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.

ARTICLE INFO

Article history:
Received 24 September 2016
Received in revised form 22 December 2016
Accepted 22 December 2016
Available online xxxx

Keywords:
Green productivity
Global Malmquist–Luenberger index
Urban agglomerations
Green city
Green innovator

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.

© 2016 Published by Elsevier Ltd.

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 (SO2) 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.
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 produce 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 (CO₂) 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 CO₂ 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 \( (x^{1t}, y^{1t}, b^{1t}) \), where the production technology can produce \( M \) desirable outputs, \( y = (y_1, y_2, \ldots, y_M) \) in \( \mathbb{R}^M_+ \) and \( J \) undesirable outputs, \( b = (b_1, b_2, \ldots, b_J) \) by using \( N \) inputs, \( x = (x_1, x_2, \ldots, x_N) \) in \( \mathbb{R}^N_+ \). 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:

\[
\tilde{D}_b(x, y, b, g) = \max \left\{ \beta : (y, b) + \beta g \in P(x) \right\},
\]

where \( g = (y, b) \) is a direction vector, and \( \beta \) 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:

\[
ML^t\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + D^t\left(x^t, y^t, b^t\right)}{1 + D^t\left(x^{t+1}, y^{t+1}, b^{t+1}\right)},
\]

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:

\[
GM^{t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D^t(x^t, y^t)}{D^t(x^{t+1}, y^{t+1})}.
\]

Please cite this article in press as: Tao F et al. Dynamics of green productivity growth for major Chinese urban agglomerations. Appl Energy (2016), http://dx.doi.org/10.1016/j.apenergy.2016.12.108
دریافت فوری
متن کامل مقاله

امکان دانلود نسخه تمام متن مقالات انگلیسی
امکان دانلود نسخه ترجمه شده مقالات
پذیرش سفارش ترجمه تخصصی
امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
امکان دانلود رایگان ۲ صفحه اول هر مقاله
امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
دانلود فوری مقاله پس از پرداخت آنلاین
پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات