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Measures, Evolutions, and Determinants of Green Efficiency: Evidence from China

Nan Wang[1], Yunning Ma[2] and Hyoungsuk Lee[3,*]

[1] *Department of International Commerce and Area Studies, Kangwon National University, Republic of Korea*

[2] *International School of Low-carbon Studies, Shandong University of Finance and Economics, China*

[3] *Department of Commerce and Finance, Kookmin University, Republic of Korea*

Abstract: This study measures urban green efficiency in 270 Chinese cities from 2008 to 2022 using an output-oriented variable-returns-to-scale (VRS) slacks-based measure data envelopment analysis model that incorporates carbon dioxide emissions as an undesirable output. It then traces the temporal evolution and city-size distribution of green efficiency and examines the factors associated with its variation using two-way fixed-effects models. The analysis further tests whether the relationships of economic openness and economic development with green efficiency differ systematically across city-size tiers. The results show that the national mean VRS green-efficiency score is 0.736 and that efficiency follows a non-monotonic pattern across city sizes, with megacities recording the highest average level and large and medium-sized cities exhibiting relatively lower levels. Over time, green efficiency displays marked fluctuations rather than a sustained upward trajectory. The cross-tier pattern is also sensitive to returns-to-scale assumptions, as the relative VRS advantage of small cities disappears under the constant-returns-to-scale specification. In the second-stage analysis, economic openness is positively associated with green efficiency at the national level, while economic development shows no uniform independent association. Their interaction is positive and significant, indicating that the relationship between openness and green efficiency becomes more favorable as development increases. City-size heterogeneity is pronounced but structurally uneven: differences in the development–efficiency relationship are broad and statistically strong across city tiers, whereas openness-related heterogeneity is concentrated in specific inter-tier contrasts rather than being uniformly distributed across all city-size groups. These findings show that national averages conceal distinct urban trajectories and conditional relationships. Policy design should therefore account for differences in city size, development conditions, and the capacity of cities to translate external economic linkages and development gains into greener production performance.

Keywords: urban green efficiency, SBM–DEA, economic openness, urban economic development, city-size heterogeneity

1. Introduction

China's low-carbon transition is, in large part, an urban production challenge. Cities must continue to generate income, employment, and infrastructure while operating under increasingly binding energy and carbon constraints. This tension has become more consequential as China seeks to peak carbon dioxide (CO_2) emissions before 2030 and achieve carbon neutrality before 2060 [1]. The policy objective is therefore not simply to suppress emissions but to improve the efficiency with which urban economies transform productive inputs into economic value under environmental constraints.

Urban green efficiency provides a perspective for analyzing this issue by incorporating economic output, resource inputs, and unintended environmental outputs into a unified evaluation framework. As a result, it captures an important dimension that absolute emissions metrics or traditional productivity indicators struggle to reveal whether cities can generate more economic value at a lower environmental cost. However, Chinese cities are far from homogeneous in this regard. According to Zhang et al. [2], there are notable regional differences in carbon emission efficiency between various cities and areas, as well as notable heterogeneity in their dynamic evolution. Consequently, China's overall low-carbon transition does not follow a single urban development trajectory but is instead shaped by a series of significantly divergent local production and adjustment processes.

A key source of these differences is economic openness. Foreign direct investment (FDI) enables cities to access capital, technology, managerial expertise, and global production networks, thereby creating opportunities for technological upgrading and cleaner production. However, when the composition of FDI is unfavorable or local enterprises are unable to effectively absorb external knowledge, openness may further reinforce pollution-intensive production. Existing empirical research fully reflects this duality. Some studies based on samples of Chinese cities have found that, on average, FDI may suppress urban green total factor productivity [3]; other studies have found a positive overall

***Corresponding author:** Hyoungsuk Lee, Department of Commerce and Finance, Kookmin University, Republic of Korea. Email: lhs2303@kookmin.ac.kr

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relationship, but one that varies significantly depending on the level of economic development, region, and city size [4]. Therefore, there is no reason to expect that economic openness will have a fixed direction of environmental impact across all urban contexts.

The level of economic development provides an important contextual dimension for understanding the relationship between openness and green efficiency. Economic development may be accompanied by an increase in production scale and higher energy and resource consumption, but it can also improve fiscal capacity, infrastructure, and technological levels as well as firms' capacity to absorb external knowledge. Therefore, rather than examining openness or income levels in isolation, it is more worthwhile to focus on how the two interact under specific development conditions. Existing research indicates that the environmental effects of FDI change as per capita income crosses different thresholds, rather than remaining constant throughout the development process [5]. This suggests that economic openness and economic development may not only have independent effects but may also interact during the process of urban green transition.

The size of the city additionally influences this connection. Agglomeration economies, communal infrastructure, and innovation clusters can improve resource allocation efficiency, yet congestion, land constraints, and energy needs might diminish some of these advantages. Consequently, increased scale does not necessarily lead to better environmental outcomes. Research indicates that socioeconomic factors, governance quality, urban design, and transportation infrastructure influence the connection between CO_2 emissions and city size in Chinese cities; larger cities do not consistently demonstrate superior low-carbon results [6, 7]. Associated research additionally shows that advancements in carbon emission efficiency differ considerably among various regions and developmental phases [8]. As a result, city size acts as a more relevant contextual factor impacting the economy–environment connection instead of merely serving as a straightforward sign of advanced development or governance.

This leads to the main research question of this paper: variations in average green efficiency among cities of varying sizes do not suggest that the link between openness, economic development, and green efficiency has the same direction and strength. A particular city tier may exhibit higher average efficiency, but further increases in openness or development levels may not necessarily lead to a stronger positive correlation; similarly, aggregate estimates at the national level may mask weaker or even inverse relationships within specific city types. While existing research has focused extensively on differences in urban environmental performance and scale effects, there remains a lack of thorough examination into whether the relationship between economic openness, economic development, and green efficiency changes across different city sizes. Therefore, this paper focuses not merely on whether cities of different sizes exhibit "different levels of efficiency" but rather on whether "the relationship among openness, development, and green efficiency varies by city size."

To address the above questions, this paper conducts an analysis using panel data from 270 Chinese cities covering the period 2008–2022. The study is divided into three steps. First, an undesirable-output slacks-based measure data envelopment analysis (SBM–DEA) model under variable returns to scale (VRS) is used to measure urban green efficiency, and the distribution of efficiency across different city-size tiers is compared based on the official five-tier city-size classification. Given that the specification of returns to scale may affect comparisons among cities of different production scales, this study further conducts robustness tests using a constant-returns-to-scale (CRS) model. Second, a two-way fixed-effects model is employed to examine the conditional relationship between economic openness and economic development on the one hand and green efficiency on the other; an interaction term between openness and development is introduced to examine whether their relationships with green efficiency are conditional on one another. Finally, by introducing city-tier interaction terms and combining joint Wald tests with pairwise Wald tests, we determine whether these relationships differ significantly across different city-size groups. Since this study uses observational data, the results of the second-stage regression are interpreted as conditional associations rather than causal effects. The entire analysis thus distinguishes between "differences in efficiency levels" and "differences in the economic relationships associated with these efficiency levels."

This study makes three main contributions to the literature on urban green efficiency. First, it conceptualizes the relationship between economic openness and green efficiency as conditional on local development rather than as a purely additive association. By explicitly examining the interaction between economic openness and economic development, the analysis provides a more nuanced account of how external economic integration is associated with urban green performance under different development conditions. Second, the study extends the analysis of city-size heterogeneity from differences in average efficiency levels to heterogeneity in the economic relationships underlying those outcomes. Using China's official five-tier city-size classification as a nationally consistent analytical framework, it formally tests whether the associations of openness and economic development with green efficiency vary across city-size groups, rather than inferring heterogeneity from cross-group differences alone. Third, the study integrates frontier-based efficiency measurement with panel-based heterogeneity analysis, thereby distinguishing differences in observed efficiency levels from differences in the relationships associated with those efficiency outcomes. The complementary comparison of VRS- and CRS-based efficiency patterns further clarifies the extent to which observed city-size differences are sensitive to scale conditions. Taken together, these contributions provide a more differentiated understanding of how development conditions and urban scale shape the relationship between external economic integration, economic development, and green efficiency across Chinese cities.

The remainder of the paper is organized as follows. Section 2 reviews the literature on urban green efficiency, openness and economic development, city-size heterogeneity, and related urban structural conditions. Section 3 presents the SBM–DEA framework, the fixed-effects and heterogeneity specifications, and the data. Section 4 reports the city-size and temporal patterns of urban green efficiency and then examines the conditional openness–development–efficiency relationships, including formal cross-tier tests and robustness analyses. Section 5 concludes.

2. Literature Review

Research on urban green performance has primarily unfolded along several interrelated lines. Existing research looks at how cities reduce environmental pressures while producing economic output under specific labor, capital, and energy input conditions. It also looks into whether external economic ties, such as FDI, actually improve or worsen environmental performance. In addition to highlighting the heterogeneity brought about by variations in city size, spatial form, and infrastructure, an increasing amount of research has started to look at how technological,

industrial, financial, and institutional conditions limit the environmental effects of economic development. Because economic openness and economic development are enmeshed in particular production structures, infrastructure systems, and environmental governance circumstances rather than operating independently of the urban context, it is especially crucial to integrate various research perspectives.

Urban green efficiency evaluates the relationship between economic resource use and environmental pressure from a production perspective. Compared to single emission intensity indicators, frontier efficiency methods can simultaneously incorporate multiple inputs as well as desirable and undesirable outputs, making them more suitable for evaluating urban production efficiency under environmental constraints. In recent years, non-radial DEA methods have gradually gained widespread application in this field. For example, Long [9] employed a super-efficiency SBM–DEA model incorporating undesirable outputs to evaluate the green efficiency of Chinese cities; Zhang et al. [2] found that carbon emission efficiency in Chinese cities exhibits significant variations across both spatial and temporal dimensions. These studies indicate that frontier methods based on slack variables can effectively characterize the efficiency performance of heterogeneous urban production systems under environmental constraints. Following this measurement approach, this paper focuses on estimating urban green efficiency under VRS, using real gross domestic product (GDP) as the desirable output and CO_2 emissions as the undesirable output.

Recent research has predominantly viewed economic openness—especially FDI—as a crucial element linked to urban green performance, despite ongoing discussions regarding the nature of this relationship. The "pollution halo" hypothesis suggests that foreign investment can enhance environmental performance through the introduction of clean technologies, management skills, and higher production standards; in contrast, the "pollution haven" hypothesis argues that pollution-heavy industries may move to areas with less stringent environmental regulations. Empirical studies in China also illustrate this ambiguity. Zhao et al. [3] found that, overall, FDI exhibits a negative correlation with urban green total factor productivity, although technological innovation acts as a positive transmission channel; Zheng et al. [10] further indicated that the effects of FDI on the environment are influenced by different types of environmental regulations. In contrast, Yu and Liu [11] discovered that FDI typically improves the efficiency of urban green development, though its effects differ according to the strictness of environmental regulations; however, Chen et al. [4] revealed that FDI usually has a beneficial correlation with green total factor productivity, and this correlation significantly varies with various levels of economic development, geographic regions, and city sizes.

Level of economic development is one of the key conditional factors. As income rises, local fiscal capacity, technological capabilities, infrastructure, and enterprises' ability to adopt clean production technologies typically improve; however, economic expansion may simultaneously drive up energy demand and environmental pressures. Therefore, the relationship between economic openness and green performance may vary with the level of development rather than consistently maintaining a fixed, additive effect. Wang et al. [5] found that the relationship between FDI and carbon emissions changes as per capita GDP crosses different thresholds. Ma et al. [12], based on super-efficiency SBM measures for "Belt and Road" economies, further identified a nonlinear relationship between openness and green economic efficiency, as well as spatial spillover effects. At the Chinese city level, Chen et al. [4] similarly demonstrated that the relationship between FDI and green productivity varies depending on development conditions. The aforementioned studies provide direct evidence for treating economic openness and economic development as two interrelated dimensions and for further testing their interaction in empirical analyses.

City size further constitutes an important source of heterogeneity in urban green performance. Larger cities may benefit from economies of agglomeration, more developed labor and technology markets, dense innovation networks, and more mature infrastructure, but they also face more severe congestion, land and energy demands, and environmental pressures. Therefore, existing research does not support the simplistic conclusion that "the larger the city, the better its green performance."

Li and Cheng [13] found that larger Chinese cities possess certain advantages in terms of green total factor productivity growth, with technological progress playing a significant role. Yang and Zhao [6], based on a sample of 340 Chinese cities and using multiple dimensions to measure city size, found that the scaling relationship between city size and CO_2 emissions varies depending on the size indicators, socioeconomic conditions, and governance environment; larger cities do not necessarily exhibit better climate performance. Guo et al. [7] also highlight that urban hierarchy, urban structure, and transportation conditions impact the connection between city size and low-carbon development.

These studies indicate that city size is better understood as a contextual factor influencing green performance rather than simply as a variable with a uniform positive or negative effect. More importantly, "whether there are differences in average efficiency levels among cities of different sizes" and "whether the relationship between economic openness or economic development and efficiency differs" are two conceptually distinct issues.

Transportation and spatial infrastructure provide a concrete example of why urban contexts differ systematically. Transportation networks influence congestion, land use, energy demand, accessibility, and the spatial organization of economic activities; consequently, transportation systems are increasingly being incorporated into analytical frameworks for sustainable urban development. Existing research indicates that public transit-oriented urban development helps reduce car dependency, alleviate congestion, and ease pressure on greenhouse gas emissions [14], while green mobility and smart transportation planning are also considered to contribute to improving a city's economic, environmental, and social performance [15, 16]. At the city level in China, Zhao et al. [8] further found that low-carbon transportation policies can improve urban carbon emission efficiency, in part through green innovation, and that their effects vary significantly across different regions and stages of development. While this paper does not directly identify transportation as a mechanism of action, the aforementioned studies illustrate that infrastructure and travel conditions constitute a broader urban context and may influence the relationship between city size, economic openness, economic development, and green performance.

More recent research has further highlighted this context dependency. Tang and Huang [17] discovered that the advancement of green finance correlates with improved urban energy efficiency, mainly due to technological advancements and innovation, and this connection differs based on financial development, economic openness, and urbanization levels. Recent studies from ASEAN economies suggest that green finance and carbon market mechanisms can facilitate the shift to low-carbon energy by directing investments that align with climate objectives, yet their

real effectiveness heavily relies on institutional capacity and the degree of regulatory coordination [18]. OECD/UN-Habitat [19] highlights that intermediary cities frequently encounter specific financial, infrastructural, and institutional challenges in progressing their low-carbon transition. Although these studies do not directly identify the precise mechanisms at play in the sample analyzed in this paper, they lay a literary groundwork for an essential conclusion: systemic differences may exist between cities in their ability to convert economic and external resources into enhanced production performance. Despite the advancements noted previously in recent research, two related shortcomings remain. First, economic openness and economic development are frequently analyzed as separate elements; nevertheless, current research on threshold effects, interaction effects, and variability indicates that the environmental consequences of openness are probably influenced by the developmental circumstances of the host area. Second, studies on city size have mainly concentrated on variations in efficiency, productivity advancement, and carbon output among cities or the direct link between city size and environmental performance, often neglecting to explore whether the connection between economic openness, economic development, and green efficiency consistently shifts with city size. It is essential to differentiate between these two kinds of problems, as variations in average efficiency levels do not automatically mean that the fundamental economic connections are also diverse.

Considering these research gaps, this paper views city size as an essential contextual aspect for defining heterogeneity, instead of seeing it merely as a causal moderating factor or an institutional hierarchy. The empirical analysis initially employs an undesirable-output SBM model under VRS to assess urban green efficiency. It subsequently analyzes the conditional relationships among economic openness, economic development, and their interaction terms with green efficiency using a two-way fixed-effects model. Additionally, city-tier interaction terms along with joint and pairwise Wald tests are employed to investigate if these relationships vary among different city-size categories. Thus, this paper combines a descriptive analysis of efficiency differences across cities with a formal test of heterogeneity in economic relationships, while maintaining an associational rather than causal interpretation of the results.

3. Methods and Data

3.1. SBM–DEA model

DEA is a nonparametric frontier approach used to evaluate the relative efficiency of multiple decision-making units (DMUs) under multiple inputs and outputs [20]. Traditional radial DEA models evaluate efficiency through proportional changes in inputs or outputs, depending on the model orientation. Although radial models are mathematically convenient, they ignore input–output slacks; thus, efficiency tends to be overestimated when redundant inputs, insufficient desirable outputs, or unavoidable undesirable outputs (e.g., pollutant emissions) are present [21].

To address the aforementioned limitations, this paper adopts an output-oriented SBM–DEA model under VRS conditions that incorporates unwanted outputs. This model belongs to the non-radial, slack-variable-based DEA methods proposed by Pastor et al. [22] and Tone [21], which measure inefficiency through slack adjustments in inputs and outputs rather than assuming that all variables undergo radial changes in the same proportion. In environmental efficiency analysis, undesirable outputs can be directly incorporated into the production frontier, thereby enabling a joint evaluation of economic output and environmental pressure [23].

This paper uses fixed capital stock, energy consumption, and employment as input variables, real GDP as the desirable output, and CO_2 emissions as the undesirable output. Because CO_2 is the only undesirable environmental output included in the present specification, the resulting measure should be interpreted as a carbon-oriented measure of urban green efficiency rather than as a comprehensive indicator of all dimensions of urban environmental performance. The output-oriented approach measures a city's potential to increase desirable output and reduce undesirable output without increasing given inputs. Under the VRS assumption, cities are evaluated relative to a convex production frontier that accommodates different production characteristics across varying operational scales [24]. Therefore, the resulting VRS efficiency scores reflect pure technical green efficiency conditional on operating scale. Given the significant variations among Chinese cities in terms of economic size, resource endowments, and production scale, this framework is particularly well-suited to the research objectives of this paper.

For each city o, the output-oriented SBM formulation is expressed as:

$$\max D_o = \frac{1}{2}\left(\frac{s_o^g}{y_o^g} + \frac{s_o^b}{y_o^b}\right) \tag{1}$$

subject to

$$\begin{aligned} X\lambda &\le x_o \\ Y^g\lambda &\ge y_o^g + s_o^g \\ Y^b\lambda &\le y_o^b - s_o^b \\ 1'\lambda = 1, \quad \lambda \ge 0, \quad s_o^g \ge 0, \quad s_o^b &\ge 0 \end{aligned}$$

where x_o denotes the input vector of city o, y_o^g and y_o^b denote the desirable and undesirable outputs, respectively, and s_o^g and s_o^b represent the corresponding output slacks. The intensity vector λ defines the reference production set, while the restriction $1'\lambda = 1$ imposes the VRS assumption [24].

The output inefficiency measure D_o is converted into the reported efficiency score as:

$$\rho_o = \frac{1}{1 + D_o} \tag{2}$$

where $0 < \rho_o \le 1$. A value of one indicates that the city lies on the efficiency frontier, whereas a value below one indicates potential for desirable-output expansion and/or undesirable-output reduction relative to its reference frontier.

