Energy-Saving Bias in Green Technology Innovation A Spatial and Temporal Analysis of manufacturing in China

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Abstract—This study presents an in-depth analysis of the energy-saving bias in green technology innovation across 30 provinces in manufacturing from 2011 to 2021, utilizing a novel Malmquist-Luenberger multidimensional decomposition index based on the directional distance function. The research reveals that green innovation, characterized predominantly by energy conservation, plays a pivotal role in driving China's green total factor productivity. The impetus for innovation in energy saving is found to surpass that of emission reduction in manufacturing enterprises. Energy-saving biased green technology innovation, originating in economically advanced provinces, has gradually expanded to the northern region, and it encompassed the majority of provinces in China. This type of innovation serves as the primary driver of regional green innovation. The study also identifies a conspicuous spatial aggregation effect of energy-saving biased green technology innovation, linked intrinsically to the degree of industrial aggregation and the spatial correlation effect of innovation.

1. Introduction

As one of the world's largest manufacturing hubs, China is at the forefront of energy-efficiency innovation challenges. The manufacturing industry, while being a significant contributor to China's GDP and employment, is also a major consumer of energy, accounting for nearly 70% of the country's total energy use [1]. Innovation-driven green industrial manufacturing is proliferating [2]. However, the choice of direction for green technology innovation is not clear, resulting in the inability to assess energy-efficient green innovation on a regional macro level. To address this issue, this paper proposes a nonparametric model to measure the energy efficiency bias of industrial manufacturing and its spatial evolution characteristics. The parametric method, which enhances the production function by deriving a comprehensive total factor productivity function [3], allows researchers to unravel the driving forces behind changes in total factor productivity. Non-parametric methods, on the other hand, focus on analyzing the factor bias of technological progress by examining the non-isometric movement of the production frontier across different time periods. This movement induces changes in the marginal output ratio of various factors, providing insights into how technological innovation tend to favor specific input factors such as capital, labor, or energy [4]–[6]. In contrast, the parametric approach has more stringent modeling assumptions and some difficulties in dealing with non-expected outputs [7]. In the context of green technology innovation, it is crucial to account for unexpected outputs and incorporate negative environmental outcomes into the analytical framework [8]. This approach enables a comprehensive analysis of the biased allocation of factors at the input stage, which is of significant importance for exploring energy-saving biases in green innovation. Due to the certain spatial association characteristics of green development [9], [10], a clear understanding of spatial evolution characteristics of green biased innovation in manufacturing will help policy-making departments to suit the remedy to the case.

This study draws on manufacturing data from 30 provinces in China, excluding Hong Kong, Macao, Taiwan, and Tibet over the period from 2010 to 2021. By calculating the degree of green technology innovation bias, decomposing the substitution effects of input factors, and obtaining the results of energy-saving bias for green innovation of each province and year, this study aims to analyze the spatial evolution characteristics of these biases.

2. Method and Model

We draw on Färe and chung's study [11], [12]by imposing a weak disposability constraint on non-desired outputs and combine it with the Malmquist-Luenberger productivity index methodology in order to compute the green technology innovation bias as follows:

$$\begin{aligned} ML_0^t(\mathrm{x}^t,\mathrm{y}^t,\mathrm{x}^{t+1},\mathrm{y}^{t+1}) &= D_0^t(\mathrm{x}^{t+1},\mathrm{y}^{t+1})/D_0^t(\mathrm{x}^t,\mathrm{y}^t), t \\ &= 1,\dots,T-1 \\ &= \Delta\mathrm{T}(\mathrm{x}^{t+1},\mathrm{y}^{t+1})\cdot\Delta\mathrm{TE}(\mathrm{x}^t,\mathrm{y}^t,\mathrm{x}^{t+1},\mathrm{y}^{t+1}) \end{aligned}$$

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$$= \left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})}\right] \cdot \left[\frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}\right]. \quad (1)$$

$$\mathrm{GII}\left(x^t, y^t, x^{t+1}\right) = \left[\frac{D_i^{t+1}(y^t,x^{t+1})}{D_i^t(y^t,x^{t+1})} \Big/ \frac{D_i^{t+1}(y^t,x^t)}{D_i^t(y^t,x^t)}\right] \quad (2)$$

$$\mathrm{GIO}\left(y^t, x^{t+1}, y^{t+1}\right) = \left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})} \Big/ \frac{D_0^t(x^{t+1},y^t)}{D_0^{t+1}(x^{t+1},y^t)}\right] \quad (3)$$

Where x^t denotes the set of input factors, y^t denotes the set of expected output factors, and the set of unexpected output factors as b^t . The ML index can be decomposed into efficiency change (ΔT) and technological change (ΔTE), as in equation (1). Further, the ΔTE index is decomposed to obtain the input bias of green technological innovation (GII) and the output bias of green technological innovation (GIO), as in equation (2) and (3).

