

Technological gaps and green efficiency in urban agglomerations: evidence from China and the United States

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Abstract. This study benchmarks green efficiency in the Yangtze River Delta (YRD) in China and the San Francisco Bay Area (SFBA) in the United States to diagnose whether emerging megaregions' green gap reflects managerial inefficiency or technological backwardness. Using a Slacks-Based Measure (SBM) model with undesirable outputs within a meta-frontier framework, it decomposes Meta-Frontier Efficiency (MTE) into Group Technical Efficiency (GTE) and the Technology Gap Ratio (TGR) for 35 cities and counties over 2004 to 2023. The two agglomerations achieve nearly identical managerial efficiency, with average GTE of 0.920 and 0.914, but the SFBA's MTE of 0.920 far exceeds the YRD's 0.795. This gap stems from technology: the SFBA's TGR is 1.000, meaning its group frontier coincides with the global meta-frontier, whereas the YRD's TGR is only 0.873 and has widened over time. Spatial autocorrelation analysis reveals no significant clustering of green productivity, indicating that green technologies are highly localized and do not diffuse spontaneously across city boundaries, so that economic integration has outpaced environmental and technological integration. These findings imply that the YRD should shift its policy focus from managerial tightening toward green technology research and development, and promote policy-driven green technology transfer from leading cities to peripheral manufacturing ones.

Keywords: green total factor productivity, meta-frontier, technology gap ratio, urban agglomeration, Yangtze River Delta, San Francisco Bay Area

1. Introduction

Over the past few decades, urban agglomerations have emerged as the primary engines of global economic growth [1]. As globalization and urbanization deepen, economic activities, population, and innovation resources have become increasingly concentrated in a handful of world-class metropolitan regions, most notably the Yangtze River Delta (YRD) in China and the San Francisco Bay Area (SFBA) in the United States. Although both are celebrated as powerful engines of prosperity, they represent distinctly different positions along the global green technology frontier. The San Francisco Bay Area has largely transitioned into a knowledge-intensive, low-emission economy and consistently defines the global frontier in clean innovation and carbon efficiency. The Yangtze River Delta, while rapidly catching up, still navigates the tension between a massive manufacturing base and environmental sustainability, and consequently operates further inside this frontier. Against the backdrop of global carbon neutrality commitments and the urgent need for sustainable

urban development [2], understanding the nature and sources of the green productivity gap between these two world-class urban agglomerations has become a critical analytical and policy priority. Green Total Factor Productivity (GTFP), which simultaneously accounts for economic output and environmental externalities [3, 4], serves as an ideal metric for this cross-regional benchmarking.

A growing body of literature has measured GTFP for various Chinese city clusters using nonparametric frontier techniques [5-11]. However, most existing studies evaluate green efficiency within a single national or regional framework, implicitly assuming that all cities share a common technology set. This conventional approach masks a fundamental question: when the green performance of an emerging urban agglomeration like the YRD is found to be subpar, is it primarily due to managerial inefficiency in resource allocation, or is it because the region as a whole has not yet accessed the cutting-edge green technologies that define the global frontier? Without a well-defined international benchmark, these two sources of underperformance cannot be separated. The meta-frontier framework [12-14] provides a powerful tool to address this issue. By enveloping group-specific frontiers into a common global frontier, it allows overall Meta-Frontier Efficiency (MTE) to be decomposed into Group Technical Efficiency (GTE) and the Technology Gap Ratio (TGR). Although metafrontier techniques have been applied in cross-country green productivity comparisons [15] and in decomposing environmentally sensitive productivity growth within China [16], very few studies have used this framework to directly benchmark a major Chinese urban agglomeration against a technologically mature global counterpart. This gap leaves a critical blind spot in the understanding of whether the green development bottleneck in emerging megaregions stems from inadequate management or from structural technological backwardness.

To fill this gap, this study conducts a systematic benchmarking of green efficiency in two representative world-class urban agglomerations, the Yangtze River Delta and the San Francisco Bay Area, over the period 2004 to 2023. It employs the Slacks-Based Measure (SBM) model with undesirable outputs [6, 7] within a meta-frontier framework, which allows overall green efficiency to be decomposed into Group Technical Efficiency (GTE) and the Technology Gap Ratio (TGR). This enables us to directly diagnose whether the YRD's green challenges stem more from management deficits or from a lack of advanced green technologies relative to the global meta-frontier. In addition, this study explores the spatial heterogeneity of green efficiency through spatial autocorrelation analysis, to examine how green productivity is distributed across cities and whether green technologies diffuse across city boundaries.

The contributions of this study are threefold. First, it provides one of the first direct meta-frontier comparisons of green efficiency between a major Chinese urban agglomeration and an established global technology leader, the San Francisco Bay Area, offering a rigorous diagnostic tool to identify the nature of the green development gap. Second, by decomposing overall green efficiency into managerial efficiency and the technology gap, it shifts the analytical focus from generic regional drivers to the structural technological constraints that hinder green catch-up. Third, the spatial heterogeneity analysis reveals the extent to which green technologies remain locally confined, yielding direct implications for targeted intercity technology transfer policies. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on GTFP measurement and benchmarking. Section 3 introduces the methodology, data, and variable selection. Section 4 presents the meta-frontier decomposition results and the spatial heterogeneity analysis. Section 5 concludes the study, draws policy implications, and outlines directions for future research.

2. Literature review

Literature on urban agglomerations and green development has expanded rapidly in recent years, and two strands are particularly relevant to this study. The first examines urban integration and its economic and environmental consequences, establishing the integrated urban agglomeration as the setting of modern economic activity. The second focuses on the measurement of GTFP and its driving forces, providing the methodological toolkit for assessing the quality of green growth. This review draws the two strands together for a specific purpose: to lay the foundation for benchmarking an emerging Chinese urban agglomeration against a technologically mature international counterpart. Section 2.1 briefly reviews the urban integration literature as background. Section 2.2 traces the evolution of GTFP measurement approaches. Section 2.3 introduces the meta-frontier framework, which allows green performance to be compared across groups operating under different technologies. Section 2.4 then summarizes the research gaps that motivate this study.

2.1. Urban integration as the research backdrop

Urban integration refers to a process in which one or two central cities serve as the core and, through close economic, social, and cultural interactions, gradually form an integrated urban region with surrounding cities, encompassing primarily megacities and large cities but also small and medium-sized cities, counties, and towns [17]. Integrated urban agglomerations typically exhibit synergistic effects along two dimensions, cooperation and complementarity [18], enabling cities to leverage functional specialization and strategic coordination to generate collective advantages that exceed the sum of individual urban performances. Existing evidence documents both sides of this process. On the positive side, urban integration significantly promotes economic growth and efficiency [1], facilitates intercity division of labor and industrial collaboration [19], enlarges urban population size through the spatial functional division of labor within urban clusters [20], and helps achieve higher emission-reduction efficiency [2]. On the negative side, it may intensify tensions in human–land relationships, resulting in land-use fragmentation, ecological degradation, and environmental pollution [21]. Amid these opportunities and risks, how urban agglomerations perform in terms of green productivity has attracted increasing scholarly attention.

A growing body of studies has examined green productivity within Chinese urban agglomerations, documenting the spatial network structure and heterogeneous evolution of GTFP across cities [22]. Some find that market integration enhances regional GTFP by improving both efficiency and technological progress [23], while others emphasize the roles of human capital structure and population agglomeration, with the latter's positive effect being stronger in central cities than in peripheral ones [24, 25]. Although these studies differ in focus, they share a common setting: each evaluates green performance within China's national framework, leaving the international benchmark dimension unexplored. The present paper adopts a different perspective. Rather than testing the causal effects of integration, this paper uses the integrated urban agglomeration as the analytical setting and benchmark the Yangtze River Delta against a technologically mature international counterpart, the San Francisco Bay Area, in order to diagnose the nature and sources of the green productivity gap.

2.2. Measuring GTFP: evolution of measurement approaches

This section reviews the evolution of GTFP measurement approaches. The central challenge in measuring GTFP is that environmental pollution must be treated as an undesirable output alongside desirable economic outputs, and the way this challenge has been addressed defines the trajectory of the measurement literature. Early studies widely employed the classical Data Envelopment Analysis (DEA) method to assess relative

efficiency under multiple inputs and multiple outputs [5]. Within this framework, Decision-Making Units (DMUs) are evaluated based on whether they lie on the production frontier, with an efficiency score equal to one indicating full efficiency. This approach laid the theoretical foundation for subsequent green efficiency measurement.

However, traditional DEA assumes that all outputs are desirable and therefore cannot adequately address environmental pollution, which is pervasive in real-world production processes. To overcome this limitation, Tone [6] proposed the Slack-Based Measure (SBM) model, which directly captures input redundancies and output shortfalls. The SBM framework was subsequently extended to accommodate undesirable outputs [7], enabling efficiency evaluation to simultaneously capture input redundancies, shortfalls in desirable outputs, and excessive pollutant emissions, thereby allowing the measurement of static green efficiency for cities and industries in a given period.

Building on static efficiency measurement, scholars have further explored intertemporal approaches to GTFP assessment by introducing productivity indices based on distance functions. Early studies mainly relied on the traditional Malmquist index to measure changes in total factor productivity. However, this index is derived from DEA models that consider only desirable outputs and thus fails to reflect the green expansion of the production frontier under environmental constraints. Chung et al. [8] addressed this limitation by integrating undesirable outputs into the Malmquist framework and proposing the Malmquist–Luenberger (ML) index, which measures intertemporal productivity changes while accounting for environmental pollution. Oh [9] further developed the Global Malmquist–Luenberger (GML) index, which constructs a single global frontier from data across all periods, thereby improving comparability over time. These approaches have become the foundational methods for empirical GTFP analysis.

In recent years, as research contexts have become more diversified, scholars have proposed new index systems based on the ML framework. For example, Chen et al. [10] developed a novel Malmquist-type GTFP index that improves measurement stability and interpretability. Meanwhile, extended DEA models, particularly the SBM-DEA approach, have been increasingly applied to GTFP analysis [11]. A growing body of literature has identified various factors that significantly influence GTFP. Technological progress is widely recognized as a key driver of GTFP growth [3]. In addition, the development of new economic forces, such as the digital economy, has emerged as an important contributor to GTFP improvement in recent years [4, 26].

