Promoting Green Technical Efficiency: A Regional and Urban Agglomeration Cluster Analysis

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Abstract

Using 2010 to 2017 provincial data on China, this paper is the first to systematically compare conventional technical efficiency (TE) and green TE, which takes carbon emissions into account. This is done using an improved version of the two-stage double bootstrap data envelopment analysis to explicitly model carbon emissions as an undesirable output to analyse green economic growth. New evidence shows that the conventional and green TE rankings are broadly similar, but there are variations in the intertemporal trends of China's provinces, regions and clusters. Although urbanisation is positively associated with both measures of TE, its role is overestimated in conventional TE gains. Furthermore, while the service sector share plays no significant role in conventional TE gains, it is significantly associated with green TE. This highlights the importance of the industry structure (i.e., the share of the service sector) in sustainable economic growth when carbon emissions are accounted for, a result that was masked when conventional TE was analysed. Our results further show that provinces with a similar urbanisation rate can have differences in green TE in part due to green TE also being associated with the GDP share of services. The study cautions that varying strategies for different provinces, regions and clusters are necessary for a "win-win" green transformation towards sustainable economic growth.

JEL classification: O44, Q52, C13, C44

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1. Introduction

For the first time ever, in the 2020 World Economic Forum's Global Risk Report – which assesses both the likelihood and impact of major risks in the coming years – environmental risks occupied the five top spots. This reinforces the global concern of combating climate change, specifically carbon emissions (CO2) as it makes up 82% of total greenhouse gases. At the same time, sustaining economic growth has always been the pursuit of all economies. Meeting these goals simultaneously is a challenge as many case studies on various economies have highlighted the conflict between these two objectives in the examination of the Environmental Kuznets Curve. It is thus vital to understand how countries can achieve their maximum potential gross domestic product (GDP) while minimising carbon emissions using a single efficiency measure – we call this green technical efficiency.

Adding to the difficulty of balancing GDP and carbon emissions is the phenomenon of urbanisation, often used as a development strategy to modernise an economy. According to the United Nations (UN 2019), cities are responsible for 75% of global CO2 emissions, with transport and buildings being among the largest contributors. In some cities, urban expansion threatens to destroy habitats in key biodiversity hotspots and contribute to carbon emissions associated with tropical deforestation and land use change (UN 2019). Today, 55% of the population lives in urban areas and this is expected to increase to 68% by 2050 (ibid). Although the empirical evidence to date on the effect of urbanisation on economic growth and carbon emissions remains mixed (Mahadevan and Sun 2020), a low carbon-emission growth path is imperative for both developing and developed countries.

Even as green growth is prioritised, the necessity of ensuring social inclusivity remains a critical yet frequently neglected dimension, as formalised by the United Nations Sustainable Development Goals. If such growth were specific to some regions/provinces and not balanced within an economy, this would hinder long-term green growth of the whole economy. Similar concerns on regional inequality within the economy have been discussed in the literature. For example, Cui et al. (2017) highlighted the tension between Scotland's regional economic development and its environmental targets; Tian et al. (2021) examined regional inequality in China's carbon intensity; Benos et al. (2017) considered differences in the role of public and human capital in regional development of the 48 states in the United States.

China is chosen as a case study given its impressive economic growth in the last two decades which conflicts with China also being the top polluting economy contributing 27% of total carbon emissions in the world. Indeed, China's carbon emissions per capita more than doubled from 2.7 metric tons in 2000 to 7.78 metric tons in 2017 (Mahadevan and Sun 2020). China issued its first National Climate Change Program in 2007, subsequently launching a low-carbon pilot programme in five selected provinces in 2010. By March 2011, China's initiatives were dubbed China's "Green Leap Forward" (Chang et al. 2016), and at the 2015 Paris Agreement, China announced that it would increase the share of non-fossil fuels in primary energy consumption to around 20% by 2030. In 2020, China's leader pledged a new target of net-zero emissions by 2060 and several binding targets in green development were then set out in China's 14th Five-Year Plan for 2021–2025.

Another reason for using China as a case study is its modernisation strategy, in which urbanisation is an inevitable part of its pursuit of economic development (Shan et al. 2018); this is explicit in the New Urbanisation Plan 2014–2020. The national urbanisation rate rose from 47.9% in 2009 to 60.3% in 2019, and by 2050, the country is projected to add 255 million urban dwellers (UN 2019). This trend has, however, been noted as unsustainable by Ji et al. (2019), while Cheshmehzangi (2016) highlighted major challenges for decarbonisation brought about by the national strategy. As cities produce 85% of the country's carbon emissions, managing urbanisation plays an increasingly important role in efforts to reduce emissions (Shan et al. 2018). Concurrently, an emphasis on accelerating and improving the service sector has been a key feature of Five-Year Plans since 2016. As an increasing share of the service sector typically accompanies economic development and urbanisation, it is relevant to consider these impacts on the move towards a low-carbon and efficient economy.

Against this background, this paper on regional green efficiency performance compares across and within regions using the case study of China's provinces to examine inter- and intra-regions (namely the Eastern, Western and Central regions) and intra-urban agglomeration cluster differences (namely the Beijing-Tianjin-Hebei cluster and the Yangtze River Delta comprising Shanghai, Anhui, Jiangsu and Zhejiang). In doing so, we examine the role of urbanisation and service sector growth in influencing provincial technical efficiency (TE) which is measured by the gap or how far the province is operating from its maximum potential green economic growth. This is done by explicitly modelling carbon emissions as an undesirable output, for the first time, in the two-stage double bootstrap data envelopment analysis (DEA) framework of Simar and Wilson (2007), hereafter referred to as SW. The SW approach has been used for TE analysis in different contexts such as hospital services in Ontario (Chowdhury and Zelenyuk 2016), commercial banks in China (Du et al. 2018) and economic complexity using a cross-country dataset (Du and O'Connor 2021). But unlike our study, none of these studies have incorporated any undesirable output in the SW model they adopted.

Our paper contributes to the existing literature in two ways. First, we test our improved SW model on a panel of 30 provinces in China from 2010 to 2017 to obtain reliable and robust efficiency scores. This empirically contributes to a dynamic (since panel data of two periods are compared) TE analysis of three main regions and two clusters in China. The formation of three urban agglomeration clusters (the above-mentioned clusters and the Pearl River Delta cluster comprising Guangdong, Hong Kong and Macau) was spearheaded as part of China's New Urbanisation Plan 2014–2020. The purpose of this urbanisation plan was to benefit from agglomeration economies as studies (Krugman 1991, Quigley 2008) have explained that urbanisation (the geographical agglomeration of people and firms) can lead to lower production costs related to low transportation costs and potentially a local market, higher productivity and economic growth. Due to data constraints, the Beijing-Tianjin-Hebei cluster and the Yangtze River Delta cluster are examined in this study but not the Pearl River Delta cluster as data on Hong Kong and Macau are unavailable.

Our analyses consider inter-temporal trends of the provinces, regions and clusters from 2010–2013 to 2014–2017, unlike most panel studies using the DEA model on China (Ji and Zhou 2020, Ren et al. 2018, and Song et al. 2018) which do not distinguish between time periods and assume that the same production technology exists over time, which is unrealistic. It is critical to divide the time span appropriately to account for technology shifts over time. For China, converging evidence points to 2013 as a structural turning point. China's coal consumption peaked in 2013 and national CO2 emissions growth decelerated from a rapid pace to near-stagnation (Qi et al. 2020, Green and Stern 2017), coinciding with the State Council's launch of the Air Pollution Prevention and Control Action Plan in September 2013 – the start of what has been termed China's "war on pollution" (He and Ancora 2019). From 2014, the economy entered what President Xi Jinping characterised as a "new normal" of slower but higher-quality growth (Green and Stern 2015), and the November 2014 USA–China Joint Announcement on Climate Change committed China to peak CO2 emissions by around 2030. These shifts in the emissions–growth relationship also align with two policy events directly relevant to our variables of interest: China's New Urbanisation Plan 2014–2020 and the 2013 launch of the Belt and Road Initiative, which Russel and Berger (2019) argue has been used to pursue green growth by reducing domestic carbon emissions. Taken together, these developments provide a well-motivated basis for the setting of our analysis.

Our second contribution is both theoretical and empirical. We extend the SW approach by modelling carbon emissions as an undesirable output, incorporating them as constraints within the linear programming framework. This acknowledges that emissions are an unavoidable joint product of production (Shephard 1970, Färe et al. 1989, Zhou et al. 2008b) and addresses the fact that performance rankings are highly sensitive to the inclusion of undesirable outputs (Färe et al. 1989). This enables a direct comparison of conventional and green TE scores, which we use to examine the role of urbanisation and service sector-led strategies in green economic growth — filling a gap left by studies such as Feng et al. (2017), Song et al. (2020) and Zheng et al. (2019) that did not explicitly consider these factors. Lastly, based on our empirical results, we draw lessons and strategies for low-carbon and high economic growth applicable to other economies on a similar growth trajectory.

To summarise, using provincial data, the following hypotheses are tested:

H1: Efficiency ranking of provinces based on green and conventional TE is similar.

H2: Trends of provincial, regional and cluster-oriented TE over time based on green and conventional TE are similar.

H3: A higher urbanisation rate is associated with higher conventional and green TE.

H4: A higher service sector GDP share is associated with higher conventional and green TE.

The remainder of the paper is structured as follows. Section 2 reviews related literature while Section 3 details the methodology, with the full bootstrap procedure documented in Appendix 1. Section 4 describes the data and variables. Section 5 discusses the empirical results, and Section 6 concludes with a summary and policy suggestions. All appendices are provided in the Supplemental Material.

2. Literature Review

The production frontier method has been widely used to analyse economic growth related to energy efficiency with a focus on pollutants such as carbon emissions. This is often done using a parametric or nonparametric approach. The advantage of the latter is that unlike the parametric approach, there is no need to impose a functional form for the production frontier and importantly, it is suitable to describe the relationship between desirable and undesirable outputs using a multi-input and output structure. For the purposes of our study, the nonparametric approach such as the DEA is an appropriate tool to explicitly model carbon emissions as an undesirable output. There is a growing literature on DEA focused on the environmental performance of economies and Zhou et al. (2008a) provide a review of earlier DEA studies while Mardani et al. (2018) provide a review of more recent DEA studies.