To ensure that each city is compared with comparable cities from the same period, this paper estimates the production frontiers on an annual basis rather than using a pooled or global frontier. In MaxDEA, the window width is set to 1, meaning that each city in a given year is evaluated for efficiency only relative to the production frontier constructed from the sample of that year. The empirical analysis period for this paper is 2008–2022.

Given that efficiency estimates under the VRS assumption may be influenced by the treatment of scale effects—particularly for DMUs at the extremes of the city-size distribution—this paper further re-estimates the model under the CRS assumption as a robustness test. By comparing the VRS and CRS results, we can distinguish between differences in efficiency attributable to pure technical efficiency and those caused by scale effects and examine

whether the efficiency patterns across different city sizes depend on the assumption of returns to scale.

Subsequently, this paper uses the VRS green-efficiency scores as the dependent variable in a second-stage panel regression.

3.2. Panel regression and heterogeneity analysis

In the second stage, this paper employs a two-way fixed-effects panel model to examine the conditional relationship between economic openness, economic development, and urban green efficiency. The model controls for city-specific characteristics that do not change over time through city fixed effects and for common macroeconomic and policy shocks through year fixed effects. City fixed effects account for inter-city differences that may be related to city size and exhibit strong persistence—including geographic location and relatively stable administrative and institutional characteristics—but they cannot eliminate omitted heterogeneity that varies over time. To address potential correlations within the same city over time, standard errors are clustered at the city level [25].

The baseline specification is expressed as:

$$GE_{it} = \beta_0 + \beta_1 Open_{it} + \beta_2 Dev_{it} + \gamma' Z_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (3)$$

where β_0 denotes the intercept, GE_{it} denotes the VRS-based green-efficiency score of city i in year t, $Open_{it}$ represents the degree of openness, Dev_{it} represents the level of economic development, and Z_{it} denotes a vector of time-varying control variables. μ_i and τ_t represent city and year fixed effects, respectively, while ε_{it} is the idiosyncratic error term.

To examine whether the relationship between openness and green efficiency varies with the level of economic development, an interaction term between openness and economic development is introduced:

$$\begin{aligned} GE_{it} = {} & \beta_0 + \beta_1 Open_{it} + \beta_2 Dev_{it} + \beta_3 (Open_{it} \times Dev_{it}) \\ & + \gamma' Z_{it} + \mu_i + \tau_t + \varepsilon_{it} \end{aligned} \quad (4)$$

The coefficient β_3 captures whether the conditional association between openness and green efficiency changes with the level of economic development.

To further examine city-size heterogeneity, openness and economic development are interacted with the five city-size categories. Using medium-sized cities as the reference group, the heterogeneity model is specified as:

$$\begin{aligned} GE_{it} = {} & \beta_0 + \beta_1 Open_{it} + \beta_2 Dev_{it} + \gamma' Z_{it} + \mu_i + \tau_t \\ & + \sum_{k \neq M} \delta_k (Open_{it} \times Tier_i^k) \\ & + \sum_{k \neq M} \theta_k (Dev_{it} \times Tier_i^k) + \varepsilon_{it} \end{aligned} \quad (5)$$

where $Tier_i^k$ is an indicator for city-size category k and M denotes the medium-sized-city reference group. Because the city-size classification is fixed over the study period, the main effects of the city-size indicators are absorbed by the city fixed effects. The interaction coefficients δ_k and θ_k therefore capture differences in the estimated associations of openness and economic development relative to medium-sized cities. City and year fixed effects, μ_i and τ_t, are included in Model (5).

City-tier-specific marginal associations are calculated from the relevant combinations of the baseline and interaction coefficients. Joint Wald tests are used to examine whether the interaction coefficients are jointly equal to zero, while pairwise Wald tests compare the estimated marginal associations across city-size groups. This provides a direct statistical test of heterogeneity across city tiers.

Prior to estimation, all continuous explanatory variables are standardized, and the interaction terms are constructed using the standardized variables. Since the analysis is based on observational panel data, the estimated coefficients are interpreted as conditional associations rather than causal effects.

3.3. Selection of variables and data description

This study focuses on Chinese cities at the prefectural level and above from 2008 to 2022. The initial sample consisted of 274 cities; however, 4 cities were excluded due to missing data on control variables required for the second stage of analysis. Consequently, the final sample comprises 270 cities across 15 years, resulting in a total of 4,050 city-year observations. The data were primarily sourced from publicly available official statistical yearbooks, including the China Urban Statistical Yearbook (2009–2023) and relevant city statistical yearbooks.

City size is classified according to the "Notice on Adjusting the Standards for Classifying City Sizes" issued by the State Council in 2014[1], using 2020 urban-area permanent resident population as the reference-year population. Cities with an urban-area permanent resident population of less than 0.5 million are classified as small cities, those with 0.5–1.0 million as medium-sized cities, those with 1.0–5.0 million as large cities, those with 5.0–10.0 million as very large cities, and those with 10.0 million or more as megacities. The 2020 population is used as the reference because it provides a consistent cross-sectional benchmark for assigning cities to fixed size categories. The resulting classification is held fixed throughout 2008–2022 to maintain a consistent basis for cross-tier comparison. Some cities may nevertheless have crossed the official population thresholds during the study period, which is acknowledged as a limitation of the fixed-classification approach. The final sample includes 7 megacities, 14 very large cities, 78 large cities, 106 medium-sized cities, and 65 small cities. Figure 1 illustrates the spatial distribution of the various city categories.

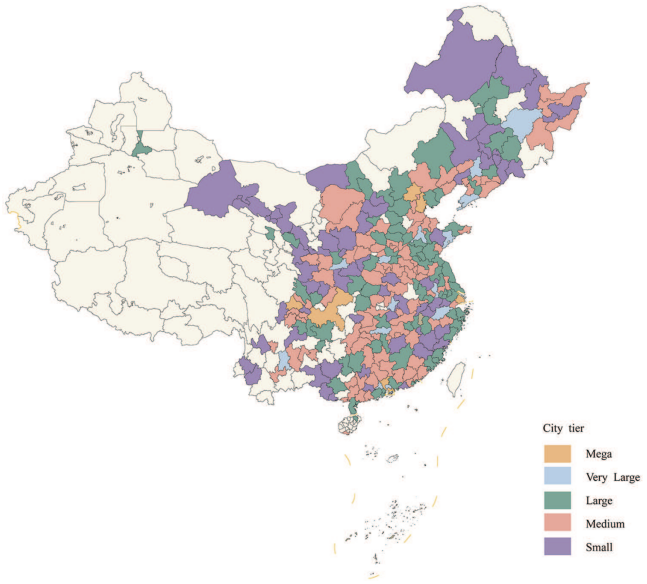
In the first stage of the DEA analysis, fixed capital stock, energy consumption, and employment were used as input variables, with real GDP as the desirable output and CO_2 emissions as the undesirable output. The relevant city-level data were primarily sourced from the National Bureau of Statistics and various official statistical yearbooks.