Overall, by embedding resource consumption and environmental pollution as undesirable outputs within the traditional TFP framework, GTFP has become a core indicator for assessing the quality of economic growth under resource and environmental constraints. Yet one methodological gap remains: these techniques, on their own, evaluate efficiency within a single technology set and cannot compare groups operating under different technologies. The meta-frontier approach, introduced in the next section, is designed to address exactly this problem.

2.3. The meta-frontier framework and technology gap measurement

The meta-frontier approach traces its origins to Battese and Rao [12], who introduced a stochastic meta-frontier to compare firms operating under different technologies, and was subsequently formalized for nonparametric efficiency analysis by Battese et al. [13] and O'Donnell et al. [14]. The central idea is to envelop group-specific production frontiers into a common meta-frontier, thereby allowing heterogeneous groups operating under different technologies to be evaluated on a common basis. Under this framework, overall Meta-Frontier Efficiency (MTE) can be decomposed into two components: group technical efficiency (GTE), which reflects performance relative to a group's own frontier, and the Technology Gap Ratio (TGR), which measures the distance between the group frontier and the common meta-frontier. Formally, $MTE = GTE$

× TGR. A TGR close to one indicates that a group's technology essentially coincides with the global frontier, whereas a persistently lower TGR reveals a structural technological gap that cannot be closed by managerial improvements alone.

This decomposition has direct diagnostic value for the question motivating this paper. A region may exhibit low overall green efficiency for two very different reasons. If GTE is low, resources are poorly allocated relative to what the region's own technology allows, and the remedy lies in better management, institutional reform, and resource reallocation. If, instead, GTE is high but TGR is low, the region manages its existing technology well, yet its technological frontier itself lags far behind the global frontier. This situation calls for technology acquisition, green R&D, and cross-regional technology transfer rather than further managerial tightening. Distinguishing between these two scenarios is precisely what an international benchmark such as the San Francisco Bay Area makes possible, and it constitutes the central diagnostic question of this study.

The meta-frontier approach has been widely applied in cross-group and cross-country energy and environmental efficiency studies, for example in benchmarking carbon emission performance across heterogeneous production technologies [15]. These applications demonstrate the framework's strength in comparing units operating under different technologies on a common basis, which is precisely the situation facing a comparison between an emerging Chinese urban agglomeration and a mature U.S. technology hub. However, very few studies have applied this framework to directly benchmark a major Chinese urban agglomeration against a technologically mature international counterpart such as the San Francisco Bay Area, leaving the nature of the green development gap between them largely unexplored.

2.4. Research gap and the present study

Taken together, the preceding review points to three gaps in the literature.

First, despite the continuous methodological advances, the way GTFP has been applied leaves a fundamental question unanswered. Most applications evaluate green performance within a single national or regional framework, implicitly assuming a common technology set. When a region underperforms under such a framework, the result cannot reveal whether the deficit is managerial or technological. A managerial deficit arises when resources are poorly allocated relative to what the region's own technology allows, whereas a technological deficit arises when the region's frontier itself lags behind the global frontier. Because the two diagnoses call for fundamentally different remedies, this inability to separate them is a consequential, not merely technical, limitation.

Second, emerging Chinese urban agglomerations have rarely been placed on the same yardstick as mature international counterparts. Existing studies compare Chinese cities with one another, which documents relative positions within China but is silent on where Chinese agglomerations stand relative to the global green technology frontier. Consequently, both the size and the nature of the green development gap between an emerging megaregion like the YRD and a mature global hub like the SFBA remain unknown.

Third, the spatial dimension of green productivity remains underexplored. Little evidence exists on how GTFP is distributed across cities within an agglomeration and, more importantly, whether green technologies diffuse spontaneously across city boundaries. This matters directly for policy: if green technologies do not flow naturally from core cities to peripheral ones, achieving agglomeration-wide green upgrading will require deliberate, policy-driven intercity technology transfer.

The present study addresses these gaps. Using a unified meta-frontier framework, it benchmarks green efficiency in the Yangtze River Delta and the San Francisco Bay Area over 2004–2023, decomposing green performance into GTE and TGR to diagnose whether the YRD's green challenges stem from managerial inefficiency or from technological backwardness relative to the global frontier. This study further examines the

spatial heterogeneity of green efficiency across cities to establish whether green productivity is locally confined, with direct implications for the design of intercity green technology transfer policies.

3. Methodology and data collection

3.1. Research scope and data sources

This study selects two representative world-class urban agglomerations as research objects: the Yangtze River Delta (YRD) in China and the San Francisco Bay Area (SFBA) in the United States. As two of the most economically advanced regions in their respective countries, both exhibit strong technological innovation capacities and face significant environmental governance pressures. Furthermore, the availability of reliable public data ensures strong comparability and substantial research value.

Spatially, based on the *Development Plan for the Yangtze River Delta Urban Agglomeration* issued by the State Council of China, the YRD encompasses 26 core cities across Shanghai Municipality and Jiangsu, Zhejiang, and Anhui Provinces. The SFBA consists of its nine constituent counties. In this study, individual cities or counties are treated as the basic Decision-Making Units (DMUs) (see Table 1). Temporally, considering data availability and statistical consistency between the two countries, the sample period spans from 2004 to 2023. Because the capital input is measured by GDP in the preceding period, GDP data begin in 2003, whereas all other variables are observed over 2004 to 2023.