More broadly, the studies relevant to ours can be categorised into the radial and non-radial measurement of efficiency as seen in Appendix 2. The non-radial measure of DEA efficiency provides the changes which are not necessarily proportional in outputs (inputs) that can be achieved with a fixed level of inputs (outputs). This is often done using various slacks to represent the potential change in each output (input). One drawback here is that weights need to be attached to these slacks corresponding to each output (input). These weights are often assigned in an ad hoc manner by the researcher(s) depending on the structure of their constructed DEA model. Another drawback of the non-radial measure is that the underlying assumption that desirable and undesirable outputs are independent complicates interpretation. For example, for an increase in the overall DEA efficiency score, it is unclear if this improvement necessarily reflects an increase in the desirable output with a decrease in undesirable output or an increase in desirable output that outweighs an increase in the undesirable output, as the DEA score is the sum of changes in desirable and undesirable outputs in the non-radial approach. A sample of studies on non-radial DEA efficiency is provided in Appendix 2 and these primarily discuss trends in the DEA efficiency and possible reasons underlying these trends.

To address these drawbacks, the radial DEA measure provides the proportional change in outputs (inputs) that can be achieved with a fixed level of inputs (outputs). In the literature, these are labelled as output-oriented when outputs are maximised with fixed input levels and input-oriented when the use of inputs is minimised for fixed output levels. Within the radial DEA approach, similar to the non-radial DEA studies, existing studies examine the DEA efficiency trends and do not further use regression analysis to explain the factors affecting DEA efficiency. Our study contributes to the existing literature by using the two-stage double bootstrapping DEA model of SW as it has the following important improvements over the conventional DEA models in the existing studies in this research area.

In the first stage, SW use a bootstrapping algorithm that coherently describes the data generation process to correct the downward bias in DEA efficiency estimates which previous studies did not correct for. In the second stage, to examine the factors influencing the DEA scores, previous studies often use regression analysis without considering the problem of serial correlation in the DEA efficiency estimates (SW 2007). Serial correlation arises because perturbations of observations on the estimated frontier cause changes in the efficiency estimates of other units. This dependence makes it difficult to satisfy the assumption of independently distributed units that underlies many statistical tests, thereby rendering the inferences invalid (Hawdon 2003, Simar and Wilson 2007). To address this problem, we use appropriate confidence intervals for the factors influencing the DEA scores. This is done by bootstrapping and using a logically consistent data generation process aligned with the structure of the DEA model in the first stage as was devised by SW (2007) and undertaken using Monte Carlo simulations by Du et al. (2018) for panel data.

In addition, we use a truncated regression for the second stage analysis on DEA scores to provide reliable inference for the estimates unlike the ordinary least squares (OLS) or Tobit models (SW 2007, 2011). While the OLS model is only suitable for data under strict conditions, the Tobit model (also known as the censoring regression model) is appropriate for censored data. But DEA scores are truncated data and not censored. Hence, OLS used by Ren et al. (2018) or Tobit models used by studies such as Geng et al. (2023), Shuai and Fan (2020), Ervural et al. (2018), Lin and Du (2015), and Sağlam (2017) that have examined energy efficiency using two-stage DEA do not provide valid inferences for the parameter estimates of the factors analysed. Jebali et al. (2017) on the other hand used the SW two-stage DEA model but calculated the input-oriented DEA efficiency score, that is, finding the proportional change in inputs that can be achieved with a fixed level of outputs. In their regression analysis, the input-oriented DEA score has a limited range of zero to one and it is unclear how this was truncated appropriately for valid estimation. Importantly, the input-oriented DEA efficiency score of Jebali et al. (2017) is not aligned to the regression analysis of SW (2007, 2011) which was only proven for the output-oriented DEA score being valid for estimation and inference. Thus, our study computes the output-oriented DEA proposed by SW.

The studies most directly relevant to ours — Feng et al. (2017) and Song et al. (2020) — examined carbon emissions efficiency and green economic growth across Chinese provinces but neither incorporated urbanisation or the service sector share as determinants, nor did they apply the SW double-bootstrap framework. This leaves open the question of which provincial and regional factors drive the gap between conventional and green TE, and whether the two measures diverge in ways that matter for policy. Our study fills this gap.

3. Methodology

Within the framework of the two-stage DEA with double bootstrapping, we include the constraint of undesirable output (i.e., carbon emissions) and in the first stage, we measure economic efficiency of each province. As explained earlier, the selected time span is separated into two time periods given by 2010–2013 and 2014–2017. More formally, let $x^t \in \mathbb{R}_+^p$ be a vector of inputs (where p denotes the number of inputs) in a given period t ($t = 1$ and 2) to produce an output vector $y^t \in \mathbb{R}_+^{q_d}$ (where d denotes desirable) and an undesirable output vector $b^t \in \mathbb{R}_+^{q_b}$ (where b denotes bad), using technology characterised by a set Ψ^t defined in general terms as

$$\Psi^t = \left\{(x, y) \in \mathbb{R}_+^{p+(q_d \times q_b)} \middle| x \text{ can produce } y \text{ with } b \text{ in period } t\right\} \quad (1)$$

Our underlying argument is that all provinces have access to the same technology (in a given time period), in which the undesirable output cannot be avoided. Intuitively, $\widehat{\Psi}^t$ under the constant returns to scale assumption is the observed best-practice frontier of the technology in period t.

