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Measuring the Efficiency of High-Quality Development in the Yangtze River Basin: A DEA-SBM Approach and Convergence Analysis

PhD Dissertation

CHEN RURONG

Budapest University of Economics and Business

Doctoral School of Entrepreneurship and Business

Supervisor: Prof. Dr. Miklós Losoncz

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DECLARATION

Hereby, I certify that the Ph.D. theses entitled **Measuring the Efficiency of High-Quality Development in the Yangtze River Basin: A DEA-SBM Approach and Convergence Analysis** is solely my work. It contains no material previously written or /and published by any other academic degree or diploma. Any previously published materials used in this dissertation are for bibliographical reference.

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Date: July 15, 2025

The name of the author: Chen Rurong

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Contents

List of acronyms

3Es: Energy–Economic–Environmental efficiency

AI: Artificial Intelligence

YREB: Yangtze River Economic Belt

BCC: Banker-Charles-Cooper

BRI: Belt and Road Initiative

CCR: Charles-Cooper-Rhodes

CCS: Carbon Capture and Storage

CPC: Communist Party of China

VRS: Variable Returns to Scale

MIPOs: Multiple-Input-Multiple-Output Scenarios

CSMAR: China Stock Market & Accounting Research Institution

CV: Coefficient of Variation

DEA: Data Envelopment Analysis

DMU: Decision Making Unit

ETM: Emission Trading Markets

FYP: 14th Five-Year Plan

GVC: Global Value Chain

HQD: High-quality Development

KMO: Kaiser–Meyer–Olkin

MRIO: Multi-Regional Input-Output

MIT: Diddle-income Trap

NBS: National Bureau of Statistics

NEV: New Energy Vehicle

PC: Principal Component

PCA: Principal Component Analysis

PTE: Pure Technology Efficiency

PV: Photovoltaic

R&D: Research and Development

SBM: Slacks-Based Measure

SDA: Structural decomposition analysis

SE: Scale Efficiency

TE: Technical Efficiency

TFP: Total Factor Productivity

TNDDF: Total factor Non-radial Directional Distance Function

VECM: Vector Error Correction Modelling

YREB: Yangtze River Economic Belt

YRB: The Yangtze River Basin

YRD: Yangtze River Delta

PCs: Principal Components

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Abstract

The objective of this dissertation is to analyse China's shift from the extensive growth model based on the quantity of labour and capital to the intensive growth trajectory built on new drivers such as R&D, innovation, and human capital accumulation. The dissertation presents a regional perspective with the help of the example of the Yangtze River Basin (YRB). Due to its economic importance, diverse industrial environment, and policy-driven growth efforts, this region is an appropriate candidate for comprehensive economic discussion. A composite principal component analysis–slacks-based measure (PCA-SBM) model was applied to comprehensively assess regional economic development and to pinpoint the underlying causes of economic inefficiency. This methodology enabled quantifying the productivity dynamics of twelve provinces within the Yangtze River Basin between 2012 and 2021. My dissertation's primary original methodological contribution to the existing body of knowledge is integrating an input-output model with the PCA-SBM framework to evaluate the region's transition to a high-quality growth trajectory. An extensive review of data envelopment analysis panel data (2012–2021) from 12 provinces revealed the following four principal trends: (1) Developed regions have witnessed an annual increase in high-quality efficiency, which growth is aligned with pure technology efficiency and scale efficiency. (2) The eastern and western regions exhibit disparities in structural technical efficiency, pure technology efficiency and scale efficiency, which exacerbated the distinct characteristics of the regions due to various input resources. (3) The core provinces of the YRB with relatively high-efficiency values functioned as growth engines since they can support the adjacent low-efficiency regions, thereby fostering convergence and driving regional economic development. (4) A significantly higher rate of technical efficiency convergence was recorded in the 12 provinces with faster scale efficiency gains compared to those with pure technical efficiency. This novel output reinterprets previous research on regional efficiency by assessing high-quality development efficiency in line with China's 14th Five-Year Plan indicators, and this novel output dynamically compares regional convergences while emphasising the critical importance of scale efficiency alongside pure technical efficiency. The major limitation of the dissertation is the constraint for data availability from 2012 to 2021, which results in the exclusive use of pure technical efficiency and scale efficiency as control variables in the convergence study. Future research will expand the study to encompass the 31 provinces of China and the YRB, and will compile data indicators more comprehensively from the five aspects to calculate efficiency

values. Additional control variables will be introduced to quantify the relative beta convergence of various locations, such as political system, institutions, infrastructure, and production factors.

Journal of Economic Literature (JEL) codes: C52, C67, E20, E62, O11.

Keywords: High-quality economy, energy economic transformation, PCA-SBM model, regression model, the Yangtze River Basin, China's 14^{th} Five-Year Plan of China, convergence analysis, technical efficiency, pure technical efficiency, scale efficiency.

1. Introduction

Regarding the *antecedents and the research background*, this dissertation is based on the extensive academic knowledge gained during my undergraduate education at Beijing Technology and Business University and my master's and PhD studies at Budapest University of Economics and Business over the past ten years. These experiences have equipped me with appropriate analytical skills and a thorough comprehension of economic theories, research methods, and procedures, which established the intellectual foundations of my PhD dissertation.

In addition to my broad professional background, *the dissertation is firmly rooted in scientific research conducted during my PhD studies*. Besides coursework, it heavily relies on assignments, research reports, and scientific publications I produced while completing my PhD program. My publications and research papers are included in the dissertation not as separate units but are presented in a synthesised form as part of a coherent scientific research concept with the appropriate methodology that meets the academic standards of PhD dissertations. (The list of my publications is presented at the end of the dissertation.)

Concerning my *motivations* in choosing the topic, as a Chinese citizen, I tried to combine the advantages of my Chinese language knowledge and familiarity with the local circumstances with the human capital accumulated during my studies in Hungary. The dissertation may provide insights for Hungary as this country, like China, encounters issues of structural adjustment amid limitations of data availability, regional heterogeneity, and international competition. Despite the disparity in the magnitude of the two economies, the fundamental challenges of efficiency, sustainability, and convergence characterising these countries are comparable.