Data are mainly sourced from official statistical agencies. For the SFBA, economic and employment data are obtained from the U.S. Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS). Energy consumption is sourced from the California Energy Commission, and pollutant emissions are derived from the California Air Resources Board (CARB). For the YRD, data are collected from the statistical yearbooks of Shanghai, Jiangsu, Zhejiang, and Anhui.

Table 1. Studied cities (DMUs)

Group	Urban agglomeration	Cities (DMUs)
1	San Francisco Bay Area	Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, Sonoma
2	Yangtze River Delta	Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Yancheng, Taizhou, Hangzhou, Ningbo, Wenzhou, Huzhou, Jiaxing, Shaoxing, Jinhua, Zhoushan, Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou, Xuancheng

3.2. Variable selection

In this study, the selection of inputs and outputs is guided by established economic theory and the precedent of prior environmental efficiency literature. Each city is modeled as a DMU. Following the classical Cobb-Douglas production function framework, it selects capital, labor, and energy as inputs.

Capital is represented by Gross Domestic Product (GDP), which serves as a proxy for economic scale and capital stock. Because consistent capital stock data at the city or county level are unavailable for both countries over the long sample period, GDP offers a comparable proxy across the two urban agglomerations. Employment (*L*) reflects the contribution of labor to economic output [27]. Electricity consumption (*E*) is employed as a proxy for energy input, which is standard practice when comprehensive energy statistics are unavailable.

GDP in period t (Y) is selected as the desirable output, reflecting the economic performance achieved after utilizing inputs in preceding period. Sulfur oxide emissions (S) are selected as the undesirable output. SOx is a major pollutant generated from fossil fuel combustion and industrial production. Given practical constraints in long-term, cross-regional data collection, SOx provides the most consistent and comparable pollution indicator across the sample period [28].

To ensure clarity in the empirical analysis, the selected variables are formally defined as follows:

G denotes GDP in period $t - 1$;

L denotes employment in period t ;

E denotes electricity consumption in period t ;

Y denotes GDP in period t ;

S denotes Sulfur Oxide (SOx) emissions in period t .

Capital input is measured by GDP in period $t - 1$, whereas labor, electricity, the desirable output, and the undesirable output are measured in period t . This lagged capital structure reflects the time required for capital accumulation to translate into economic output.

3.3. Static green efficiency: SBM model

Data Envelopment Analysis (DEA) provides a non-parametric framework for evaluating the relative efficiency of Decision-Making Units (DMUs) by constructing a Production Possibility Set (PPS) based on observed input-output combinations. The efficient frontier, derived from this set, represents the best attainable performance under given technology.

Among the early DEA models, the CCR model [5] adopts a radial approach to measure efficiency by proportionally reducing inputs and projecting each DMU onto the efficiency frontier. However, a key limitation of radial models is that, even after the proportional adjustment is completed, they fail to capture input excesses and output shortfalls, commonly referred to as slacks. As a result, a DMU may be deemed efficient in a radial sense while still exhibiting inefficiencies in specific inputs or outputs.

To address this limitation, Tone [6] proposed the Slacks-Based Measure (SBM) model, a non-radial and non-oriented DEA approach that directly incorporates input and output slacks into the efficiency measure. Unlike radial models, SBM evaluates efficiency by considering the average proportional reduction of inputs and expansion of desirable outputs, while explicitly accounting for all slacks, thereby providing a more comprehensive and accurate assessment of performance.

Furthermore, in many real-world applications such as environmental and energy studies, production processes generate not only desirable outputs but also undesirable outputs such as pollution emissions, which should be minimized rather than maximized. The SBM framework was extended by Tone [7] to accommodate undesirable outputs by treating their excesses as inefficiency through slack variables that are required to be reduced rather than expanded. This allows the model to simultaneously account for input redundancy, desirable output shortfalls, and undesirable output excesses, leading to a more comprehensive and realistic efficiency assessment in sustainability analysis.

For notational simplicity, the time subscript is suppressed in the following specification; capital input is measured in period $t - 1$, whereas all other variables are measured in period t , as defined in Section 3.2. The SBM model with undesirable outputs is specified as follows (Equation (1)):

$$\min \rho = \frac{1 - \frac{1}{3} \left(\frac{s_G^-}{G_0} + \frac{s_L^-}{L_0} + \frac{s_E^-}{E_0} \right)}{1 + \frac{1}{2} \left(\frac{s_Y^+}{Y_0} + \frac{s_S^+}{S_0} \right)} \quad (1)$$

subject to the constraints in Equations (2)-(7):

$$G_0 = \sum_{j=1}^n \lambda_j G_j + s_G^- \quad (2)$$

$$L_0 = \sum_{j=1}^n \lambda_j L_j + s_L^- \quad (3)$$

$$E_0 = \sum_{j=1}^n \lambda_j E_j + s_E^- \quad (4)$$

$$Y_0 = \sum_{j=1}^n \lambda_j Y_j + s_Y^+ \quad (5)$$

$$S_0 = \sum_{j=1}^n \lambda_j S_j + s_S^b \quad (6)$$

$$\lambda_j \geq 0 \quad (7)$$

where s_G^- , s_L^- , and s_E^- represent excesses in capital, labor, and electricity inputs, respectively; s_Y^+ denotes shortfall in desirable output GDPt; and s_S^b measures excessive Sulfur Oxide (SOx) emissions.