Fixed capital stock was estimated using the perpetual inventory method, with the depreciation rate set at 9.6%, following Zhang et al. [2]. Real GDP was uniformly converted to constant prices with 2006 as the base year. Energy consumption included natural gas, liquefied petroleum gas (LPG), and electricity and was uniformly converted to standard coal equivalents in accordance with the General Rules for Calculation of the Comprehensive Energy Consumption [26]. City-level CO_2 emissions were estimated from natural gas, LPG, and electricity consumption using standard emission factors, following Zhou and Zhou [27]. Descriptive statistics for the input and output variables are presented in Table 1.

The core explanatory variables in the second-stage analysis are economic openness and the level of economic development. Economic openness is measured by the ratio of actual FDI to regional GDP (FDI/GDP), which reflects the relative

[1] Available at: https://www.ndrc.gov.cn/xwdt/ztzl/xxczhjs/ghzc/201605/t20160509_971910.html

Figure 1
Spatial distribution of the 270 sample cities by city size in China[2]



importance of foreign capital in the local economy and the extent of its external economic linkages. Higher levels of openness may improve urban production performance through technology, management expertise, and knowledge spillovers, but their environmental impacts still depend on the structure of foreign investment and local conditions. The extent of economic development is assessed by the natural logarithm of per capita GDP to indicate the general level of regional development and variations in capital accumulation, technological proficiency, and resource utilization methods.

[2]Base map source: National Platform for Common Geospatial Information Services (Tianditu), https://cloudcenter.tianditu.gov.cn/administrativeDivision/. Map approval number: GS(2026)4921.

The model further incorporates three control variables to account for structural and institutional differences among cities. Industrial structure upgrading is measured by the ratio of value added in the tertiary sector to that in the secondary sector; a higher ratio indicates that the economic structure is shifting toward the service sector and relatively less resource-intensive activities; the level of urbanization is measured by the proportion of the urban permanent resident population relative to the total permanent resident population, reflecting differences in population concentration, infrastructure provision, and urban resource demand; and the degree of government intervention is measured by the ratio of local fiscal expenditure to regional GDP, reflecting the relative scale of local government participation in economic activities and the provision of public services.

In the second stage, observations with missing or invalid values required for the second-stage estimation were excluded on a complete-case basis without imputation. Because 68 city-year observations had missing or invalid openness data, the final second-stage estimation sample contained 3,982 observations. The SBM–DEA efficiency assessment was carried out with MaxDEA; panel fixed-effects regression, interaction term models, Wald tests, and robustness checks were executed using Stata 18.

4. Results and Discussion

4.1. City-size differences and temporal evolution of green efficiency

The VRS SBM–DEA estimates show substantial variation in urban green efficiency across city-size groups. Over the 2008–2022 period, the nationwide average efficiency score is 0.736. As reported in Table 2, megacities exhibit the highest average efficiency at 0.895, followed by very large cities at 0.790 and small cities at 0.762. Large and medium-sized cities record lower averages of 0.718 and 0.715, respectively. The ordering therefore does not indicate a monotonic increase in green efficiency with city size.

Figure 2 provides a more detailed view of the distribution of urban green efficiency across the five city-size groups. The pattern is non-monotonic: efficiency declines from megacities to large and

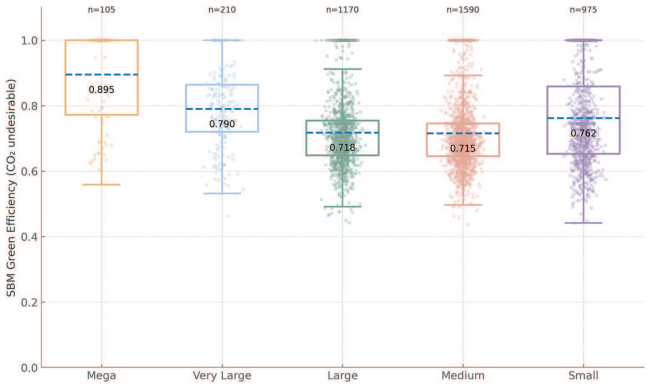
Table 1
Descriptive statistics for the input and output variables (2008–2022, N = 4,050 city-year observations)

Variables		Unit	Mean	SD	Max.	Min.
Input	Fixed capital stock	10,000 CNY	75,988,224	88,937,376	993,605,790	3,589,664
	Energy consumption	tons of standard coal	2,183,075	3,693,413	41,648,440	12,860
	Labor input employment	10,000 people	55	87	1,143	4
Output	Desirable: real GDP	10,000 CNY	19,236,786	28,990,865	333,289,530	884,980
	Undesirable: CO_2 emissions	10,000 tons	4,162	8,385	113,835	552

Table 2
Average urban green efficiency by city tier (2008–2022)

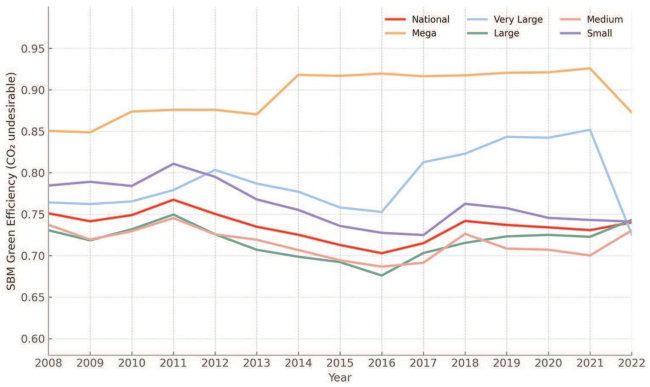
City size	Average urban green efficiency
Mega	0.895
Very large	0.790
Large	0.718
Medium-sized	0.715
Small	0.762
Nationwide average	0.736

Figure 2
Distribution of SBM green efficiency by city size (2008–2022)



Note: The figure presents the distribution of annual VRS SBM–DEA green-efficiency scores across five city-size categories over 2008–2022, based on 4,050 city-year observations from 270 Chinese cities.

Figure 3
Evolution of urban green efficiency by city size 2008–2022



medium-sized cities but rises again among small cities. Megacities have the highest group mean and a comparatively large concentration of observations near the efficiency frontier, whereas large and medium-sized cities are more concentrated at lower efficiency levels. Small cities exhibit a wider distribution, with some observations attaining relatively high efficiency despite their smaller economic scale.

