9}$$

$$D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 0, \tag{10}$$

where the first condition indicates that in period $t + 1$ it is possible to both increase GRP and decrease the level of wastewater, SO_2 and soot (dust) emissions compared with period t for the given inputs. The second condition indicates that production in period $t + 1$ occurs outside the PPS of period t. This means the technology of period t cannot produce the outputs of period $t + 1$ using the inputs of period t. Compared with the reference technology of period t, the value of the DDF of period $t + 1$ is therefore less than zero. The third condition indicates that an innovative city should be on the country technology frontier. If these three conditions are met at the same time, then the city under consideration is a green innovator that has helped shift the efficiency frontier in the direction of more desirable and fewer undesirable outputs from period t to period $t + 1$.

Note that the criteria we use here to identify a green innovative city differ entirely from those used to categorize a city as green or yellow. In particular, a green city is not necessarily a green innovator. A green city would only be a green innovator when the adopted technology is on the national technology frontier and can shift the frontier in the direction of more desirable outputs and fewer undesirable outputs. Conversely, when the green productivity growth index (GML index) for a green innovator city is larger than its conventional productivity growth index (GM index), we can identify it as a green city. Similarly, a yellow city can be a green innovator if it adopts green technology that is on the national frontier. Consequently, green innovation would make a yellow city become a green city after a certain period.

Table 6 details the green innovators in each year. Of the 51 cities in the three urban agglomerations, 10 are green innovator cities: Shenzhen, Huizhou, Guangzhou, Dongguan, Lianyungang, Beijing, Foshan, Jiangmen, Tangshan, and Yancheng. This implies that each of these cities helped shift the frontier at least once. Some cities are green innovators for a longer period, for example, Shenzhen (five times) and Huizhou (five times); however, we should note here that these two cities were identified as yellow cities in Section 3.3. In comparison, other cities are green innovators for only a short