This dissertation focuses on China's evolving growth model or development trajectory. The starting point for identifying the problem is that China is confronting *multiple short- and long-term challenges*, such as tensions in the real estate market and the financial system, an ageing population, declining birth rates, severe environmental problems, fierce global technology competition, and decelerating GDP growth. The transition to the new development trajectory occurs in a *specific international environment* that has unfolded over the past few years. The major *external challenges* emanating from global trends comprise inter alia different aspects of globalisation, trade wars, weakening of the rules-based world order, the Covid-19 pandemic in the short term, as well as environmental, climate and demographic issues, digitisation, the development of artificial intelligence (AI) and the future of global value chains (GVC) in the long term. The unfolding impacts of the external environment are diverse: some of the elements underpin China's transition, while others impede it. Both factors affect China's shift in one way or another. The transition concerns domestic regional economic development as well. Analysing the identified problems offers promising perspectives for scientific research with theoretical and practical implications.

From a broader perspective, the *primary reasons* behind these challenges include the exhaustion of the former driving factors of GDP growth, including a cheap unskilled or semiskilled labour force, cheap fuels and raw materials and considerable investments in traditional heavy industries. These challenges call for a transition from an *extensive economic development model* based on quantitative factors of GDP growth, such as the mere quantity of labour and capital, to an *intensive development model* that relies on qualitative factors, such as research, development and innovation (R+D+I), highly skilled human capital (knowledge-based economy), and economic structure upgrading with reduced regional disparity and income inequality (Losoncz, 2017).

In a different approach, with the decline of conventional growth engines, China's economic transition denotes the shift from *a factor-driven growth model*, which model is historically dependent on labour force expansion and capital accumulation, to a *high-quality development model* emphasising innovation, sustainability, and efficiency. The transition requirements can be examined using the *United Nations Human Development Index* (HDI) (UNDP, 1990), which measures a country's or a region's human development comprehensively based on per capita income, life expectancy and education. However, the HDI does not include the efficiency of the input-output process and resource waste.

In responding to the current challenges and the promotion of long-term, sustainable economic development, the primary task of economic policy decision-makers is to transform China into a *high-quality economy* that is characterised by five factors: (1) sustainability, (2) innovation, (3) efficiency, (4) stability and (5) coordination (Pacetti, 2016). A high-quality economy should employ innovation to boost economic efficiency and productivity while avoiding irreparable environmental and natural resources harm, securing regional coherence, and establishing regional connections (Li & Yi, 2020).

The change in the growth trajectory is based on *theoretical considerations and empirical evidence* of the *middle-income trap* (MIT) concept, according to which countries that have reached a specific economic development level in terms of per capita GDP encounter difficulties in maintaining their former high GDP growth rates and thereby catch up with the advanced economies for a significant number of reasons. The transition to the new technology-intensive and knowledge-based growth path is a precondition of leaving behind MIT and of enabling countries to gradually approximate their per capita income level to that of advanced economies.

Following the above-mentioned challenges, the importance of this dissertation is obvious. The Sustainable Development Goals (SDGs) of the UN, especially SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure), are closely related to high-quality economic development on a worldwide scale (Assembly, 2015). This study offers developing nations aiming to strike a balance between ecological goals and economic growth a methodological reference by measuring efficiency under environmental restrictions. China is moving from “high-speed growth” to “high-quality growth,” a shift that is directly related to the 2020 “dual circulation” plan (Bairam et al., 2025). According to the dual circulation framework, innovation and upgrading of consumption propel domestic circulation, which is the primary engine of the economy. The Yangtze River Economic Belt’s development efficiency is evaluated in this study in order to specifically analyse how this strategy is being implemented regionally. With significant policy ramifications for maximizing domestic circulation structure, the observed convergence in technological efficiency might, for instance, be a reflection of advancements in inland provinces to modernize industrial value chains and integrating into domestic markets.

This dissertation assumes that the transition to the new development trajectory may occur spontaneously, relying on inherent processes and trends supported by governmental economic policies. Changes in the external environment may trigger spontaneous reactions. Nevertheless, it is assumed that the shift is not exclusively spontaneous, and government policies also play a part. According to empirical evidence, the Chinese government has promoted this process with various policy measures. While high-quality development is primarily conceptualized in Chinese policy as a supply-side transformation, the demand-side dynamics (e.g., weak domestic consumption and strong external demand) can distort regional growth patterns. This study acknowledges this tension but focuses mainly on production-side efficiency, suggesting that future research should integrate demand indicators. As for the methods side, regional development methodologies, including Data Envelopment Analysis (DEA) and convergence analysis, provide empirical tools to evaluate relative performance across territories. While DEA offers a non-parametric approach to measuring technical efficiency, it remains fundamentally descriptive and lacks the capacity to isolate causal mechanisms. That means that the DEA-SBM model is inherently non-parametric and descriptive. Accordingly, this approach measures relative efficiency but does not establish causal relationships between input variables and efficiency outcomes. Convergence models attempt to capture dynamic adjustment processes but often rely on simplified assumptions about homogeneity and exogeneity that may not hold in rapidly developing economies such as China's Yangtze River Basin.

The *general objective of my dissertation* is to analyse this transformation process. Regarding the research background, the dissertation relies on a broad range of my papers focusing on the in-depth analyses of various industries in the context of China's shift to the new growth model, which contributes to the scientific foundations of this dissertation. They include the following topics:

(1) a detailed literature review based on Scopus data, combined with CiteSpace software for research to identify the relevant literature according to specific keywords,
(2) the MID, discussing the definitions, the interpretations and the analytical tools with implications for China (Chen & Losoncz, 2025b),
(3) the impact of energy transition on China's economic growth under carbon neutral climate policies (Chen, 2023a),
(4) The global implications of China's new energy policy initiative that analyses the relationship between the electricity sector and high-tech industries using an east-west regional approach. The conclusion was that electricity consumption significantly affects software businesses' revenues, while hydropower and thermal power generation suffer significant adverse effects (Chen, 2024),
(5) The future of new electric vehicles as part of the energy transition and policy (Chen et al., 2023),
(6) Tourism' contribution to China's new development strategy concludes that the tourism industry's future lies in technological innovation (Chen, 2022a),
(7) The effects of the Covid-19 pandemic on SME enterprises (Chen, 2022b).