The cross-tier ordering differs from the inverted-U relationships reported in some previous studies of urban scale and environmental performance [28, 29]. Because the five city-size categories used here are discrete groups rather than observations along a continuous city-size function, the result is more appropriately interpreted as a non-monotonic pattern of descriptive heterogeneity than as a formally identified U-shaped relationship.

Several mechanisms discussed in the existing literature may help interpret this pattern. Very large cities and megacities often combine denser innovation networks, more diversified industrial structures, and stronger fiscal and administrative capacity, which may facilitate cleaner technology adoption and environmental infrastructure. At the other end of the distribution, some small cities may retain less carbon-intensive industrial structures or benefit from relatively favorable ecological conditions, while large and medium-sized cities may face greater adjustment pressures during industrial and urban transition [30]. These mechanisms are not directly recognized by the DEA estimates and are thus regarded as interpretations informed by the literature instead of as independently validated explanations.

The cross-tier ordering is also sensitive to the returns-to-scale assumption. Under the CRS specification, mean efficiency is 0.763 for megacities, 0.740 for very large cities, 0.666 for large cities, 0.627 for medium-sized cities, and 0.599 for small cities. Thus, the small-city rebound observed under VRS disappears under CRS, whereas megacities remain the highest-performing group. This comparison indicates that the VRS results primarily describe pure technical green efficiency conditional on scale and that part of the cross-tier pattern is associated with scale effects.

Figure 3 shows that urban green efficiency also varies substantially over time. At the national level, the average score rises from approximately 0.751 in 2008 to 0.767 in 2011, followed by a prolonged decline to about 0.703 in 2016. Efficiency subsequently recovers to approximately 0.742 in 2018 and remains within a relatively narrow range during 2019–2021 before increasing slightly to about 0.740 in 2022. The overall trajectory is therefore characterized by cyclical fluctuations rather than a continuous upward trend.

The trajectories differ across city-size groups as well. Megacities remain at comparatively high efficiency levels throughout most of the sample period, whereas large and medium-sized cities generally remain below the national average. Very large cities show a marked recovery after the middle of the sample period, while small cities display relatively high efficiency in the earlier years followed by a decline and subsequent stabilization. These trajectories indicate that the differences summarized in Table 2 are not driven by a single year or a short-lived disturbance but persist, with varying intensity, over much of the study period.

The temporal changes occur alongside several major shifts in China's economic and environmental policy environment. The improvement in the early sample period coincides with strengthened energy-conservation and emission-reduction policies during the late 11th Five-Year Plan, whereas the subsequent decline overlaps with a period of continued industrial expansion and adjustment in energy-intensive sectors. The recovery after 2016 also coincides with supply-side structural reforms, overcapacity reduction, and greater emphasis on industrial upgrading and low-carbon development during the 13th Five-Year Plan. Earlier SBM-based evidence similarly documents gradual improvement alongside substantial spatial and temporal heterogeneity in Chinese cities [2]. These policy developments provide relevant institutional context for the observed trajectory, although the present DEA analysis does not separately identify their causal contributions.

The COVID-19 period further illustrates why changes in the efficiency index should not be interpreted solely through changes in emissions. Although the pandemic disrupted industrial production, energy use, and emissions in 2020 [31, 32], the nationwide green-efficiency score did not show a uniform rebound, and the five city-size groups followed different trajectories. This is consistent with the joint nature of the SBM measure, in which economic output, resource inputs, and CO_2 emissions simultaneously determine relative efficiency. The pandemic period is therefore better viewed as an unusual macroeconomic disturbance than as evidence of a common improvement in urban green efficiency.

Overall, the results are consistent with the broader literature in showing substantial heterogeneity and temporal variation in urban environmental efficiency, but they also indicate that city size alone does not determine green performance. Previous studies have reported nonlinear scale relationships [29, 30] and pronounced regional differences, including higher carbon-efficiency performance in many eastern developed cities relative to central

and western regions [33]. In the present sample, megacities and very large cities are concentrated largely in the eastern coastal region, whereas smaller cities are more widely distributed across central and western China. Accordingly, the observed city-tier differences may partly overlap with regional, industrial, and institutional characteristics rather than reflecting a scale effect in isolation.

Methodological differences may also contribute to variation across studies. Research using three-stage DEA, productivity indices, or other dynamic efficiency measures emphasizes different components of environmental performance and convergence [34], whereas the present analysis focuses on VRS-based urban green efficiency and its variation across official city-size categories. The five-tier comparison therefore provides a complementary descriptive perspective rather than a substitute for continuous or region-based analyses.

Taken together, Section 4.1 establishes persistent but descriptive heterogeneity in urban green efficiency across city-size groups and over time. These patterns motivate the second-stage analysis in Section 4.2, which examines the conditional associations of openness and economic development with urban green efficiency and formally tests whether these associations differ across city-size tiers.

4.2. Conditional associations and city-size heterogeneity

Table 3 reports the second-stage panel estimates. Model (1) establishes the average conditional associations before complementarity and city-size heterogeneity are introduced. All continuous regressors are standardized before estimation; the

Table 3
Second-stage fixed-effects estimates and city-size heterogeneity

Variable/test	(1) Baseline Fixed Effects (FE)	(2) Complementarity FE	(3) Tier-interaction FE
Panel A. Regression coefficients			
Openness	0.00323*** (0.00077)	–0.00967 (0.00626)	–0.03883** (0.01848)
Economic development	–0.01198 (0.01177)	–0.00719 (0.01126)	–0.00715 (0.01304)
Openness–development interaction	–	0.01588** (0.00721)	–
Openness interaction: Mega	–	–	0.04986** (0.01933)
Economic-development interaction: Mega	–	–	0.05355* (0.02766)
Openness interaction: Very large	–	–	0.03570 (0.04042)
Economic-development interaction: Very large	–	–	0.05866*** (0.01403)
Openness interaction: Large	–	–	0.04258** (0.01848)
Economic-development interaction: Large	–	–	0.00954 (0.00925)
Openness interaction: Small	–	–	0.05839** (0.02488)
Economic-development interaction: Small	–	–	–0.01595 (0.01223)
Industrial structure upgrading	0.00686 (0.00832)	0.00720 (0.00830)	0.00431 (0.00863)
Urbanization	–0.00078 (0.00860)	0.00062 (0.00861)	0.00248 (0.00840)
Government intervention	–0.00603 (0.00628)	–0.00561 (0.00623)	–0.00272 (0.00607)
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	3,982	3,982	3,982
Within *R*-squared	0.005	0.008	0.024