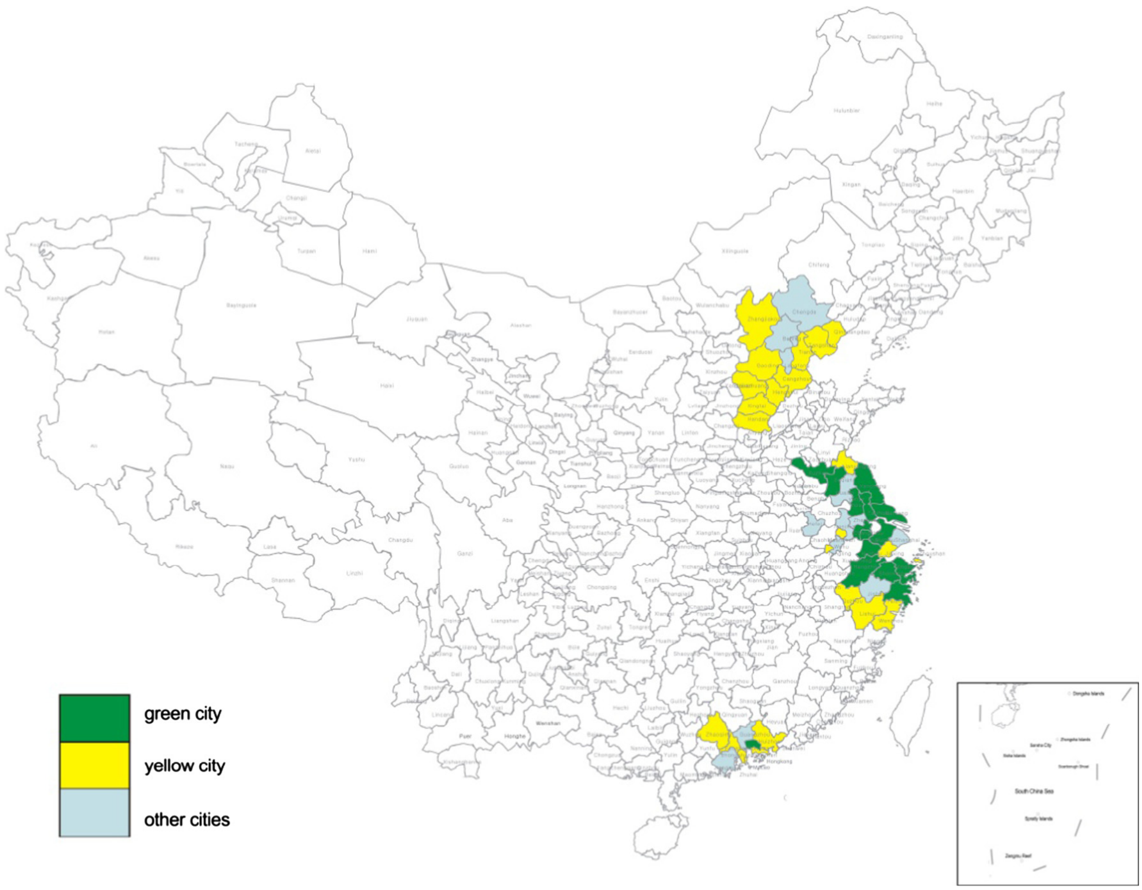

Fig. 6. Green cities and yellow cities in three urban agglomerations of China (2003–2013). Note: Other cities here are the omitted cities where the values of GML/GM lie in the interval 0.99–1.01. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
Green innovators.

Year	Cities
2003–2004	Guangzhou
2004–2005	Guangzhou, Huizhou
2005–2006	–
2006–2007	–
2007–2008	–
2008–2009	Lianyungang, Shenzhen
2009–2010	Tangshan, Lianyungang, Shenzhen, Huizhou
2010–2011	Beijing, Shenzhen, Huizhou, Dongguan
2011–2012	Guangzhou, Shenzhen, Huizhou, Dongguan
2012–2013	Yancheng, Guangzhou, Shenzhen, Foshan, Jiangmen, Huizhou, Dongguan

period, for example, Beijing, Foshan, Jiangmen, Tangshan, and Yancheng. Of the nine cities in the Pearl River Delta, five are green innovators, along with three of the 29 cities in the Yangtze River Delta, and only one of the 13 cities in the Beijing–Tianjin–Hebei region. As discussed in Section 3.2, overall green productivity growth in the Pearl River Delta is lower than in the other two agglomerations. This is because the Pearl River Delta was the first to step into industrialization in China in the 1980 s and now faces relatively more significant challenges in energy saving and emission reductions. As shown in Table 3, cities in the Pearl River Delta have the highest average level of electricity consumption (2,622,709 in tens of MW h) and the highest average annual growth rate of wastewater (2.2%) and soot (8.4%) emissions. The tremendous pressure on environmental protection has motivated enterprises in this region to adopt green technology; therefore, relatively more cities compared with the other regions have become green innovators, and are pushing the national technology frontier.

In addition, there is no innovative city in 2005–2008 possibly because of the business cycle in China. This result is similar to Färe et al. [5], who show that there appears to be a relationship between the business cycle and the number of states shifting the frontier in any given year in manufacturing in the United States. That said, we should note that the number of innovative cities has significantly increased since 2009, which may represent the contribution from the 11th and 12th Five-Year Plans issued in 2006 and 2011, respectively. In both these plans, energy savings and emissions reduction were the Chinese government's main targets for public policy.

3.6. Drivers of green productivity growth

To investigate the determinants of green productivity growth, we specify an econometric model. Following previous studies in the area, we include the following determinants in our model. (1) Urban agglomeration intensity (AG). Nonagriculture output value per unit area is chosen as a proxy of the agglomeration intensity, and its squared term is also introduced into the model to test the inverted U-shaped relationship between agglomeration and productivity asserted by the economic geography. (2) Environmental regulations (ER). Following Antweiler et al. [27], we use GRP per capita as a proxy for environmental regulations to test the Porter hypothesis [28]. (3) Industrial structure (IS). The proportion of secondary industry to GRP serves as a proxy of industrial structure. (4) Endowment structure (K/L). We employ the capital–labor ratio as a proxy for factor endowment structure. (5) Foreign direct investment (FDI). We use the ratio of real FDI to real GRP to measure

FDI inflows. (6) Infrastructure conditions (INFRA). We select road size per capita as a proxy for infrastructure conditions. We collected or calculated all data from the Chinese City Statistical Yearbook [1] and the China Statistical Yearbook [26]. Hausman tests support the fixed effects model. Table 7 reports the estimated results for the three subsamples assuming both fixed and random effects.