As the low-carbon form of economic growth is the focus of this study, we use an output-oriented radial DEA model to maximise this type of economic growth using the best possible technology and inputs. The resulting DEA efficiency score ($\hat{E}_i^t$) for an observation on province i representing (x_i^t, y_i^t, b_i^t) is estimated in time period t via the following linear programming problem:

$$\begin{aligned} \hat{E}_i^t = \max\{\delta : \ \delta y_i^t &\leq \textstyle\sum_{j=1}^{n_t} \lambda_j^t y_j^t, \\ x_i^t &\geq \textstyle\sum_{j=1}^{n_t} \lambda_j^t x_j^t, \\ b_i^t &= \textstyle\sum_{j=1}^{n_t} \lambda_j^t b_j^t, \\ \delta \geq 0,\ \lambda_j^t \geq 0,\ j &= 1, \ldots, n_t\} \end{aligned} \quad (2)$$

where $\lambda_1^t, \ldots, \lambda_{n_t}^t$ are intensity variables determined jointly with δ in the process of optimisation. Appendix 2 provides an explanation of all the above equations in detail. Codes for use in MATLAB software are available upon request. The efficiency scores ($\hat{E}_i^t$) represent the potential proportional increase in the desirable output that can be produced without altering the input quantities. Based on (2), the most efficient observations in the sample will have an efficiency score equal to one, indicating 100% efficiency. The higher the efficiency score, the greater the gap of the observation from the DEA-estimated best-practice frontier, suggesting higher inefficiency. In the second stage of the analysis, we regress these efficiency estimates on various covariates deemed to influence efficiency. Specifically, we consider a linear function with an additive noise term, i.e.,

$$\hat{E}_i^t = Z_i^t\beta + D^t\gamma + \epsilon_i^t, \quad i = 1, \ldots, n_t \text{ and } t = 1 \text{ and } 2 \tag{3}$$

where Z_i^t is a vector of factors possibly influencing the efficiency of province i in time period t via a vector of parameters given by β. D^t is a dummy taking the value of one for 2014–2017 with γ as the corresponding parameter denoting time effects on efficiency. It is notable that the DEA-estimated scores are regressed as suggested by Du et al. (2018), in which the Monte Carlo simulation shows a valid inference from the proposed regression model. However, the efficiency scores from different time periods might be comparable only subject to the observations on their frontiers. As $\hat{E}_i^t$ ranges from one to positive infinity, we use the truncated regression (SW 2007) in which $\epsilon_i^t \sim \mathcal{N}(0, \sigma_\epsilon^2)$ with left-tail truncation at $1 - Z_i^t\beta - D^t\gamma$.

4. Data and Variables

We use panel data of 30 Chinese provinces (excluding Tibet, Taiwan, Hong Kong, and Macao due to data limitations) from 2010 to 2017. The start year aligns with the launch of China’s low-carbon pilot programme and the baseline year of the 12th Five-Year Plan’s binding carbon intensity reduction targets. The sample ends at 2017 because China's Fourth National Economic Census (NBS 2019) used 2018 as its reference year, and the resulting revisions to provincial GDP and sectoral output were not uniformly back-applied to earlier years, creating a structural break in the data series. In addition, the escalation of the US–China trade war from mid-2018 introduced an immediate and asymmetric external shock across provinces that would confound cross-provincial efficiency comparisons.

Real GDP in constant 1985 prices was obtained from China Statistical Yearbook. Carbon emissions data measured in metric tons were available from China Energy Statistical Yearbook. Data on real (1985 prices) fixed capital stock and number of workers employed were obtained from China Centre for Human Capital and Labour Market Research, and China Labour Statistical Yearbook, respectively. Urbanisation rate, given by the standard definition as the proportion of people living in the urban areas of each province, is from CEInet Statistics Database, and the service sector GDP share is from China Statistical Yearbook. It is important to include control variables to account for province-specific heterogeneity in the regression analysis, so we use energy consumption, which is measured in tons of standard coal equivalent from China Statistical Yearbook; education is given by the share of university graduates in the employed population from China Labour Statistical Yearbook; trade openness is measured by the ratio of the sum of exports and imports to GDP from CEInet Statistics Database. A dummy variable (taking the value of zero for 2010–2013 and one for 2014–2017) is used to capture time-varying factors between these two time periods. However, provincial dummy variables are not included as there is too little "within" variation in the DEA score, which usually ranges from 1 to 3.

Table 1 provides summary statistics for the variables explained above. The maximum real GDP value is that of Guangdong in the Pearl River Delta Economic Zone, which is a core area for high technology, manufacturing and foreign trade. The lowest real GDP is that of Qinghai, a landlocked province in the northwest of China. Shandong has the highest carbon emissions while Hainan, the smallest and southernmost province of China, consisting of various islands in the South China Sea, is the least polluting province.

Figure 1a shows a rising trend in GDP, based on the mean value of provinces in each year. The trend in carbon emissions as seen in Figure 1b is relatively stable, especially from around 2013–2014 when China entered the "new normal" growth stage (Zheng et al. 2019). Urbanisation represented in Figure 1c has increased quite rapidly over time with Beijing, Shanghai and Tianjin being the most urbanised provinces outside the 75th percentile range. The service sector share (Figure 1d) has been increasing more slowly than the urbanisation rate and the mean provincial service sector GDP share is well below 50% in 2017. However, Beijing (77.61% in 2017) and Shanghai (63.21% in 2017) are highly service-oriented, unlike the other provinces.

Figure 2 shows the average amount of carbon emissions of each province (measured by the size of the bubble) in relation to its GDP and urbanisation rate. Interestingly, while the GDP of the least (Hainan) and highest (Shandong) polluting provinces is low and high, respectively, their urbanisation rate is very close, although they have different industrial structures. The highly service-oriented economies of Beijing and Shanghai are also highly urbanised (correlation coefficient between service sector and urbanisation is about 0.72 as seen in Appendix 3) but have fairly low carbon emissions. The correlation coefficient between emissions and GDP is about 0.71, indicating that high GDP is often associated with greater carbon emissions.