3.4. Urban agglomeration comparison: meta-frontier framework

In this study, the Green Total Factor Productivity (GTFP) of each city is measured by its Meta-frontier Technical Efficiency (MTE). Accordingly, GTFP and MTE are used interchangeably hereafter.

To further compare green production performance between the two urban agglomerations, this study adopts the meta-frontier SBM-DEA framework, which is more suitable than the conventional DEA framework for cross-regional analysis under heterogeneous technological conditions.

The meta-frontier approach was originally proposed by Battese and Rao [12] and further developed by Battese et al. [13] and O'Donnell et al. [14] to evaluate Decision-Making Units (DMUs) operating under heterogeneous technologies. Unlike the conventional DEA framework, which assumes that all DMUs share a common production frontier, the meta-frontier framework allows different groups to possess their own group-specific frontiers while simultaneously constructing a common meta-frontier that envelops all groups. This makes it possible to distinguish differences in managerial efficiency from differences in technological capability across groups.

In recent years, the meta-frontier framework has been increasingly applied in studies of green total factor productivity, energy efficiency, and regional environmental performance, particularly in cross-regional and cross-country comparative analyses. By combining the meta-frontier approach with the SBM model that incorporates undesirable outputs, this study compares GTFP between the two urban agglomerations while accounting for environmental constraints.

Group Technical Efficiency (GTE) is first calculated relative to the group-specific production frontier and is defined as (Equation (8)):

$$GTE_i = \rho_i^G \quad (8)$$

where ρ_i^G represents the SBM efficiency score of DMU_i relative to its corresponding group frontier. GTE reflects the relative green production efficiency within each urban agglomeration.

Meta-frontier Technical Efficiency (MTE) is then calculated relative to the common meta-frontier and is defined as (Equation (9)):

$$MTE_i = \rho_i^M \quad (9)$$

where ρ_i^M denotes the SBM efficiency score of DMU_i relative to the global meta-frontier. Compared with GTE, MTE reflects the green production efficiency of each DMU under the frontier technology shared across all groups. Both ρ_i^G and ρ_i^M are computed by applying the SBM model specified in Section 3.3 to the respective frontiers.

To measure the technology gap between the group frontier and the meta-frontier, the Technology Gap Ratio (TGR) is calculated as shown in Equation (10):

$$TGR_i = \frac{MTE_i}{GTE_i} \quad (10)$$

where TGR_i represents the distance between the group frontier and the global meta-frontier. A higher TGR indicates that the production technology of the DMU is closer to the global frontier, whereas a lower TGR suggests a larger technological gap. Accordingly, a high GTE combined with a low TGR indicates that a region manages its own technology efficiently yet lags behind the global frontier, which is precisely the diagnosis this study seeks to make.

4. Results and empirical analysis

4.1. Descriptive statistics and group comparison

Table 2 presents the descriptive statistics for the entire sample, while Table 3 details the independent samples t-test comparing the two urban agglomerations. The t-test reveals significant differences at the 0.1% level ($p < 0.001$) for employment, electricity consumption, and SOx emissions, with the YRD exhibiting substantially higher resource inputs and pollution levels. By contrast, the desirable output measured by $GDP(t)$ shows no statistically significant difference between the two groups ($p = 0.189$), indicating comparable average economic scales. Capital input measured by $GDP(t-1)$ also differs only marginally between the groups ($p = 0.076$).

Table 2. Descriptive statistics of the full sample

	Obs	Mean	Std. Dev	Min	Max
GDP(t-1) (million USD)	700	71,641	85,548	912	669,896
Employment (1,000 persons)	700	824.80	1,063.38	63.80	7,304.60
Electricity (10k kWh)	700	2,868,303	3,473,600	119.44	18,488,109
GDP(t) (million USD)	700	77,286	90,606	1,117	669,896
SOx (tons)	700	35,865.06	54,672.82	16.02	496,377

Note: GDP is expressed in millions of USD and converted using annual exchange rates. $GDP(t-1)$ denotes capital input measured by the preceding period's GDP, while $GDP(t)$ denotes the desirable output measured by the current period's GDP.

Table 3. Group comparison (t-test)

Variable	Mean (SFBA)	Mean (YRD)	Difference (SFBA – YRD)	t-statistic	p-value
GDP(t-1) (million USD)	80,733	68,494	12,240	1.78	0.076
Employment (1,000 persons)	392.48	974.44	-581.96	-10.28	< 0.001
Electricity (10k kWh)	570,388	3,663,735	-3,093,348	-18.56	< 0.001
GDP(t) (million USD)	84,396	74,824	9,572	1.32	0.189
SOx (tons)	1,726.61	47,682.22	-45,955.61	-17.72	< 0.001

Note: The San Francisco Bay Area (SFBA) comprises nine counties, while the Yangtze River Delta (YRD) comprises twenty-six cities.