For the Yangtze River Delta and the Pearl River Delta, the coefficients for agglomeration intensity, AG, are positive and significant, while their squared terms, AG2, display a negative and significant sign. This implies that the relationship between agglomeration intensity and green productivity growth is an inverted U-shaped curve. That is, below some critical value, the increase in urban agglomeration intensity can promote green productivity growth. However, above this critical value, it may damage green productivity growth. Nonetheless, for the Beijing–Tianjin–Hebei region, the estimated coefficients for both AG and AG2 are insignificant. For the three subsamples, the coefficients for environmental regulations are significantly positive. Therefore, we provide empirical evidence supporting the Porter hypothesis [27,28]. That is, for the three major urban agglomerations in China, strict environmental regulations can lead to a win-win situation, where both economic prosperity and environmental quality can improve.

The coefficients of industrial structure are negative and significant for both the Yangtze River Delta and the Beijing–Tianjin–Hebei region. This shows that an increase in the proportion of industry serves as an obstacle to green productivity growth because industry is the main source of pollutant emissions in Chinese cities. For both the Yangtze River Delta and the Pearl River Delta, the coefficients for the capital–labor ratio are significantly negative, suggesting that increasing capital intensity hinders green productivity growth. This is because when the capital–labor ratio increases, labor-intensive industries are substituted by capital-intensive industries, most of which in China are heavy chemical industries, and generally dirtier than light industries.

The coefficients for FDI are significantly positive only in the Yangtze River Delta, revealing that FDI can promote green productivity growth only in this region. This result is similar to Wen [29], who suggested that the impacts of FDI on productivity differed by region in China. That is, the 'pollution haven hypothesis' does not appear to be present in our sample. Across the three subsamples, the coefficients for infrastructure conditions are not significant, which indicates that the improvement of infrastructure cannot assist green productivity.

4. Conclusions and implications

This is the first known study of green productivity growth in cities of the three major urban agglomerations in China. The results calculated by GML index show that the cumulative growth rate of green productivity in the Beijing–Tianjin–Hebei region was higher than the two other agglomerations in most years studied. However, for the whole sample period, the Yangtze River Delta obtained the largest cumulative increase (30.1%) in green productivity, which increased by only 25.1% and 18.8% in the Beijing–Tianjin–Hebei region and the Pearl River Delta, respectively. We note that green productivity in all three agglomerations increased significantly during the period of China's 11th Five-Year Plan (2006–2010), given that the central government goal of building a resource-saving and environment friendly society was firmly established.

Using the criterion of eco-friendliness, cities are categorized into green and yellow city groups. Most green cities lie in the Yangtze River Delta, while most cities in the Beijing–Tianjin–Hebei region and the Pearl River Delta are yellow cities. This suggests that the Yangtze River Delta has successfully harmonized economic growth with a decrease of pollution emissions relative to the other two agglomerations. Of the sample cities, we identified 10 green innovator cities that pushed China's technology frontier in the direction of more desirable outputs and fewer undesirable outputs. Five of these innovative cities are located in the Pearl River Delta, largely because this agglomeration faces greater challenges in reducing energy consumption and pollution emissions than the other two agglomerations.

Green productivity growth most benefits from technical change rather than efficiency change for the three agglomerations. Efficiency deterioration significantly prevents green productivity growth in the Yangtze River Delta and the Pearl River Delta. The

Table 7
Estimated determinants of green productivity growth.