This dissertation is grounded in two in-depth publications. In the first publications, the economic models and comprehensive analytical techniques for the analysis of the shift to a new development trajectory were identified. This dissertation applies the tools models with real-world data to validate the model's validity. (Chen, 2023b). Based on the methodological report, the second paper evaluated China's high-quality economic development model (Chen & Losoncz, 2025a). Significant statements and conclusions are incorporated into this dissertation.

The dissertation discusses China's transition to the high-quality growth model *using the Yangtze River Basin* (YRB) as an example. (See the map in the Annex indicating the YRB's location in China.) The following factors justify this choice:

(1) The region includes some of China's most economically active provinces, encompassing Shanghai, Wuhan and Chongqing.

(2) It is the core of China's regional economic development, and its coastal area traverses China from the west to the east, comprising 40% of the nation's population and GDP on 20% of China's territory. China's GDP and industrial output are greatly influenced by economic trends in the YRB, offering a mesocosm for examining a wide range of policy-related, social, environmental and economic issues.

(3) Given the region's economic significance, diversity and ongoing development initiatives, it is an appropriate object for in-depth economic and development policy analyses. Based on this, conclusions can also be drawn with respect to the Chinese economy.

The dissertation's *time horizon* is associated with the Chinese policy framework. The analysis starts in 2021 with China's launch of the 14th Five-Year Plan (FYP) and ends in 2024, when the dissertation was completed. This planning document summarises the primary policy objectives of the Chinese government for the subsequent five years. The historical data typically go back to as late as 2010-2012.

Regarding *the nature of the dissertation*, it applies a *mixed methodology* combining quantitative and qualitative analysis. The latter is based on statistical figures that are analysed with different tools and are organised into economic models. The critical overview of publicly available relevant literature highlights the dissertation's conceptual framework and identifies possible *research gaps.* The dissertation also contains elements of impact assessment.

The *specific objective* of this dissertation is, first, to construct a novel evaluation framework for economic development by *establishing an index system based on an efficiency model* with which the transition to a high-quality economy can be analysed. The second objective is to apply the evaluation framework to the Yangtze River Basin, pointing out the differences in the economic development of the eastern and western areas.

The *general research question* is the following: using the example of the YRB region, to what extent has China accomplished the transition to a sustainable and innovative economy in stage-by-stage steps? The *specific research questions* are as follows:

(1) How do efficiency scores (TE, PTE, SE) vary across the eastern, central, and western provinces of the YRB?
(2) To what extent have the observed efficiency disparities decreased over time, as measured by β-convergence and α-convergence?
(3) What are the patterns of convergence in total efficiency, pure technical efficiency, and scale efficiency before and after the 2016 policy adjustments?
(4) How are economic factors such as the consumer price index (CPI) and per capita income inputs associated with variations in efficiency and convergence patterns?

The *approach of the dissertation* is based on *positive economics*, building on objective data analysis combined with elements of *normative economics*, which reflect evaluations, judgments, and conclusions on economic development, investment projects, statements, and scenarios. Building on the qualitative and quantitative analysis of underlying spontaneous trends emanating from the economy's autonomous development, this *dissertation focus*es on *efficiency assessment* associated with the switch to the new trajectory in the context of the sustainability framework.

The *research gaps* are defined in Subchapter 2.3 of section 2. Literature review since they are derived from the analysis of the existing relevant literature. The *hypotheses* are included in Subchapter 3.4 of section 3. Research methodology since they are derived from the chosen methodology.

The remainder of this paper is organised as follows. *Chapter 2* presents the literature review focusing on the significant terms and definitions, theoretical approaches and efficiency measurement methods for identifying the research gaps. *Chapter 3* includes a description of the research methodology, covering the research approaches, the conceptual framework of the research design, the model selection, and data collection and processing. *Chapter 4* contains the results of the efficiency measurement and the convergence analysis. The subject of *Chapter 5* is the discussion of the results, the interpretation of the key findings, the comparisons with other papers, and the theoretical and practical implications. Chapter 6 displays the summary and conclusions, highlighting the scientifically new and novel elements of the dissertation, the limitations of the analysis, and future research directions. Finally, the List of references and the Annex with the list of the candidate's publications are located at the end of the dissertation.

2. Literature review and theoretical background

2.1 Terms, definitions and theoretical approaches

2.1.1 International perspectives: from growth quantity to quality

The notion that "quality" is just as important as "quantity" in economic growth emerged in the discourse on global development in the latter half of the 20th century. The Brundtland Commission provided a well-known definition of sustainable development in 1987 (Development, 1987). It stated that sustainable development "meets the needs of the present without compromising the ability of future generations to meet their own needs." This introduced the concept that economic advancement must harmonise economic, social, and environmental dimensions, establishing the foundation for the U.N. Sustainable Development Goals, which incorporate qualitative elements such as inequality reduction and environmental preservation into growth objectives (Biermann et al., 2017). The World Bank's 2000 report stated that long-term sustainability and stability of growth relied on its quality, including equitable opportunity, environmental stewardship, and strong governance (Bank, 2000). According to Thomas et al., enhancing income distribution, investing in human capital, and safeguarding natural capital contribute to more stable and long-lasting growth (Thomas et al., 1999).

In the 2010s, international economists progressively advocated expanding policy emphasis beyond GDP. In order to control climate change and inequality, for instance, Daniel Susskind argues that governments should "confront the trade-offs" by balancing the social and environmental costs of expansion with its advantages. Major institutions like the IMF have reiterated these concepts (SUSSKIND, 2024). In an IMF assessment of China, Zhou quoted the sentence from Kang that with structural reforms, "sustainable, high-quality growth is well within China's reach," implying that higher-quality growth – even at a more moderate rate – is desirable and achievable (Zhou, 2023). Consequently, there is a global consensus that *high-quality development* (HQD) encompasses sustained, inclusive, environmentally sustainable, and resilient growth—a viewpoint that has shaped China's adoption of the HQD concept.

2.1.2 Chinese Perspective: From high-speed growth to high-quality growth

High-quality development has emerged as a guiding paradigm in economic policy and research, emphasising that growth should be efficient, inclusive, and sustainable rather than rapid.