4.2. Spatial heterogeneity of green efficiency

Figures 1 and 2 present the spatial distribution of average green efficiency, measured by the Meta-frontier Technical Efficiency (MTE) averaged over 2004 to 2023, in the San Francisco Bay Area (SFBA) and the Yangtze River Delta (YRD).

In the San Francisco Bay Area, most counties reach MTE values close to the global frontier, with Marin, San Francisco, Napa, Solano, and Santa Clara at 1.000 and San Mateo at approximately 0.998. By contrast, only three counties, Alameda, Contra Costa, and Sonoma, record markedly lower values of approximately 0.77 to 0.78, creating a clear spatial divide between frontier and lagging counties.

The Yangtze River Delta exhibits a wider dispersion. Shanghai reaches the frontier at 1.000, followed by Chizhou at 0.983, while a middle tier of cities, including Hangzhou, Nanjing, Suzhou, Wuxi, and Changzhou, ranges from roughly 0.80 to 0.88. Many peripheral manufacturing cities, such as Huzhou, Jiaxing, Shaoxing, Yangzhou, and Wenzhou, fall below 0.78, with the lowest value around 0.71. This wide range indicates substantial technological heterogeneity across the agglomeration.

Although cities with relatively high MTE tend to be geographically adjacent in both agglomerations, the Global Moran's I and Local Moran's I (LISA) analyses reveal no statistically significant spatial autocorrelation. This result is informative in its own right. It indicates that the observed spatial patterns reflect heterogeneity rather than significant clustering or spillover effects, and that green productivity is highly localized, driven primarily by city-specific characteristics such as local industrial structure and environmental regulation rather than by spillovers from neighboring cities. This finding stands in sharp contrast to the strong spatial interconnectedness documented for economic activity and market integration within Chinese urban agglomerations [1, 29]. The absence of significant spatial autocorrelation in green efficiency therefore highlights a key challenge of urban agglomeration development: the pace of economic integration has outpaced that of environmental and technological integration. Because green technologies do not appear to diffuse spontaneously across city boundaries, achieving agglomeration-wide green upgrading will require deliberate, policy-driven intercity technology transfer rather than reliance on market-driven spillovers.

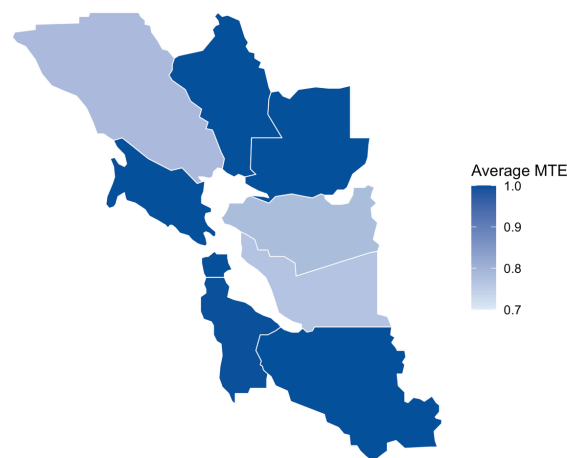


Figure 1. Spatial distribution of average MTE in the San Francisco Bay Area

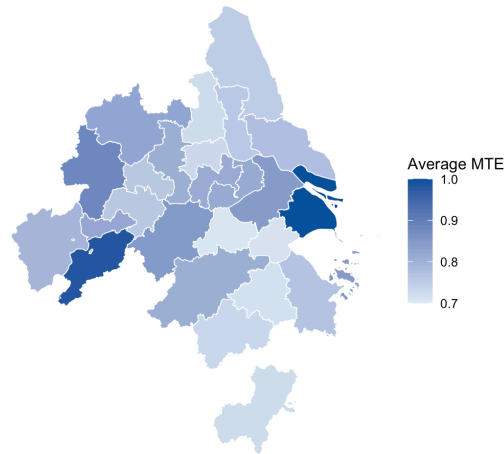


Figure 2. Spatial distribution of average MTE in the Yangtze River Delta

4.3. Inter-urban agglomeration comparison based on the meta-frontier framework

4.3.1. Group-level comparison

To further compare green production performance between the Yangtze River Delta and the San Francisco Bay Area, this study applies the meta-frontier SBM-DEA framework and calculates the Group Technical Efficiency (GTE), the Meta-frontier Technical Efficiency (MTE), and the Technology Gap Ratio (TGR) for each urban agglomeration. Table 4 reports the descriptive statistics of these three indicators.

As Table 4 shows, the San Francisco Bay Area records a slightly higher average GTE (0.920) than the Yangtze River Delta (0.914), indicating that the two agglomerations achieve broadly comparable levels of managerial efficiency within their respective production frontiers. By contrast, the average MTE differs substantially, reaching 0.920 in the SFBA but only 0.795 in the YRD. This gap is driven almost entirely by the technology gap ratio: the SFBA exhibits a TGR of 1.000 with an almost zero standard deviation, meaning that its group frontier essentially coincides with the global meta-frontier. In contrast, the YRD records an average TGR of only 0.873, with a standard deviation of 0.124 and values ranging from 0.630 to 1.000, indicating noticeable technological heterogeneity across cities.