5. Empirical Results

Two separate technology frontiers were estimated for the periods of 2010–2013 and 2014–2017 to examine changes in the DEA efficiency scores over time. Table 2 shows that, as expected, all green TE scores are larger than the conventional TE scores without emissions, for all provinces. This is because when maximising a function, adding a constraint on carbon emissions can never make the maximum larger. Overall, Shanghai and Hunan appear to be the best practice green-efficient provinces and they are good benchmarks for more developed and less developed provinces respectively.

Provincial efficiency rankings remained largely consistent across the different TE measures, with the notable exceptions of Ningxia and Shanxi. These two provinces ranked relatively low (23rd and 20th, respectively) under the green TE measure, yet performed significantly better (10th and 15th) when using conventional TE scores. Shanxi is a coal-producing province that provides energy to other provinces and has the second largest carbon emission intensity (defined as carbon emissions/GDP) as seen in Table 3 where, for each unit of GDP produced in Shanxi, 19.370 units of carbon emissions were generated. Thus, when carbon emissions are not included as in the conventional DEA score, Shanxi's efficiency is misguidedly high. On the other hand, Ningxia has the highest carbon emission intensity in China averaging 26.639.

Temporal variations in provincial performance also emerge when comparing the two DEA scores. Under the green TE framework, Beijing and Jiangxi exhibit a deterioration in performance — a trend not observed in their conventional TE scores. Conversely, Ningxia, Xinjiang, and Yunnan show improvements in green TE that are absent in the conventional metrics. Our results indicate that the eastern region remains the most efficient, followed by the central and western regions. It is unsurprising that the eastern region has not registered significant gains in green TE; having historically outperformed other regions through technological advancement, robust infrastructure, and high-value-added industries, it is already operating close to the frontier. Consequently, further frontier shifts will likely materialise slowly. Furthermore, as the eastern region largely defines the frontier, shifts within it are not easily captured by this study.

Table 3 shows how provinces' green TE ranks against their energy and emission intensity levels. The energy and emission intensity levels are divided into Low, Middle and High categories. Around 70% of the eastern provinces have low energy and emission intensity, while over 50% of the western provinces have high energy and emission intensity. Within each level of energy and emission intensity, there is also wide variation in the green TE of the provinces. In the mid-level emission intensity group, green TE varies from 1 (Hunan, the highest-ranked province) to 2.482 (Henan, the lowest-ranked province). Among the high energy and emission intensity group, Inner Mongolia is seen to perform better than Qinghai and Gansu. Nevertheless, several western provinces such as Gansu, Ningxia, Xinjiang, and Yunnan, and central provinces such as Henan, Shanxi, and Inner Mongolia, have shown some improvement in green TE over time.

As noted above, provinces like Ningxia and Shanxi illustrate how conventional TE rankings can mask poor green performance. The improvement noted for several western and central provinces is, in part, attributable to the low-carbon pilot schemes and policy initiatives (Pang et al. eds. 2018). In summary, the provincial efficiency rankings under green and conventional TE are broadly consistent, supporting H1, although notable exceptions such as Ningxia and Shanxi illustrate how conventional rankings can mask poor environmental performance. However, intertemporal trends diverge for several provinces. For example, Beijing and Jiangxi show deterioration under green TE but not conventional TE, while Ningxia, Xinjiang, and Yunnan show the opposite pattern, thereby rejecting H2.

Table 4 shows that the Beijing-Tianjin-Hebei cluster (1.246, mean green TE) outperforms the Yangtze River Delta cluster (1.301), despite the latter containing Shanghai (1.029), the most green-efficient province. Within each cluster, individual province performance varies considerably: Jiangsu (1.393) and Zhejiang (1.267) outperform Hebei (1.429), while each cluster contains a lagging province — Anhui (1.514) and Hebei (1.429) — with relatively low service sector shares and urbanisation rates. Hebei's high carbon emission intensity (12.416) is notable given that Beijing and Tianjin are geographically within Hebei. The movement of heavy industries from Beijing and Tianjin into Hebei (Zhang et al. 2020) has worsened Hebei's environmental performance, illustrating how cluster-level policies can inadvertently increase intra-cluster inequality. While the cluster strategy supports leading provinces such as Shanghai, Beijing, and Tianjin, it may not directly benefit peripheral provinces, and this adverse side effect should be carefully considered in future cluster development planning. These cluster-level differences further illustrate how green and conventional TE can yield different assessments of relative performance, consistent with the broader pattern underlying the rejection of H2.

Table 5 shows the regression results from the improved model of green economic growth in Panel A and the DEA model without carbon emissions as undesirable output in Panel B for comparison. Appendix 3 reports the pairwise correlations and variance inflation factors (VIFs) of the regressors. Several pairwise correlations are high, such as Education–Services (0.85), Urbanisation–Education (0.81), and Urbanisation–Openness (0.81), which is expected given that urbanisation, service-sector development, education, and trade openness tend to co-evolve during economic development. While all VIFs remain below 10 (the highest being Education at 5.55), VIFs above 5 suggest that the standard errors of Education and Urbanisation may be inflated, reducing statistical power for these variables individually.

We address this concern in three ways. First, Models 2–4 in Table 5 systematically omit one regressor at a time following Du and O'Connor (2021) and Mahadevan et al. (2023). The key results on the efficiency impact of urbanisation and the service sector are qualitatively unchanged across all specifications, indicating that multicollinearity does not drive our central findings. Second, the bivariate models (Models 5 and 6) estimate each key variable in isolation, confirming that the signs and significance hold outside the multicollinear environment. Third, the non-significance of Education across most specifications (and the inconsistency of Openness) may partly reflect variance inflation rather than a true zero effect, and we caution against strong inferences on these control variables.