After decades of rapid growth, China has responded to new socioeconomic issues by embracing the HQD concept. By the middle of the 2010s, Chinese policymakers realised that the previous paradigm of rapid GDP development had resulted in inefficiencies and imbalances, ranging from inequality to surplus capacity and environmental degradation. In 2015, the Chinese government established Five Major New Development Concepts – innovation, coordination, green, openness, and sharing – as a strategy framework for development (KUHN, 2016). President Xi Jinping's address at the 19th CPC (Communist Party of China) National Congress officially stated that "China's economy has shifted from a phase of rapid growth to a stage of high-quality development" (Xinhua, 2017). This signified a pivotal moment that economic policy would subsequently emphasise quality, efficiency, and equilibrium rather than mere rapidity. The primary paradox in Chinese society has been recast as the disparity between "unbalanced and inadequate development and the people's increasing demands for an improved quality of life," highlighting the necessity for more equitable and sustainable progress. During the 20th CPC Congress in 2022, Xi reiterated that "high-quality development is the primary objective in constructing a modern socialist nation," positioning HQD at the centre of China's long-term plan (Xinhuanet, 2023).

Since the 19th CPC Congress, there has been an increase in scholarly efforts, both domestic and international, to define, quantify, and assess HQD. Early studies in China struggled to come to terms with the connotation of HQD (Lingming Chen & Congjia Huo, 2022). Most academics consider it a multifaceted idea that includes social welfare, sustainable environmental practices, economic performance, and innovation. For example, HQD is defined by Wang and Yin as development that, under the direction of new development principles, delivers superior outcomes in social welfare, environmental impact, and resource efficiency, eventually satisfying people's demands for a better living (Wang & Yin, 2019). According to Ma et al., HQD is a more effective, stable, and open development model for the modern period that reflects China's strategic decision in the face of structural difficulties and resource or environmental limitations (MA et al., 2019). However, these criteria reflect the global focus on sustainable and inclusive growth and are adapted to China's specific environment.

Given that HQD is abstract, academicians have made a concerted effort to quantify it through indicator systems. The initial endeavours employed singular proxies for "quality," such as total factor productivity (TFP) growth, as a shorthand for intensive growth or labour productivity and per capita GDP growth for development quality. Recent studies, however, support composite index systems. One popular method is to create a hierarchical index using the five pillars of the development concept: (1) sharing, (2) innovation, (3) coordination, (4) green, and (5) openness (Lingming Chen & Congjia Huo, 2022). Shi Dan et al. are often referenced for developing a five-dimensional evaluation framework (Dan & Peng, 2019). Other researchers have put forth different frameworks: for instance, Li et al. created an index for marine economy HQD with even more detailed sub-indicators (Li et al., 2021), while Yang et al. (2020) constructed indices that emphasise the structure, efficiency, and advantages of growth. Chen and Huo conducted a noteworthy study in English that used five parameters in line with the new development concepts to create a provincial HQD index for China from 2006 to 2019. They discovered that with the composite index shifting from negative (pre-2013) to positive growth, China's total HQD level improved progressively, signifying a shift from widespread low-quality growth to gradually rising quality. According to their index, coordination, greenness, and openness advanced more slowly than innovation-driven and shared development (inclusive growth), which improved the fastest due to significant policy support (L. Chen & C. Huo, 2022). Coastal provinces with sophisticated economies and a propensity for innovation, such as Beijing, Shanghai, Jiangsu, and Zhejiang, routinely topped the HQD rankings. These results highlight that, despite improvements across the country, China's HQD still exhibits regional inequities, a topic covered in numerous research.

Innovation is widely viewed as the core engine of HQD. This resonates with classical growth theory (where technological progress drives long-run growth) and with China's policy mantra of moving from "factor-driven" and "investment-driven" growth to innovation-driven development. The relationship between innovation and HQD has been the subject of numerous studies. For instance, Xiao et al. empirically examined the impact of China's innovation-driven development strategy (introduced in 2012) on the character of economic development. They discovered that China's innovation initiative substantially enhanced the overall development quality by employing an entropy-weighted index of economic development quality (EDQI) and an innovation input index (Xiao et al., 2022). These results bolster the academic consensus that innovation is essential for high-quality development. It boosts TTF, establishes new industries, and assists economies in evading the diminishing returns of extensive input-driven growth (Xin-gang & Jin, 2022). Simultaneously, the results underscore the necessity of innovation policy to prioritise innovation quality, rather than merely the quantity of R&D, to improve development quality genuinely.

The recurring theme is the transition from extensive growth characterised by high resource consumption, labour-intensive expansion, and environmental neglect to intensive growth focused on efficiency and productivity. This transformation fundamentally embodies what HQD represents (Xinhua, 2018). A lot of academics use China's historical development to support this argument. Hu cites the remarkable "quantity-driven" accomplishment of China's GDP growth from 1978 to 2017, which averaged over 9.5% per year (inflation-adjusted). (HU, 2023) However, this came with unbalanced effects, including inequality, low efficiency, pollution, and structural inequities (Zhao et al., 2022). The previous model reached its limits by the mid-2010s when marginal returns on capital were declining. Since then, much has been written about implementing an aggressive growth strategy. TFP is a critical indicator that has been examined. Intensive development is synonymous with an increase in TFP, as it entails more significant output from the same inputs (through technological advancements or efficiency improvements). Studies such as those conducted by Xu et al. contend that China's TFP growth is essential for HQD, mainly to assuage external scepticism regarding the sustainability of China's growth (Xu, 2018). Empirical analyses (e.g., based on Solow residuals or DEA, as discussed below) suggest that China's TFP growth experienced a decline in the 2010s, which has led to demands for an innovation-driven stimulus (XU et al., 2022). Optimising resource allocation is an additional aspect of intensive growth. For instance, productivity can be enhanced by minimising misallocation in capital, labour, and land markets (Huang & Lin, 2025). Institutional inefficiencies impede HQD, as evidenced by a study that demonstrates that land resource misallocation significantly reduces urban green productivity in China. Similarly, digital transformation is recognised as a catalyst for rapid expansion: digital infrastructure and platforms enhance the efficacy of allocation. They can "upgrade" conventional industries, enhancing development (Guo et al., 2024).

In conclusion, the literature agrees that a fundamental shift in the growth paradigm is necessary for high-quality development, as it must transition from a reliance on factor accumulation to productive and efficient practices. This entails implementing institutional reforms, technological innovation, and human capital development to address the three critical changes (quality, efficiency, and motivation) promoted in policy discourse.