These results carry a clear interpretation. Because MTE equals GTE multiplied by TGR, the similar GTE values combined with the much lower TGR imply that the YRD's weaker overall green performance stems primarily from a technological gap rather than from managerial inefficiency. The YRD manages its own production frontier efficiently, yet that frontier itself lags behind the global frontier embodied by the SFBA. The identical GTE and MTE values in the SFBA further confirm that its group frontier almost coincides with the meta-frontier, highlighting its frontier leadership in green technology. The heterogeneity in the YRD's TGR warrants further attention: the wide range from 0.630 to 1.000 indicates that the region's technology gap is not uniform, with some cities approaching the global frontier and others lagging significantly. This internal differentiation suggests that the YRD's overall green technology gap is concentrated in a subset of cities, which has direct implications for targeting intercity technology transfer. The following section examines such city-level differences in more detail.

Table 4. Descriptive statistics of meta-frontier efficiency indicators

Panel A. San Francisco Bay Area				
	Mean	Std. Dev.	Min	Max
GTE	0.920	0.127	0.644	1
MTE	0.920	0.127	0.644	1
TGR	1	0.000	1	1
Panel B. Yangtze River Delta				
	Mean	Std. Dev.	Min	Max
GTE	0.914	0.103	0.647	1
MTE	0.795	0.138	0.573	1
TGR	0.873	0.124	0.630	1

4.3.2. Temporal evolution of GTE, MTE, and TGR

Figure 3 illustrates the temporal evolution of GTE, MTE, and TGR for the Yangtze River Delta (YRD) and the San Francisco Bay Area (SFBA) from 2004 to 2023.

The San Francisco Bay Area exhibits a highly stable pattern throughout the period. Its TGR remains constant at exactly 1.000, indicating that the regional production frontier consistently coincides with the global meta-frontier. As a result, the GTE and MTE curves almost completely overlap, fluctuating narrowly around 0.90 with only minor variation. This stability confirms the Bay Area's persistent and unchallenged technological leadership in green production.

In contrast, the Yangtze River Delta displays pronounced temporal fluctuation. Its GTE remains relatively stable at around 0.90 to 0.93, reflecting consistently high managerial efficiency within its own frontier. However, the MTE is consistently lower and far more volatile, falling from approximately 0.93 in the early years to around 0.72 in 2012, recovering to about 0.83 around 2018, and declining again to roughly 0.68 towards the end of the period. The TGR follows a similar pattern, tracing the gap to the global frontier: it starts close to 1.00 in 2004, falls to approximately 0.75 in 2012, rebounds to about 0.92 in 2018, and drops again to about 0.74 in 2023.

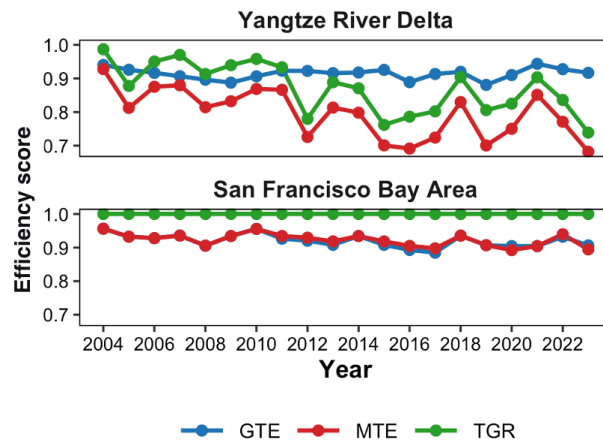


Figure 3. Temporal trends of GTE, MTE, and TGR in the Yangtze River Delta and the San Francisco Bay Area

The widening divergence between the stable GTE and the declining MTE likewise indicates that the deterioration in overall green performance is driven primarily by an expanding technology gap rather than by changes in managerial efficiency. These temporal patterns suggest that while the YRD has largely maintained its internal production efficiency, its technological progress has failed to keep pace with the global frontier embodied by the SFBA. By contrast, the persistent stability of the SFBA confirms its role as the technological benchmark under the meta-frontier framework.

4.3.3. *Intra-urban agglomeration comparison*

To further explore the heterogeneity within each urban agglomeration, this section compares cities with the highest and lowest Meta-frontier Technical Efficiency (MTE). Table 5 summarizes the representative frontier cities and the low-MTE groups identified in this comparison.

In the San Francisco Bay Area, San Francisco consistently achieves the frontier level of 1.000, reflecting its strong innovation capacity, concentration of knowledge-intensive industries, and mature environmental governance. At the other end, Alameda records the lowest average MTE of about 0.770, with Contra Costa and Sonoma at similar levels. Crucially, because the TGR of the SFBA equals one, these relatively low MTE values reflect lower group technical efficiency rather than any technology gap. Their lag is thus a matter of local structure and management, associated with a larger share of manufacturing, logistics, and energy-intensive activities.

The Yangtze River Delta shows a contrasting pattern. Shanghai reaches the frontier with an MTE of 1.000, leading the region in technological innovation, industrial upgrading, and green development. Yet the lowest performers are not a single outlier but a group of peripheral manufacturing cities, including Huzhou (0.708), Jiaxing (0.712), and Shaoxing (0.714), together with Yangzhou and Wenzhou, all clustering in the range of approximately 0.71 to 0.73. Unlike the SFBA, these cities maintain relatively high group technical efficiency but exhibit low technology gap ratios, meaning their weakness is a technology gap rather than managerial inefficiency.