Panel B. Implied tier-specific slopes from Model (3)		
City tier	Openness slope	Economic-development slope
Mega	0.01102 (0.00725)	0.04640* (0.02692)
Very large	–0.00313 (0.03585)	0.05151*** (0.01611)
Large	0.00375*** (0.00048)	0.00239 (0.01257)
Medium-sized	–0.03883** (0.01848)	–0.00715 (0.01304)
Small	0.01956 (0.01633)	–0.02309 (0.01441)

Panel C. Wald tests of slope heterogeneity			
Test	Wald statistic	*p*-value	df
Openness heterogeneity	7.775	0.100	4
Economic-development heterogeneity	24.269	<0.001	4
Joint heterogeneity	35.831	<0.001	8

Notes: Clustered standard errors at the city level are reported in parentheses. Medium-sized cities are the reference category in Model (3); the main openness and economic-development coefficients in that model are therefore the slopes for medium-sized cities, while the interaction coefficients represent differences relative to that reference group. Panel B reports the implied tier-specific slopes. All continuous regressors are standardized before estimation, and interaction terms are constructed from standardized variables. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

specifications include city and year fixed effects, and standard errors are clustered at the city level. The preferred estimation sample contains 3,982 city-year observations. As shown in Table 3, openness is positively and statistically significantly associated with urban green efficiency in the baseline specification. By contrast, economic development does not exhibit a statistically significant pooled association, and the three baseline controls are also insignificant. The starting point is therefore asymmetric: openness has a positive average association with green efficiency, whereas economic development does not have a uniform independent relationship across the full sample.

Model (2) of Table 3 then asks whether openness and economic development are interdependent rather than purely additive. The openness–development interaction is positive and statistically significant at the 5% level. This result changes the interpretation of the pooled development coefficient. The absence of a significant average development slope does not imply that economic development is irrelevant to green efficiency under all conditions; instead, its relationship becomes more favorable when openness is higher, and the openness–efficiency relationship likewise becomes more favorable as economic development rises. The second-stage evidence therefore points to conditional complementarity rather than two universally positive independent effects.

Model (3) provides the formal test of the paper's central city-size proposition. The joint Wald test rejects equality of the openness and economic-development slopes across the five city tiers at the 1% level. When the two dimensions are tested separately, heterogeneity is especially strong for economic development, while heterogeneity in the openness relationship is considerably weaker and does not reach the 5% significance level. The two core variables therefore display different forms of heterogeneity: development varies broadly across city tiers, whereas openness is characterized by more selective between-tier contrasts. This distinction is important because it prevents the overall heterogeneity result from being interpreted as evidence that every openness slope differs across every city-size category.

Panel B of Table 3 identifies the contrasts that drive the aggregate test. For large cities, the openness slope is positive and highly significant, whereas the medium-sized-city slope is negative and significant; the difference between the two slopes is itself significant at the 5% level. For economic development, very large cities display a positive and significant slope, while the corresponding medium-sized-city slope is statistically indistinguishable from zero; this difference is significant at the 1% level. The megacity development slope is positive but only weakly significant, and the development slopes for large and small cities are not significant. The estimated pattern therefore does not follow a simple gradient whereby larger cities exhibit more favorable relationships between openness or development and green efficiency. Instead, the pooled estimates mask uneven and sometimes offsetting relationships across city tiers.

The first- and second-stage results answer different but complementary questions. Section 4.1 shows how average VRS-based green-efficiency levels differ across city-size groups, whereas the fixed-effects estimates in Section 4.2 describe conditional within-city associations over time. A city tier with a high average efficiency score therefore need not exhibit the strongest openness or development slope. Megacities illustrate this distinction: they have the highest average green efficiency in Section 4.1, yet neither second-stage slope is significant at the 5% level. Read together, the two stages shift the interpretation away from a simple "bigger-is-greener" argument. City size is informative about the context in which economic and external resources are associated with efficiency, not merely about the level of efficiency itself.

The interaction and heterogeneity findings also help reconcile mixed results in the recent FDI literature. Chen et al. [4] find a positive relationship between FDI and green total factor productivity in Chinese cities, but they also show that the relationship varies across regions and city characteristics. Zhao et al. [3], by contrast, report a negative average relationship between FDI and urban green total factor productivity while identifying a positive technological-innovation channel. These apparently different findings point to the same analytical lesson: openness should not be assigned a fixed environmental sign in advance. Consistent with that lesson, the present study finds a positive pooled openness association but also shows that the relationship changes with development conditions and, for specific contrasts, with city size.

A deeper interpretation of the combined evidence concerns the capacity of cities to convert economic and external resources into cleaner production performance. OECD/UN-Habitat [19] documents that many intermediary cities face lower fiscal capacity, weaker infrastructure, and constraints in urban governance, which can restrict the implementation of climate-oriented investment. Tang and Huang [17] show, using Chinese prefecture-level cities, that green-finance development is associated with higher urban energy efficiency through technological progress and innovation and that the relationship varies with local financial development, openness, and urbanization. These studies provide a plausible context for why similar increases in openness or income need not translate into the same efficiency response across city tiers. In this paper, this conversion-capacity interpretation is a synthesis of the significant openness–development interaction and the formal tier heterogeneity tests, rather than a directly measured mechanism. Absorptive capacity, governance quality, industrial upgrading, and infrastructure should therefore be viewed as candidate channels for future empirical testing.

The robustness checks reported in Supplementary Table S1 provide further support for the stability of the city-size heterogeneity results. The joint Wald test remains statistically significant under the expanded-control specification, the one- and two-year lagged specifications, the exclusion of DEA-frontier observations, and the fractional-logit specification. The heterogeneity associated with economic development is also consistently significant across these alternative specifications. In addition, the openness-related results remain more tier-specific, with statistically significant differences concentrated in particular city-size contrasts rather than uniformly across all city-size groups. Taken together, these results reinforce the main finding that the relationships between openness, economic development, and urban green efficiency vary systematically across city-size groups and are not specific to the baseline model specification.