2.1.3 Regional patterns: the Yangtze River Basin versus other regions

The Yangtze River Basin has an intermediate position with much internal variance, but the overall trend is that China's eastern regions perform better in HQD than the interior. The YRB, frequently analysed as the Yangtze River Economic Belt (YREB), is a crucial area connecting the developed coast and the interior west. Research concentrating on the YRB provides some comparative insights.

The YRB provinces often get scores higher than inland averages, although lower than the leading coastal clusters. Wang and Yang demonstrated that YRB's HQD index surpassed that of the Yellow River Basin from 2006 to 2019, indicating a more robust economic foundation and enhanced innovation capacity (Wang & Yang, 2023). Sun et al. noted that YREB's sub-index scores were "close to the national average" in most dimensions (Sun et al., 2020). Within the YRB, studies concur on a pronounced east-west gradient. HQD levels are highest in the lower reaches (eastern provinces/cities) and decline to move upriver (Wang & Yang, 2023). For instance, Ni et al. position Shanghai, Jiangsu, and Zhejiang as national frontrunners, whereas Yunnan and Guizhou (located in the extreme west of YRB) are ranked near the lowest (NI et al., 2025). This is similar to conventional development patterns. Interestingly, when shifting the focus from absolute levels to efficiency, the observed disparity tends to diminish or even invert. This is because efficiency improvements often accelerate development, thereby enabling less-developed regions to catch up more rapidly with their more advanced counterparts, thus narrowing—or even reversing—the initial gap. This was demonstrated by Zhang et al., who observed that certain western YRB cities had higher HQD efficiency than their peers (Zhang et al., 2022). The Yangtze River Delta stands out as a core driver of HQD in the YRB. Several studies isolate the delta urban agglomeration and show it has virtually world-class performance in innovation, economic efficiency, and green development, but also stress its inadequacies in inclusion (Sun et al., 2020). Simultaneously, the Chengdu-Chongqing city cluster in the upper YRB is developing as an additional high-quality development engine. Chongqing and Chengdu have demonstrated significant technological and industrial enhancement, contributing to the overall HQD of upstream regions, as indicated by specific efficiency assessments (Zhang et al., 2022).

The YRB and the Yellow River Basin (another critical region) are commonly compared in Chinese studies. Wang & Yang revealed that the Yellow River basin lags substantially in overall HQD, primarily due to lower innovation and openness (Wang & Yang, 2023). However, the Yellow River region scored slightly higher in green development since that region, being less industrialised, has comparatively better environmental quality. This demonstrates a trade-off: the YRB's rapid industrial growth has come at an environmental cost, whereas the Yellow River basin's challenge is to begin growth without ruining its ecological advantage (Xu et al., 2020).

To sum up, the transition to high-quality development represents a substantial change in China's development ideology, bringing it into line with worldwide trends towards inclusivity and sustainability. The international and Chinese literature on HQD emphasises that development quality is multifaceted, including social justice, technological innovation, economic efficiency, and environmental sustainability. Using techniques ranging from composite indices to frontier efficiency analysis, research on China has improved our understanding by evaluating HQD across areas and over time. Examining how to strike a balance between economic logical, and social goals has been centred on the YRB, which serves as a microcosm of China's diversified economy. The current research indicates that there has been steady progress but persistent disparities. Coastal and urban areas are at the forefront of HQD, while interior and rural areas are lagging. Complementary insights into these gaps are obtained through the use of various methods. The literature's main contributions include demonstrating the necessity of structural reforms to maintain quality growth, diagnosing regional coordination problems, and recognising innovation and human capital as the engines of HQD. The following subchapter contains an overview of the efficiency measurement methods.

2.2 Efficiency measurement methods

Along with introducing the new concept for China's high-quality economic transformation in the 2020s, increased attention has been paid to the digital economy, social welfare, carbon neutrality and regional coordination. High-quality development is a new target for economic transformation covering these aspects (Fang, 2022). The prerequisite for achieving economic transformation is upgrading the industrial structure by promoting a shift from low-value-added to high-value-added fields (Cheong & Wu, 2014). Measuring high-quality development is becoming a popular topic in the academic field. Measuring high-quality development requires a multidisciplinary approach, but the current theoretical framework is still fragmented. Various scientific fields concentrate on different aspects: economics emphasises efficiency analysis, sociology emphasises equality concerns, and environmental science investigates ecological sustainability. Developing a cohesive analytical framework that produces different viewpoints poses a considerable challenge.

Current evaluation systems for high-quality development rely on composite indicators, and the two most popular regional econometric models include comprehensive evaluation and input-output analysis.

The *comprehensive evaluation* of economic development involves assessing a wide range of factors contributing to a region's economic growth, prosperity and overall well-being. This approach typically considers multiple dimensions of economic development using *principal component analysis* (PCA), *weighted scoring, hierarchical analysis* and other approaches. PCA was introduced by Karl Pearson in 1901 and further developed by Harold Hotelling in the 1930s. It is a key method for dimensionality reduction. Furthermore, PCA scores, which indicate the data's projection onto these components, are effective tools for evaluating and summarising complex datasets (Hotelling, 1933) (Pearson, 1901). Jia in 2007 collected 12 economic indicators from Jiangsu Province using PCA to extract common factors and calculate the composite score based on typical factors. (Jia Wanjing, 2007)

The primary factors affecting the composite score included local taxation, industrial profits and central government taxes (Jia Wanjing, 2007). Ma et al. established a *weighted scoring method*, proposing a high-quality development index covering high-quality supply and demand, economic operation and openness to the outside world for 30 provinces. The authors concluded that China's high-quality economic development is regionally unequal, and differences decrease from the east to the west (Ma et al., 2019). Cui et al. examined government guidance funds for the Beijing–Tianjin–Hebei region between 2005 and 2018. They examined 518 policies, using three dimensions of policy intensity, objectives and measures to construct a policy efficiency evaluation system (Cui et al., 2022). The study conducted a hierarchical analysis to determine whether government funds and performance are influential. It concluded that the efficiency of policy-related fund allocation by the government required improvement.

Yin proposed a network-input-output-service provider index to empirically analyse China's local data, decompose it from the production and environmental governance stage and compare sustainability under different economic growth models (Yin Xiangfei, 2019).