In this paper, we further decompose GII so as to construct the substitution relationship between input factors in order to calculate the substitution index of green technology for energy, i.e., the energy-saving biased green technology innovation index (EBGI), as in equation (4).

$$EBGI_{I,E} = \left(\frac{I^{t+1}}{E^{t+1}} / \frac{I^t}{E^t} - 1\right) \times (GII - 1) \quad (4)$$

where I gauges the green technology innovation, represented by number of green patents; E refers to energy input, represented by comprehensive energy consumption per unit of industrial added value; $\frac{I^{t+1}}{E^{t+1}} / \frac{I^t}{E^t}$ is the ratio of the marginal substitution rates of factors I and E from stage t to $t+1$. $EBGI_{I,E} > 0$, it indicates that I realizes the bias of green technology innovation by substituting E , which is the energy-saving green technology innovation of factor E.

3. Data and Varialbes

The data are mainly from China Statistical Yearbook (2011-2022), China Industrial Statistical Yearbook (2011-2022), and China Environmental Statistical Yearbook (2011-2022). The variables are designed in table 1 as follows:

Table 1. Variable description

Types	Variable		
	variable name	*indicators*	*Sign*
Input	Energy	Comprehensive energy consumption per unit of industrial added value	+
	Technology	Number of invention patents of industrial enterprises above designated size	+
	Labor	Manufacturing employment	+
Output	Non-expected outputs	COD emissions per unit of industrial added value	-
		Ammonia nitrogen emissions per unit of industrial added value	-
		SO2 emission per unit of industrial added value	-
		Nitrogen oxides per unit of industrial added value	-
		Solid Waste Generation per unit of industrial added value	-
		Wastewater emissions per unit of industrial added value	-
	Expected outputs	Industrial value added as % of GDP	+

4. Results

4.1. GII and GIO index

As depicted in Fig 1, it is evident that the influence of input bias on green technology innovation was more pronounced prior to 2014. Post-2014, however, the scenario changed significantly, with the output bias of green technology innovation emerging as a key driver of green total factor productivity. Furthermore, an examination of the factor substitution bias at the input end reveals that the Green Technology Innovation Index (GII) has been greater than 1 in the majority of years, suggesting that green technology in the manufacturing sector has had a positive impact on the substitution of intergroup bias of energy and labor input factor groups.

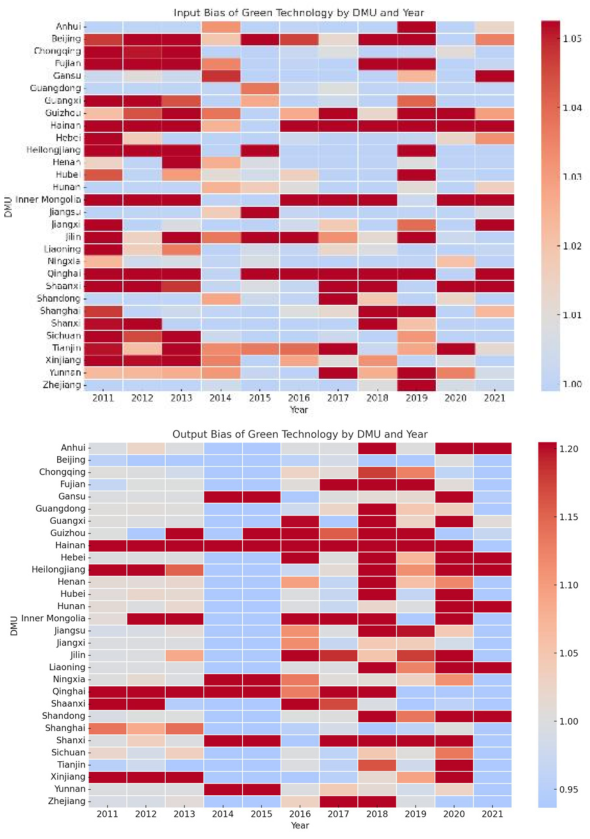

Figure 1. Heatmaps of GII and GIO

On a regional scale, there are marked differences in green technology innovation across various provinces in China. Specifically, between the years 2016 and 2020, the