Table 5 also shows that in both Panels A and B, a higher proportion of urban population is associated with higher provincial efficiency, albeit a smaller effect (0.438 compared to 0.544) in green TE than in conventional TE. This suggests that urbanisation may increase carbon emissions even as it contributes to economic growth. Lin and Du (2015), however, argued that there are two opposing effects of urbanisation that may offset each other. First, the construction of infrastructure (e.g., transportation and communication) consumes a lot of energy and results in carbon emissions. Meanwhile, urbanisation also brings production agglomeration which will significantly increase efficiency.

The regression results reveal divergent impacts of service sector growth between the two panels. Unlike the results for Models 1 to 4 in Panel B, Panel A demonstrates that the less energy-intensive (or the lower carbon-emitting) service sector significantly contributes (at the 1% level) to green TE. This key finding highlights the importance of service sector-led growth in achieving China's net-zero emissions target, and it aligns with the structural shift towards services-led growth discussed earlier. Conversely, the outcomes from Panel B imply that a shift towards the service sector would not significantly contribute to conventional economic growth, which may raise concerns for China's services promotion strategy. Overall, these regression results support H3, but lead to the rejection of H4, as the service sector share is significant only for green TE. This differential effect is a central finding of this paper.

This finding is consistent with the cluster evidence in Table 4, where high green TE for Beijing and Shanghai reflects their high service orientation alongside high urbanisation, although service sector growth has lagged behind the urbanisation rate as noted in Section 4. Provinces such as Liaoning and Chongqing, which are relatively urbanised (65.9% and 60.2%, respectively, compared to China's mean urbanisation rate of 55.3%) and rely heavily on the manufacturing sector, experience low green efficiency within their respective energy and emission intensity groups (shown in Table 3). The way forward for these types of provinces lies in their comparative advantages, not a transition to services. Investment must, however, shift away from conventional heavy industrialisation that scales output while ignoring ecological impacts.

Liaoning (located in China's rust belt) has experienced a decline in economic importance due to a reduced emphasis on heavy and chemical industrial production, and the consequent movement of people to other provinces after the 1978 economic reform. It is important for these provinces to shift their energy mix towards non-fossil fuels and to upgrade their pollution-intensive technologies to cleaner technologies. As firms are typically profit-oriented, switching to or undertaking research and development for environmental innovation will often be viewed as cost-ineffective. Thus, it is necessary for provincial governments to implement reasonable yet stringent policies to guide firm behaviour, as well as to incentivise them to innovate and adopt green technologies (see Wu et al. 2012). As robustness checks, the regression models are re-estimated using energy intensity as an alternative DEA input (Appendix 4) and after excluding super-inefficient observations (Appendix 5). The key findings on urbanisation and the service sector remain qualitatively unchanged across both specifications.

With respect to the control variables in Table 5, an increase in energy consumption is seen to diminish green efficiency when carbon emissions are considered in Panel A. This is in line with the expectation that using energy generates more pollution. The positive coefficient on education is significant only in Model 3 of Panel A and hence not robust for interpretation. In reality, it is somewhat difficult to interpret the education coefficient as it may mask the true effect, since we do not have information on the distribution of university graduates in various industries. The impact of trade openness on efficiency is also not consistent and this is not surprising as this variable has mixed effects on the carbon emissions of China's regions (Mahadevan and Sun 2020) and similar ambiguous effects on economic growth have been widely documented in the trade literature (Feasel 2018).

6. Conclusion

By extending the two-stage double-bootstrap DEA framework to treat carbon emissions as an undesirable output, this paper provides the first systematic comparison of conventional and green TE across China's provinces. The divergence between these two measures is the paper's central empirical finding: the extent to which urbanisation and the service sector contribute to efficiency depends fundamentally on whether carbon emissions are accounted for.

Our results support two of the four hypotheses of interest: provincial rankings are similar across both metrics, and urbanisation acts as a driver for both TE measures. However, intertemporal trends diverged across the two measures for several provinces, regions, and clusters. The empirical results of this study show that the Beijing-Tianjin-Hebei cluster outperforms the Yangtze River Delta cluster in green efficiency, yet the latter contains the most green-efficient province in the sample, Shanghai. This intra-cluster heterogeneity — where lagging provinces such as Hebei and Anhui coexist with high performers within the same cluster — means that cluster-level averages mask important province-level differences. Targeted strategies are therefore needed not only across regions but within clusters, directing support towards lagging provinces without imposing uniform targets that may be counterproductive for leading ones.

A critical finding is that had only conventional TE been analysed, the significance of the service sector GDP share would have been missed entirely, creating a systematic bias in policy advice. The service sector's less energy-intensive nature makes it a key driver of green TE — yet this channel is invisible in conventional TE analysis. The expansion of the service sector GDP share therefore bodes well for green growth, particularly as a counterbalance once the urbanisation rate approaches the threshold beyond which further urbanisation no longer yields net efficiency gains (though the linear specification used in this study does not estimate this threshold directly). Consequently, one policy implication from this study is to encourage urbanisation in China, as it is strongly associated with both conventional and green TE through agglomeration economies and higher productivity. However, urban growth per se will not necessarily lead to efficiency gains for all countries. In developing nations, where the rate remains relatively low, there is still room to increase the urban share of the population and benefit from efficiency improvements, but a point will eventually be reached where the rate exceeds a certain threshold (as observed in developed countries), beyond which efficiency may be reduced.