Many studies calculated composite scores by assigning weights to their indicators after index quantification. However, evaluating high-quality economies did not involve each region's supply and demand perspectives of economic efficiency.

The *input-output analysis* is another method to evaluate a regional economy's performance. It is a widely used tool for evaluating the economic impact of regional development initiatives. It initially studies the interdependence of a region's industries and calculates the impact of changes in one sector on the whole regional economy. It begins with the assumption that economic progress is due to more efficient utilisation of inputs such as labour, capital and raw resources. Leontief first devised the input-output model in the 1930s, and its impact has been significant and wide-ranging, from regional and sectoral studies to environmental impact assessments. This model depicts the flow of products and services between different sectors of an economy, providing insights into how outputs from one sector are used as inputs in another (Leontief, 1987).

The *data envelopment analysis* (DEA) is another input-output analysis introduced by Charnes et al. (1978). It is an empirical tool for measuring the productivity efficiency of decision-making units. It is particularly useful in assessing the socioeconomic impact of policies by comparing inputs and outputs, given the subjective nature of policy evaluation. Its primary characteristics include measuring relative efficiency by managing numerous inputs/outputs without specified weights, building an efficiency frontier, being non-parametric, incorporating slack variables and enabling broad applicability with static and dynamic analysis. (Charnes et al. 1978) (Charnes et al. 1994) (Charnes et al. 1997)

Building on this, Tone developed the *slacks-based measure (SBM) model* as a non-radial efficiency measure, enhancing the traditional DEA approach by addressing input–output slackness and accounting for undesirable outputs such as environmental pollution. This makes the SBM model more accurate and realistic for evaluating economic efficiency, particularly in regional economic development where policy impacts are multifaceted (Tone 2001) (Tone 2015). In most articles using DEA models for efficiency calculations, input-output analysis has been considered from the Perspective of one industry or in terms of a specific environmental issue. For example, Yan et al. (2018) evaluated the environmental sustainability of 48 cities, *assessing energy, economic and environmental efficiency (3Es)* based on improved technologies, ranking the eastern region highest in 3E performance, followed by the central region, with the western region as the lowest (Yan et al., 2018). Quan assessed green inefficiency values and industrial enterprises' green total factor productivity in 30 Chinese provinces from 2007 to 2016, analysing their influence using the system generalised method of moments model (Quan Liang, 2019).

To solve the vast, complicated indicators system, many previous studies have used the PCA model to reduce the input data before calculating the DEA efficiency, demonstrating the effectiveness and rationality of combining PCA and DEA methods. For example, Ueda & Hoshiai (1997) integrated PCA with DEA to address the issue of dimensionality in DEA models. Adler & Golany (2001) improved the complexity and big dimensionality of the data used in airline network analysis by combining DEA and PCA. Deng et al. (2020) used PCA to simplify indicator dimensions and SBM-DEA to evaluate performance with and without carbon emissions constraints, revealing significant regional differences and determining that low-scale efficiency hampers logistics development. Minghui (2022) applied the PCA-DEA method to construct a performance evaluation system for talent housing strategies in nine Nanjing districts. The study assessed the effectiveness and efficiency of talent housing programs' input-output using BCC and CCR models.

Despite this, the DEA-SBM model predominantly assesses efficiency from an input-output standpoint, yet its capacity to examine the deeper factors contributing to efficiency disparities is comparatively constrained. Although it can give efficiency scores to various decision-making units (DMUs), its primary focus is on static efficiency evaluation: it cannot show dynamic trends in efficiency changes or the growth of efficiency gaps over time between various units. It highlights which units are highly efficient and which are less efficient. However, it does not clearly explain why these disparities exist or how they might evolve in the future because it does not explain.

The significance of convergence analysis lies herein. *Economic growth convergence analysis* is a crucial research area in economics, helping to understand whether different regions or economies converge or diverge in their development trajectories. By analysing growth trends over time, it sheds light on whether less developed regions are reducing economic gaps or becoming more economically unequal. Convergence can address the shortcomings of the DEA-

SBM model by evaluating whether efficiency disparities among various regions or units are diminishing over time. In the current literature, the absolute and relative beta convergence models have been extensively used in various domains, such as industrial development, energy efficiency, and regional economic growth. In addition to contributing to the theory and methods of convergence analysis, these works have also given policymakers helpful information. The main determinants of convergence, including institutional quality, capital accumulation, technical advancement, and government interventions, are identified by applying these analyses (Robert J. Barro, 1992). This, in turn, makes it possible for policymakers to elaborate more efficient plans for increasing energy efficiency, encouraging industry upgrading, and lessening regional disparities—all of which eventually support balanced and sustainable economic growth.

Robert J. Barro and Xavier Sala-i-Martin first wrote about the *absolute beta convergence model* in their American Economic Review article "Convergence" in 1992 (Robert J. Barro, 1992). This model, grounded in neoclassical growth theory, asserts that diverse economies will converge to a uniform steady-state growth rate irrespective of initial conditions. According to absolute beta convergence, economies with lower per capita income levels will enjoy faster growth rates, enabling them to progressively catch up to economies that started with higher levels of wealth (Bernard & Jones, 1996). Nevertheless, a straightforward theoretical model cannot adequately depict the real-world economic landscape, which is more akin to a complicated and detailed tapestry. With more investigation, economists became acutely aware of the absolute beta convergence model's shortcomings, especially its utopian presumption that every economy has a single steady state (Michelacci & Zaffaroni, 2000). This assumption was simplistic in adequately representing economic growth's complex and diverse nature across many areas and nations.