https://doi.org/10.1051/e3sconf/202344103005

Green Innovation Index Outputs (GIOs) for most regions were found to be higher than 1.15. This trend aligns with the contemporary concept of low-carbon development. In 2021, the GIOs of provinces such as Anhui, Hebei, Heilongjiang, Hunan, Liaoning, and Shanghai exceeded 1.2. This suggests that innovations aimed at reducing emissions, propelled by environmental regulations, have been driving the adoption of green technologies in these regions. Concurrently, the 2021 data also shows that in provinces like Annex, Hainan, Inner Mongolia, Jiangxi, Qinghai, and Shaanxi, the GII was higher than 1.05. This indicates that under the constraints of resources and environment, input bias has been a significant factor driving green technology innovation in these regions.

4.2. EBGI index

Figure 2 illustrates the intra-group bias of the input factors associated with green technology innovation within the manufacturing sector across 30 provinces in China, spanning from 2011 to 2021. The data reveals that both prior to 2014 and post-2018, green technology innovation displays a clear inclination towards energy conservation. More specifically, when examining the bias in technology innovation between the two factors of "technology" and "energy", where the Energy Bias Green Innovation (EBGI) is greater than zero, it becomes evident that the overall generation of green innovation is characterized by energy efficiency. This suggests that, for manufacturing enterprises, the impetus for innovation in energy conservation surpasses that of emission reduction.

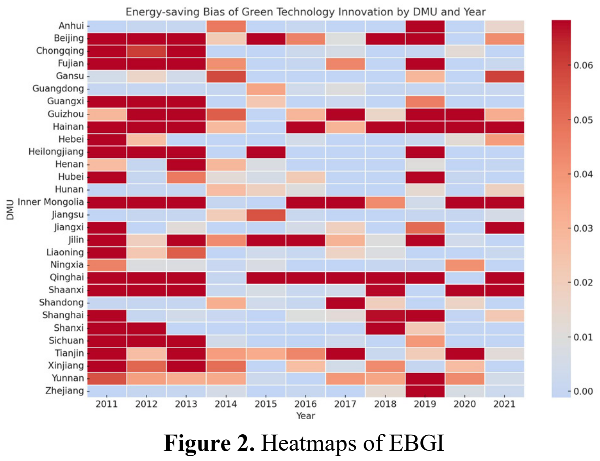

Figure 2. Heatmaps of EBGI

Upon further analysis of the spatial distribution of the energy-saving bias in green innovation, data from the most recent three years (2019, 2020, and 2021) reveal that regions such as Guizhou, Hainan, Inner Mongolia, and Shaanxi exhibit pronounced energy-saving bias characteristics. This is a departure from the traits observed in areas with higher levels of economic development in previous years. These regions have transitioned from an energy-driven technological innovation model to a model where technology drives energy-saving green technological innovation. This shift not only indicates that the technology gap is being bridged but also suggests that green technology innovation is beginning to demonstrate regional spillover effects.

4.3. Characteristics of spatial evolution

Figure 3 provides a visual representation of the spatial patterns of the Green Innovation Index (GII) at the provincial level, illustrating the bias levels for the years 2015, 2018, and 2021.

As depicted in Figure 3, the geographical distribution of Green Innovation (GI) across China is characterized by a steady expansion. The pattern of GII underwent a smooth transition throughout the study period, marked by a continuous distribution. Notably, the bias in green technology innovation in the southern regions is gradually shifting towards the input side, indicating a growing emphasis on resource allocation. Concurrently, the central region is witnessing a gradual intensification of input bias, underscoring a similar trend.

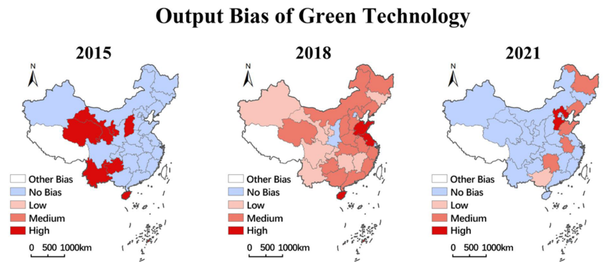

Figure 3. Spatial pattern of GII. (2015,2018,2021)

Figure 4 presents the spatial patterns of the Green Innovation Outputs (GIO) at provincial scales, visualizing the bias level for the years 2015, 2018, and 2021.