There are limitations of this study that merit acknowledgement. The optimal mix of urbanisation and service sector expansion remains an open question, with expected variations at the provincial and cluster levels. While this study identifies urbanisation as a driver of green efficiency, the specific channels of this impact remain unexamined. It is unclear if urban expansion acts as a catalyst for traditional innovation, which optimises resource use without reducing emissions, or green innovation, which directly lowers the carbon footprint. Identifying the optimal mix of these two types of innovation is also a key priority for future research.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Supplemental Material

Appendixes S1–S6 and Tables S1–S12 are available online at
https://imkaidu.net/docs/Supplemental_Materials_Final_24032026.pdf

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Table 1 Summary Statistics

	Variables	Mean	Std Dev.	Min	Max
Outputs	Real GDP (million US$)	4407.750	3446.511	274.928	17835.502
	Carbon Emissions (metric tons)	33193.157	22187.561	2580.461	94897.217
Inputs	Capital Stock (million US$)	1546.198	1302.073	109.664	7513.897
	Employment (million persons)	2629.974	1777.691	303.260	6767.000
Regressors	Urbanisation Rate	55.334	12.962	29.884	89.600
	Service Sector GDP share	43.714	9.384	28.600	80.600
	Energy Use	14072.447	8412.245	1232.520	38899.000
	Education	6.004	4.886	0.891	29.500
	Trade Openness	34.104	42.061	3.572	172.148

Notes: Excluding Tibet, Taiwan, Hong Kong, and Macao due to data limitations

Table 2 Average DEA Efficiency Scores and Intensity Measures

	Green TE		TE (without CO_2)		Energy/GDP (Energy Intensity)	CO_2/GDP (Emission Intensity)
	2010-13	2014-17	2010-13	2014-17	2010-17	2010-17
Eastern Region	1.348	1.363	1.258	1.247	2.628	6.467
Beijing[B]	1.070	1.199	1.018	1.007	1.505	2.199
Fujian	1.091	1.069	1.036	1.022	2.202	4.711
Guangdong	1.193	1.196	1.068	1.023	2.015	3.794
Guangxi	1.713	1.674	1.565	1.505	2.766	6.531
Hainan	1.597	1.484	1.356	1.239	2.380	4.957
Hebei[B]	1.426	1.433	1.271	1.417	3.014	12.416
Jiangsu[Y]	1.311	1.475	1.301	1.293	2.124	5.554
Liaoning	2.127	2.008	1.952	1.927	5.645	15.716
Shandong	1.254	1.261	1.221	1.216	3.003	7.466
Shanghai[Y]	1.019	1.040	1.016	1.000	2.245	4.264
Tianjin[B]	1.131	1.220	1.115	1.181	2.445	5.343
Zhejiang[Y]	1.241	1.293	1.181	1.140	2.192	4.651
Western Region	1.749	1.658	1.509	1.507	5.111	11.881
Chongqing	1.508	1.669	1.389	1.474	2.452	5.468
Gansu	1.838	1.654	1.730	1.622	5.191	12.048
Guizhou	1.416	1.599	1.128	1.284	4.918	13.437
Ningxia	1.808	1.583	1.130	1.205	8.663	26.639
Qinghai	2.681	2.368	2.669	2.099	7.830	10.076
Shaanxi	1.173	1.157	1.130	1.147	2.949	7.707
Sichuan	1.324	1.334	1.145	1.250	3.291	5.520
Xinjiang	1.859	1.587	1.483	1.575	6.829	18.127
Yunnan	2.133	1.973	1.782	1.903	3.874	7.906
Central Region	1.568	1.435	1.451	1.352	3.733	9.581
Anhui[Y]	1.544	1.483	1.524	1.474	2.654	8.417
Heilongjiang	1.349	1.148	1.243	1.098	3.972	9.464
Henan	2.714	2.250	2.440	2.063	4.753	9.074
Hubei	1.414	1.455	1.355	1.397	2.932	6.507
Hunan	1.002	1.000	1.001	1.000	2.851	5.622
Inner Mongolia	1.247	1.003	1.078	1.002	3.931	12.559
Jiangxi	1.373	1.472	1.364	1.330	2.338	6.225
Jilin	1.779	1.675	1.748	1.554	3.112	8.992
Shanxi	1.692	1.434	1.309	1.252	7.057	19.370
Overall Mean	1.534	1.473	1.391	1.357	3.715	9.051

Notes: Superscript 'Y' marks Shanghai, Jiangsu, Zhejiang and Anhui provinces in the Yangtze River Delta.
Superscript 'B' marks the cluster of Beijing, Tianjin and Hebei.