The *relative beta convergence model* was developed in response, serving as an important improvement that fortified and brought convergence theory closer to actual economic circumstances. Mankiw, Romer, and Weil's 1992 work in The Quarterly Journal of Economics, which suggested the expanded Solow-Swan model, was a significant turning point in this theoretical development (Mankiw et al., 1992). Their contribution was strategically adding human capital as a crucial element, changing the conventional growth equation to consider variations in labour quality, education, and skill accumulation among economies. This modification operated similarly to augmenting a model with a more advanced sensor, allowing it to identify and assess the nuanced yet significant disparities in economic development among regions. The model is more realistic and helpful for understanding economic convergence because it includes human capital, which helps explain why some countries grow faster than others even though they started with similar conditions. Cai Fang and Du Yang used absolute and relative beta convergence models to examine interprovincial economic growth in China in their 2000 study published in the Economic Research Journal (Cai & Du, 2000). According to their findings, there was a notable degree of absolute beta convergence across China's three main economic regions—Eastern, Central, and Western China—between 1978 and 1998. Nonetheless, no convergence trend was detected among these regions. This tendency, referred to as "club convergence," implies that while discrepancies between regions continued because of variations in development conditions and policy contexts, provinces within the same region showed comparable trends in economic growth. Despite economic unity within regions, this shows how hard it is to reduce regional differences. This has important implications for China's Western Development Strategy. Similarly, Peng Guohua used the relative beta convergence model to analyse China's regional income disparities and total factor productivity (TFP) convergence in his 2005 paper published in the Economic Research Journal (Guohua, 2005). His research considered capital accumulation and technical advancement to influence economic growth convergence. After adjusting for these heterogeneous factors, the results showed that China's provincial economic growth exhibited conditional beta convergence, which means that each province tended to converge toward its steady-state growth level rather than a shared national growth path.

These results highlight that various structural factors affect the economic growth rate in various provinces. Without considering technological differences, capital accumulation, and institutional variations, the convergence assessment may result in incomplete conclusions. By taking into account diverse regional characteristics, researchers can more precisely assess the dynamics of economic convergence and create strategies that are suited to regional development's needs. In order to achieve meaningful convergence, it is imperative that policymakers devise strategies that are specifically tailored to the development requirements of each region, while also considering the heterogeneity of economic structures, resource endowments, and institutional capacities. This kind of strategy can lessen regional differences while increasing efficiency.

2.3 Connecting economic theory and evaluation metrics

Although Data Envelopment Analysis (DEA) has been widely used to assess production efficiency across sectors and geographical areas, its incorporation into conventional economic theories is still comparatively undeveloped. In order to close this gap, this paper places the non-parametric efficiency framework in the larger framework of welfare economics, regional development policy, and endogenous growth theory.

The theory of endogenous growth, in particular the models that were proposed by Romer (Romer, 1994) and Aghion and Howitt (Aghion & Howitt, 1992), places emphasis on the essential role that innovation, human capital accumulation, and knowledge spillovers play as internal drivers of sustained economic growth. It is underscored in these theoretical contributions that productivity enhancements are not exclusively the consequence of exogenous technological advancements; rather, they are closely associated with intentional investments in education, research and development, and institutional capacity. The choice of innovation-related input variables (such R&D spending and patent numbers) in the current DEA model fits with this point of view. However, it is important to note that the DEA technique does not intrinsically capture dynamic feedback loops or temporal causality, which restricts its ability to completely operationalize endogenous growth mechanisms.

The social welfare indicators in China’s 14th Five-Year Plan are quite similar to the main ideas of welfare economics. This shows that the government wants to focus on fair development and the well-being of society (Sofi & Sasidharan, 2020). The government’s dedication to incorporating welfare-oriented goals into its growth plan is demonstrated by these measurements, which range from the redistribution of income and the accessibility to healthcare to educational achievement and the resolution of poverty. This kind of thinking is in line with welfare economics, which aims to improve overall social wellbeing by not just maximising total output but also the distribution of resources.

Furthermore, regional development theories, which range from the traditional location theory to the contemporary endogenous growth frameworks, consistently emphasise the significant role that spatial heterogeneity, institutional path dependence, and inter-regional spillover effects play in the formation of differentiated development trajectories. The New Economic Geography (Krugman, 1991) shows how agglomeration economies and transportation costs work together to create core-periphery dynamics. Institutional economics

(North et al., 2009) focusses on how governance structures that are embedded in a community can either help or hurt the efficiency of resource allocation.

Critically, the integration of various theoretical and methodological approaches necessitates careful consideration of their relative constraints. For instance, endogenous growth theory says that innovation is a universal driver, but differences in infrastructure, institutional quality, and demand-side limitations between regions may make its effect far less strong. In the same way, DEA and convergence analysis can show how well something is working and find patterns of catching up, but they cannot completely separate the effects of policy changes or structural problems.

By combining these different theoretical points of view, the study shows both the usefulness and limitations of the chosen method. DEA offers a significant paradigm for performance assessment, particularly in policy evaluation. However, the method's static, cross-sectional architecture exhibits significant limitations. Convergence analysis can enhance the explanatory efficacy of DEA by incorporating a dynamic aspect. DEA outputs and convergency analysis are best understood as additional indicators in a larger analytical ecosystem that focuses on high-quality development, rather than as separate assessments of these complex processes.

2.4 Gaps in the existing research

In regional economic development research, earlier studies have intensively discussed regional efficiency and convergence patterns using various modelling approaches. Nonetheless, substantial shortcomings persist in the research results, presenting the opportunity to implement the DEA-SBM-Beta model within the context of the 14th Five-Year Plan indicators to improve regional analysis.

(1) The limitations of the efficiency measurement model

The traditional DEA models, ineffective at handling input-output slacks, were the mainstream of early research. Despite its subsequent introduction to improve the accuracy of efficiency assessment, the DEA-SBM model has not been extensively applied in numerous analyses.

One major constraint is that most research papers focus exclusively on static efficiency evaluation, ignoring the temporal component. Consequently, they do not adequately reflect the dynamic progression of regional efficiency over time, constraining the analysis of long-term development patterns. It is challenging to comprehend and identify broader growth trajectories and policy implications when we limit our understanding of regional efficiency to a particular point in time.

(2) Deficiencies in the beta convergence analysis

The absolute β-convergence model also has significant shortcomings. Premises in previous studies are sometimes oversimplified, especially in the absolute beta convergence model, which postulates that all regions move toward a single steady state. Because of this, the results that do not reflect how the economy works are produced, as regions differ in resource endowments, industrial structures, and policy settings.

The relative β-convergence model improves the previous model by incorporating control variables. Nonetheless, its application is still inconsistent. Many relevant papers lack a thorough and consistent selection of control variables, which leads to inconsistent findings. Some studies consider capital investment or technical innovation, ignoring institutional considerations, gains in labour quality, and spatial spillover effects: these are all essential to identify the mechanisms underlying regional convergence. Due to this inadequate perspective, existing models have limited explanatory value.

(3) Integrated studies are in short supply.