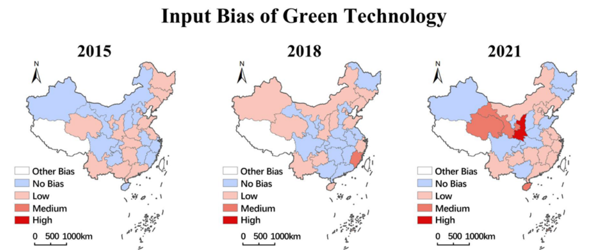

Figure 4. Spatial pattern of GIO. (2015,2018,2021)

As depicted in Figure 4, in contrast to the characteristics of input bias, the output bias of green innovation within the Chinese manufacturing industry is showing a trend of gradual attenuation. Concurrently, an examination of the bias characteristics reveals distinct regional traits of green technology innovation bias within the manufacturing industry. The eastern region predominantly exhibits environment-friendly technological innovation, while other regions are characterized by a focus on resource-saving technological innovation.

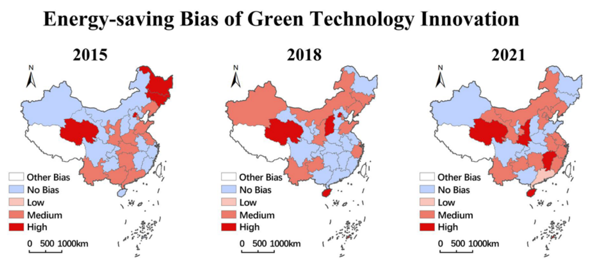

Figure 5. Spatial pattern of EBGI. (2015,2018,2021)

Figure 5 primarily investigates the regional spatial evolution characteristics of the bias towards energy-saving green technology innovation.

As depicted in Figure 5, energy-saving biased green technology innovation emerges as the principal driver of regional green innovation. The spatial characteristics of energy-saving biased green technology innovation are as follows:

(1) In 2015, prior to the introduction of the "green manufacturing" concept, energy-saving biased technology innovation was predominantly concentrated in economically developed provinces, including the eastern coastal region, Beijing, Tianjin, and other areas. This focus gradually shifted towards the northern region, and by 2021, it encompassed the majority of provinces in China.

(2) The spatial aggregation effect of energy-saving biased green technology innovation is pronounced, which correlates with the degree of industrial aggregation and the spatial correlation effect of innovation.

(3) In comparison to labor substitutability, advancements in technology and the reduced costs of green technologies have made them more accessible and feasible for adoption within the manufacturing industries.

5. Conclusions

Leveraging the directional distance function, we have constructed a novel Malmquist-Luenberger multidimensional decomposition index. This tool has been used to scrutinize the energy-saving bias of the input factors of green technological innovation across 30 provinces in China, with a particular focus on its spatial and temporal evolution characteristics. Our comprehensive evaluation explores the pivotal role of green technology innovation in propelling green total factor productivity of manufacturing in China from 2011 to 2021. The findings underscore that green innovation is predominantly characterized by energy conservation, suggesting that for manufacturing enterprises, the impetus for innovation in energy saving surpasses that of emission reduction.

In conclusion, our research illuminates the critical role of energy-saving bias in green technology innovation. The spatial evolution characteristics of this bias indicate a steady expansion of green technology innovation, with an increasingly pronounced input bias in the central region over time. We have also observed that energy-saving biased green technology innovation serves as the primary driver of regional green innovation. This type of innovation, which originated in economically advanced provinces, has gradually expanded to the northern region, and by 2021, it encompassed the majority of provinces in China.

The conspicuous spatial aggregation effect of energy-saving biased green technology innovation is intrinsically linked to the degree of industrial aggregation and the spatial correlation effect of innovation. The regional disparities identified in our study underscore the need for a deeper understanding of the factors contributing to these differences. This understanding could further inform the design and implementation of regional green technology policies.

Acknowledgment

This study was financially funded by the project of Joint Special Funds for Basic Research in Local Undergraduate Universities in Yunnan Province in 2022 (202101BA070001-170): Green-biased technological innovation and sustainable green development in Yunnan: mechanisms of action and policy conditions.

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