Table 3 Provincial Green TE Ranking by their Energy and Emission Intensity Levels (averaged over 2010–2017)

Energy Intensity			
Ranking	Low	Middle	High
1	Shanghai[Y] (1.029)	Hunan (1.000)	Inner Mongolia (1.125)
2	Fujian (1.080)	Shaanxi (1.165)	*Heilongjiang* (1.248)
3	Beijing[B] (1.135)	Shandong (1.257)	Guizhou (1.508)
4	Tianjin[B] (1.175)	Sichuan (1.329)	Shanxi (1.563)
5	Guangdong (1.194)	Hebei[B] (1.429)	Ningxia (1.696)
6	Zhejiang[Y] (1.267)	Hubei (1.434)	Xinjiang (1.723)
7	Jiangsu[Y] (1.393)	Anhui[Y] (1.514)	Gansu (1.746)
8	Jiangxi (1.422)	Guangxi (1.694)	Liaoning (2.067)
9	Hainan (1.541)	Jilin (1.727)	Henan (2.482)
10	Chongqing (1.589)	Yunnan (2.053)	Qinghai (2.524)
Mean	1.283	1.460	1.768
Carbon Emission Intensity			
Ranking	Low	Middle	High
1	Shanghai[Y] (1.029)	Hunan (1.000)	Inner Mongolia (1.125)
2	Fujian (1.080)	Shaanxi (1.165)	*Heilongjiang* (1.248)
3	Beijing[B] (1.135)	Shandong (1.257)	Hebei[B] (1.429)
4	Tianjin[B] (1.175)	Jiangxi (1.422)	Guizhou (1.508)
5	Guangdong (1.194)	Hubei (1.434)	Shanxi (1.563)
6	Zhejiang[Y] (1.267)	Anhui[Y] (1.514)	Ningxia (1.696)
7	Sichuan (1.329)	Guangxi (1.694)	Xinjiang (1.723)
8	Jiangsu[Y] (1.393)	Jilin (1.727)	Gansu (1.746)
9	Hainan (1.541)	Yunnan (2.053)	Liaoning (2.067)
10	Chongqing (1.589)	Henan (2.482)	Qinghai (2.524)
Mean	1.273	1.575	1.663

Notes: The levels of low, middle and high are given by each third of the entire distribution.
Provinces are ranked according to their green TE within each group.
Superscript 'Y' marks Shanghai, Jiangsu, Zhejiang and Anhui provinces in the Yangtze River Delta.
Superscript 'B' marks the cluster of Beijing, Tianjin and Hebei.

Table 4 Cluster Comparison

	Green TE			TE (without CO2)			Urbanisation Rate	Service Sector Share	Energy/GDP	CO_2/GDP
	2010-13	2014-17	2010-17	2010-13	2014-17	2010-17	2010-17	2010-17	2010-17	2010-17
Beijing	1.070	1.199	1.135	1.018	1.007	1.013	86.31	77.88	1.505	2.199
Tianjin	1.131	1.220	1.175	1.115	1.181	1.148	81.80	50.46	2.445	5.343
Hebei	1.426	1.433	1.429	1.271	1.417	1.344	49.25	35.45	3.014	12.416
Mean	**1.209**	**1.284**	**1.246**	**1.135**	**1.202**	**1.168**	**72.45**	**54.60**	**2.321**	**6.653**
Shanghai	1.019	1.040	1.029	1.016	1.000	1.008	88.79	63.69	2.245	4.264
Zhejiang	1.241	1.293	1.267	1.181	1.140	1.160	64.60	47.58	2.192	4.651
Jiangsu	1.311	1.475	1.393	1.301	1.293	1.297	64.72	45.99	2.124	5.554
Anhui	1.544	1.483	1.514	1.524	1.474	1.499	48.41	36.31	2.654	8.417
Mean	**1.279**	**1.323**	**1.301**	**1.256**	**1.227**	**1.241**	**66.63**	**48.39**	**2.304**	**5.722**

Table 5 Truncated Regression Results for Efficiency

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Panel A:	Economic Growth with Carbon Emissions				
Urbanisation	-0.438***	-0.522***	-0.416***	-0.391***	-0.585***	
Service Sector	-0.323***	-0.334***	-0.362***	-0.307***		-0.722***
Energy Use	0.135***	0.162***		0.158***		
Education	0.096	0.109	0.204**			
Openness	-0.092		-0.178***	-0.095		
Time Dummy	-0.363***	-0.397***	-0.320***	-0.412***	-0.337***	-0.621***
Intercept	1.292***	1.296***	1.220***	1.316***	1.174***	1.209***
$\hat{\sigma}$	0.167	0.172	0.186	0.167	0.243	0.287
Log-Likelihood	235.161	234.767	231.554	235.064	212.682	207.760
	Panel B:	Economic Growth without Carbon Emissions				
Urbanisation	-0.544***	-0.540***	-0.495***	-0.495***	-0.485***	
Service Sector	-0.114	-0.117	-0.141*	-0.096		-0.455***
Energy Use	0.138***	0.138***		0.161***		
Education	0.101	0.101	0.202**			
Openness	0.005		-0.086	0.002		
Time Dummy	-0.288**	-0.288***	-0.236**	-0.338***	-0.317***	-0.472***
Intercept	1.450***	1.446***	1.417***	1.469***	1.459***	1.432***
$\hat{\sigma}$	0.195	0.196	0.204	0.198	0.217	0.304
Log-Likelihood	185.424	185.529	181.672	184.837	174.741	155.066

Notes: A negative coefficient denotes an improvement in TE.
Algorithm II of SW (2007) was used with 2000 iterations for the bootstrapping to obtain confidence intervals (reported in Appendix 6) for valid inference. If the confidence interval for the estimate does not cover zero, the variable is statistically significant at the 10% (*), 5% (**), and 1% (***) levels of significance.

References Figure Caption List

Figure 1 Box plot of selected data on provinces

(a) GDP (logarithm)

(b)Carbon Emissions (logarithm)

(c) Urbanisation Rate

(d) Service Sector GDP Share

Figure 2 Bubble plot (based on average values from 2010-2017)