This pattern is consistent with a green transition penalty. These peripheral cities find themselves in the middle of an industrial transition: stringent environmental regulation has already tightened the constraint on traditional high-pollution activities such as manufacturing, textile, and chemical production, compressing their conventional output [30]. At the same time, the high-value-added, low-emission sectors that could take over, such as high-tech manufacturing, the digital economy, and modern services, have not yet matured sufficiently to compensate. The result is a half-completed transition in which these cities are penalized twice under the demanding global meta-frontier: their traditional output is constrained by regulatory pressure, while their fledgling green sectors do not yet generate enough output to offset the loss. This leaves them with low desirable output relative to inputs, suppressing their MTE. By contrast, cities such as Shanghai have already completed this transition, relying on technology-intensive and service-oriented activities that are both low-emission and high-output, and therefore achieve frontier efficiency. The peripheral manufacturing cities, however, are caught between an old economy that is being squeezed and a new economy that has not yet arrived.

Beyond these representative cases, the YRD displays a clear three-tier structure in MTE. A small group of frontier cities led by Shanghai sits at or close to 1.000, a middle tier comprising Hangzhou, Nanjing, Suzhou, Wuxi, and Changzhou ranges from roughly 0.80 to 0.88, and a large peripheral tier of manufacturing cities falls below 0.78, accounting for about half of the agglomeration. This ladder distribution indicates that the technology gap is systemic rather than confined to a few outliers, and that the transition penalty described above affects an entire class of peripheral manufacturing cities rather than any single case. By contrast, the middle and frontier tiers have undergone more successful upgrading towards technology-intensive activities.

The comparison is revealing. Within the two agglomerations, cities at the bottom of the efficiency distribution suffer from opposite problems. In the SFBA, the lagging cities fall behind because of managerial and structural inefficiency, with no technological gap, since their group frontier coincides with the meta-frontier. In the YRD, the lagging cities manage their own technology reasonably well yet still fall behind because of a persistent technology gap. This divergence reinforces the central message of the meta-frontier analysis: the green bottleneck of the Yangtze River Delta is not a matter of management but of technological backwardness relative to the global frontier.

Table 5. Representative cities and low-MTE groups under the meta-frontier framework

Agglomeration	Frontier city	MTE	Low-MTE group (representative cities)	MTE range
SFBA	San Francisco	1.000	Alameda, Contra Costa, Sonoma	0.76–0.78
YRD	Shanghai	1.000	Huzhou, Jiaxing, Shaoxing, Yangzhou, Wenzhou	0.71–0.73

5. Conclusion

This study benchmarks green efficiency in two world-class urban agglomerations, the Yangtze River Delta and the San Francisco Bay Area, within a unified meta-frontier framework. By applying the SBM model with undesirable outputs and decomposing overall efficiency into Group Technical Efficiency (GTE) and the Technology Gap Ratio (TGR), the study diagnoses whether the green development gap of the YRD stems from managerial inefficiency or from technological backwardness relative to the global frontier. Spatial autocorrelation analysis further examines how green productivity is distributed across cities.

The empirical results yield three main findings. First, the two agglomerations are broadly comparable in economic scale, and both achieve high managerial efficiency, with average GTE values of 0.920 and 0.914 respectively. This indicates that the YRD manages its own production frontier as effectively as the SFBA. Second, the overall green performance gap is driven almost entirely by technology: the SFBA exhibits a TGR of 1.000, meaning its group frontier coincides with the global meta-frontier, whereas the YRD records a TGR of only 0.873, ranging from 0.630 to 1.000. The temporal analysis further shows that this technology gap has widened rather than narrowed, with the YRD's stable GTE accompanied by a declining and volatile TGR. Third, green productivity is spatially localized: the Moran's I and LISA analyses reveal no significant spatial autocorrelation, indicating that green technologies do not diffuse spontaneously across city boundaries and that economic integration has outpaced environmental and technological integration.

These findings carry two policy implications for the Yangtze River Delta. First, because the YRD's managerial efficiency is already high and comparable to that of the SFBA, further pressure to improve management efficiency is unlikely to yield substantial gains. Policy should instead shift toward advancing the technological frontier, in particular through investment in green technology research and development, to narrow the TGR gap with the global frontier. Second, the absence of spatial spillovers in green productivity means that green technologies will not flow naturally from core cities to peripheral ones. The YRD therefore needs explicit policies that mandate or incentivize green technology transfer from leading cities such as Shanghai to peripheral manufacturing cities such as Huzhou and its peers, which currently bear a green transition penalty.

This study has several limitations that point to future research. The analysis covers only two urban agglomerations, which limits the generalizability of the findings. The measurement of green efficiency relies on a limited set of indicators, with SO_x as the single undesirable output. Future research could incorporate

additional pollutants such as carbon dioxide emissions and wastewater discharge, and extend the comparison to more urban agglomerations across countries, to build a broader understanding of the green technology gap between emerging and mature regions.

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