The second-stage estimates should nevertheless be interpreted as conditional associations rather than causal effects. City fixed effects absorb persistent time-invariant city characteristics, and year fixed effects absorb shocks common to all cities, but time-varying omitted factors, reverse relationships, and spatial dependence may remain. Spatial spillovers are especially relevant in urban environmental analysis; Guan et al. [35] document spatial spillover patterns across major Chinese urban agglomerations. A further limitation is mechanical overlap: real GDP enters the DEA desirable output, while GDP is also embedded in GDP per capita and FDI/GDP. Taken together, the results show that the associations of openness and economic development with urban green efficiency vary across urban contexts, with the

clearest heterogeneity appearing in the relationship between economic development and green efficiency. The analysis therefore connects the descriptive differences in green efficiency across city-size groups in Section 4.1 with the conditional relationships tested in Section 4.2, while avoiding any interpretation of city size as a causal mechanism in itself.

5. Conclusion

This paper employs an output-oriented VRS SBM–DEA framework, combined with a panel model featuring two-way fixed effects for both cities and years, to re-examine the urban green efficiency of 270 Chinese cities from 2008 to 2022. The national average VRS efficiency for Chinese cities was 0.736; however, when classified according to official city size categories, the distribution exhibited a distinct non-monotonic pattern: megacities had the highest average efficiency, followed by very large cities and small cities, while large and medium-sized cities had relatively lower average efficiencies. However, this descriptive pattern is not invariant to the returns-to-scale assumption, as the small-city rebound observed under the VRS specification disappears under the CRS specification. Results from the second stage indicate that, in a fixed-effects model, openness is significantly and positively associated with urban green efficiency, whereas economic development does not exhibit a statistically significant uniform association across the full sample. The interaction term between openness and economic development is significantly positive, indicating a conditional complementary relationship between the two, rather than each independently and universally promoting green efficiency. More importantly, the joint test confirms that the relationship among openness, economic development, and green efficiency exhibits statistically significant heterogeneity across city sizes, with the heterogeneity in economic development being particularly pronounced: compared with medium-sized cities, the association between economic development and green efficiency is significantly more favorable in very large cities. For openness, the overall heterogeneity test does not reach the 5% significance level, although specific between-tier contrasts remain significant, including the more favorable association in large cities relative to medium-sized cities.

Thus, the primary contribution of this research is not merely in implementing a classification by city size but in integrating the variations in efficiency levels identified in the initial stage with structured second-stage assessments of diverse associations. The findings suggest that the overall coefficient on a national scale could be deceptive, as the mean relationship might hide contrasting trends across varying city size categories that balance each other out. The empirical findings also further illustrate that a higher average efficiency level is not conceptually equivalent to a stronger marginal relationship. For example, megacities exhibit the highest average VRS efficiency, but in the interaction term model, neither the openness slope nor the economic-development slope is statistically significant at the 5% level. Consequently, the focus of the analysis shifts from determining whether "large cities are inherently greener" to examining whether cities of different sizes operate under distinct conditions when external economic linkages and economic development are associated with green efficiency.

The use of a city's "ability to translate openness and development into green performance" as an analytical concept should be understood as an explanatory synthesis of the above findings, rather than a mechanism directly measured in this paper. The existing model does not directly observe technological absorptive capacity, governance quality, the sectoral composition of FDI, or ecological endowments. Therefore, these factors are used only to interpret why the estimated associations may differ across different city-size tiers and should not be regarded as causal mechanisms that this paper has independently identified.

The resulting policy implications stem from this conditional pattern instead of a universally applicable, consistent rule. In medium-sized cities, the negative relationship noted with openness implies that merely increasing FDI exposure is not enough to improve green efficiency; the nature and technological aspects of the investment, along with the local ability to implement cleaner production methods, are probably significant. Chen et al. [4] also highlight that the dynamics between environmental regulations, FDI, and green total factor productivity differ based on urban and regional contexts; OECD/UN-Habitat [19] points out that intermediary cities frequently encounter unique challenges related to infrastructure, financing, and institutional factors during the transition to a low-carbon economy. For large cities, the relatively positive relationship with openness highlights the importance of sustaining external connections that promote technology and knowledge exchange instead of merely focusing on investment amounts. In very large cities, the strong link between economic development and green efficiency indicates that increased levels of development might align with improved conditions for cleaner infrastructure, innovation, and resource efficiency. Tang and Huang [17] discovered that green finance mainly boosts urban energy efficiency via technological advancements and innovation, and this relationship shows significant variation across diverse urban environments. For megacities and small cities, the initial findings provide insights into efficiency levels, but they must not be taken at face value as proof that openness or economic progress generates higher marginal returns; this warning is especially vital for small cities due to their relative VRS advantage being influenced by the returns-to-scale premise.

The conclusions mentioned above remain influenced by several research limitations. Initially, the estimation outcomes from the second stage must be understood as observational correlations instead of causal impacts. Although city fixed effects absorb time-invariant differences across cities and year fixed effects absorb common shocks, time-varying omitted factors, reverse causality, and the possible joint determination of openness, income, and green efficiency cannot be completely ruled out. Second, since real GDP serves as the preferred output in the DEA model, and GDP is also part of the definitions for GDP per capita and FDI/GDP, a certain mechanical dependence between the two stages cannot be entirely removed. Third, the descriptive efficiency rankings derived under the VRS specification are partly sensitive to the returns-to-scale assumption; furthermore, the use of fixed city-size categories over 2008–2022 cannot capture cities that may have crossed population thresholds during the study period. Furthermore, the annual DEA framework measures each city's relative efficiency against the frontier in a given year but does not decompose productivity change into technological progress and efficiency change. Finally, this study has not modeled the potential spatial dependence relationships between adjacent cities. Given that Guan et al. [35] have already found that environmental efficiency in China's major urban agglomerations exhibits spatial dependence and spillover effects, this issue constitutes an important direction for future research.

Future research can extend this framework in four directions. Dynamic SBM-Malmquist or related productivity-index approaches could separate efficiency change from technological progress over time. Mechanism analysis could directly

incorporate green innovation, environmental regulation, human capital, fiscal capacity, and the sectoral composition of foreign investment to test the channels that are only interpreted indirectly here. Spatial panel models could examine cross-city spillovers, while carefully designed quasi-experimental strategies, where credible policy shocks are available, could strengthen causal identification. A further extension would allow city-size categories to evolve and test whether changes in city scale alter the openness–development–efficiency relationship. Taken together, the present evidence suggests that the green implications of openness and economic development depend less on their absolute levels than on the urban context in which they are embedded. The central empirical message is therefore one of conditional and heterogeneous association: national averages conceal meaningful differences across city-size tiers, and these differences should be incorporated explicitly into future research and urban green-transition policy design.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

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

Author Contribution Statement

Nan Wang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Yunning Ma:** Validation, Resources, Writing – review & editing. **Hyoungsuk Lee:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision.

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