Variables	Beijing–Tianjin–Hebei		Yangtze River Delta		Pearl River Delta	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
AG	−0.020 (0.036)	−0.033 (0.034)	0.205*** (0.047)	0.172*** (0.040)	0.244*** (0.056)	0.158*** (0.046)
AG2	0.001 (0.005)	0.003 (0.005)	−0.0225** (0.010)	−0.0179** (0.009)	−0.0213*** (0.007)	−0.0196*** (0.006)
ER	0.040*** (0.006)	0.042*** (0.005)	0.012*** (0.003)	0.014*** (0.003)	0.001 (0.003)	0.006* (0.003)
IS	−0.521*** (0.164)	−0.401*** (0.138)	−0.957*** (0.187)	−0.813*** (0.155)	0.072 (0.314)	−0.003 (0.174)
K/L	0.007 (0.013)	−0.002 (0.007)	−0.015** (0.006)	−0.008** (0.004)	0.007 (0.010)	−0.006** (0.002)
FDI	0.001 (0.007)	−0.001 (0.006)	0.006** (0.003)	0.005* (0.003)	0.006 (0.007)	−0.004 (0.006)
INFRA	0.003 (0.004)	0.003 (0.003)	0.001 (0.002)	0.001 (0.002)	−0.000 (0.003)	−0.004*** (0.001)
Constant	1.118*** (0.120)	1.128*** (0.108)	1.465*** (0.111)	1.346*** (0.0920)	0.693*** (0.219)	1.098*** (0.124)
Hausman test		5.44		11.42		14.07
R-squared	0.570		0.563		0.344	
Observations	130	130	290	290	90	90

Notes: Standard errors are in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), or 1% (***) level.

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determinants driving green productivity growth differ across the three urban agglomerations. The relationship between urban agglomeration and green productivity growth also exhibits an inverted U-shape for cities in the Yangtze River Delta and the Pearl River Delta. FDI inflows can improve green productivity growth only in the Yangtze River Delta, while environmental regulations can promote green productivity growth in all three agglomerations. The increase in the proportion of industry may serve as an obstacle to green productivity growth in the Yangtze River Delta and the Beijing–Tianjin–Hebei region. For the Yangtze River Delta and the Pearl River Delta, the increase in the capital–labor ratio may instead hinder green productivity growth.

Drawing on the above conclusions, we can suggest some policy implications. First, the application and development of cleaner technologies and energy-saving technologies are the main contributors to green productivity growth and the sustainable development of Chinese cities in the future. Although technical progress is the main source of green productivity growth in the three major urban agglomerations, the green innovation capability of cities remains very low, which is the key reason behind Chinese cities trailing the world's developed cities when it comes to sustainable development. The green innovators like Shenzhen identified in this study are clearly pioneers and can serve as examples and share their experience with other cities in China and elsewhere. In particular, governments should formulate policies to induce enterprises to apply or develop cleaner technologies and energy-saving technologies.

Second, there should be an emphasis on green efficiency improvements in firm production and operation decisions. There is still much room for Chinese cities to improve green efficiency, mainly depending on innovation in the management mechanism, the transformation of operation systems, and the adjustment of corporate governance structures. Therefore, this should serve as the micro foundation when establishing modern enterprise systems and improving corporate governance structures aimed at the future sustainable development of emerging cities.

Third, the inverted U-shaped relationship between agglomeration intensity and green productivity growth supports the classified policies on industrial agglomeration according to urban density for developing countries. It is imperative to develop policies to promote industrial concentration for those medium-sized cities with lower intensity. For those cities with overintensive economic activities such as Beijing, Shanghai, and Guangzhou, there is a need for the appropriate control of the density of industries and population to prevent pollution and other 'big-city diseases' from threatening sustainable development.

Fourth, policies on industrial restructuring must take into account green productivity growth. For the Beijing–Tianjin–Hebei region and the Yangtze River Delta, it would be appropriate to control the share of heavy industry and actively develop service sectors, the latter of which emit less pollution. For the Yangtze River Delta and the Pearl River Delta, we recommend the need to adjust the internal industrial structure, encourage the inflow of capital to clean and high-tech industries, and curb the capacity expansion of heavy chemical industries, as characterized by heavy pollution and energy consumption. Therefore, yellow cities in developing countries should be the primary focus of industrial restructuring policies.

Finally, further strengthened environmental regulations are essential in developing countries. For Chinese urban agglomerations, there is a need for tougher environmental regulations and collaboration between cities in the future. Environmental regulations and policies should also place more emphasis on collaborative implementation between cities in urban agglomerations. In addition, governments should enhance environmental standards to limit the access of foreign direct investment in high-pollution and high-energy-consumption industries.

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