Another major weakness of the studies analysed is the absence of integration between convergence analysis and efficiency measurement. Most papers use the DEA-SBM model to evaluate efficiency without considering how efficiency differences change over time or the beta model to map convergence patterns without evaluating the underlying efficiency determinants driving regional development.

However, increases in regional efficiency and convergence dynamics are strongly interwoven. Improving regional efficiency directly influences whether or not regions' economic performance converges or diverges. Understanding the inherent logic of regional economic development is challenging without a thorough analytical framework that unifies these two elements.

(4) The need for a research framework aligned with the 14th Five-Year Plan

China's 14th FYP makes these gaps in the relevant literature even more pronounced. Focusing on regional high-quality and coordinated development, the 14th FYP unveils a new set of development indicators addressing innovation-driven growth, green development, and social well-being. Thus, a chance to match empirical research with national development objectives has been lost. Previous studies have not methodically included these new markers in DEA-SBM-Beta analysis.

2.5 Contribution to the Research Gap

Regional efficiency evaluation, a key topic in mainstream economic research, has long confronted methodological innovation and analysis depth advancement. The previous part examined the constraints of the current literature, which is predominantly defined by a uniform research perspective. Briefly, the traditional static efficiency analysis overly relies on the DEA model, ignoring the fundamental efficiency differences under the non-desired output constraints, and lacks a theoretical discussion on optimizing the indicator system. Conversely, the dynamic analysis primarily concentrates on decomposing the total factor productivity (TFP), failing to systematically reveal the spatial heterogeneity of the efficiency growth and the convergence mechanism. This paper achieves significant academic achievement in terms of technique, dimension analysis, and theoretical contribution by constructing a framework for "static-dynamic" coupling analysis.

First, the PCA-SBM model is innovatively introduced into the field of regional efficiency evaluation at the methodological level. By downscaling the indicator system using principal component analysis, the model successfully addresses the measurement bias issue brought on by the redundancy of indicators in traditional DEA models. At the same time, it reveals the Yangtze River Basin's accuracy efficiency level under the carbon emission constraint for the first time by addressing the undesirable outputs through the relaxation variables. Technically speaking, this work aligns more with the reality of basin evolution than previous research that used CCR or BCC models. Notable in particular is the study's creation of a dynamic efficiency database covering a 10-year period (2012–2021), which, by measuring the efficiency growth rate index, clearly illustrates the efficiency evolution trajectory of each province (DMUs) during the study period. By combining static efficiency values with dynamic growth rates, this analytical approach preserves the spatial comparative advantage of cross-sectional data while capturing the enduring features of efficiency improvement through time-series data, offering a novel quantitative tool for examining regional development disparities.

Second, it overcomes the fragmentation of conventional static or dynamic analysis regarding dimension analysis. By continuously measuring 10-year efficiency values, the study completes the static efficiency assessment of 12 provincial units and calculates the average yearly growth rate. Based on this, the study employs a novel approach by combining σ-convergence and β-convergence to showcase the efficiency gap's dynamic progression to showcase the efficiency gap's dynamic progression. In addition to compensating for the absence of trend prediction in dynamic analysis, this hybrid research paradigm maintains the precise representation of spatial distinctions in static analysis through growth rate indicators.

Lastly, this study provides new evidence for applying regional economic growth theory at the river scale while verifying the stage characteristics of efficiency convergence and the critical role of technological progress through empirical analysis. This study integrates spatial economics theory with efficiency evaluation methodologies to develop a three-dimensional analytical framework encompassing efficiency levels, growth rates, and convergence tendencies, in contrast to prior literature that solely examines differences in efficiency levels.

In summary, the methodological innovation and theoretical expansion of this study offer a solid scientific foundation for the YRB's high-quality growth and pave the way for future research on regional efficiency evaluation. It is valuable to academics because it not only fills gaps in the existing literature on the use of both static and dynamic analysis, but it also gives a methodological template that can be used for cross-regional economic research by showing the efficiency growth trajectory over the last 10 years in a transparent way. This study paradigm, which integrates static efficiency diagnosis with dynamic growth tracking, holds substantial theoretical significance and practical usefulness for comprehending the effectiveness of China's regional coordinated development policy.

3. Research methodology

3.1 Research approaches

This dissertation employs a mixed-method approach, combining qualitative and quantitative analyses to analyse economic efficiency and convergence trends. The *qualitative analysis* considers contextual factors(Elo & Kyngäs, 2008). The dissertation will identify the differences between the 14th FYP and its former counterparts based on scrutinizing government documents disclosed on official websites. The comparative analysis of documents is a necessary element of this qualitative analysis. While the 14th FYP's economic development goals are the same throughout the country, the development policies differ by region. By comparing the economic policies of different regions, one needs to find out the role of economic policies at the level of the regions under survey in promoting economic transformation. With a comprehensive analysis of policies, it is feasible to identify critical variables that affect economic efficiency. Regional coordinated development policies are essential for the efficient allocation of resources, in addition to innovation and industrial structure. The 14th FYP aims to eliminate economic barriers, facilitate the free movement of production factors, and improve the efficacy of resource allocation by promoting regional infrastructure connectivity and industrial collaboration. For example, overall economic efficiency is enhanced by reducing logistics costs, facilitating industrial relocation and integration, and optimizing industrial layouts by enhancing interregional transportation networks.

It is also essential to examine how these factors affect economic efficacy. As an illustration, the 14th FYP's green development policies prioritize a circular economy, emission reduction, incentivizing energy production technologies, and optimizing policies to reduce resource consumption and environmental costs, thereby enhancing regional sustainable development efficiency and corporate earnings. This policy analysis provides a strong theoretical foundation for subsequent quantitative analysis, ensuring that indicator selection and model construction align closely with the policy direction of the 14th FYP.

The quantitative method focuses mainly on using secondary data to quantify the consequences of economic policy implementation. Secondary data are derived from the National Bureau of Statistics of China, CSMAR, and the Wind-Data service database.

This dissertation's descriptive analysis is based on economic indicators and the statistical model, revealing the relationship between different factors, which are significant parts of quantitative research. The purpose of *descriptive statistics* is to generalize frequency and concentration trend analysis. Economic phenomena are analysed based on their unique characteristics. The data source contributes to describing the trend in the economic situation. At the same time, local governments must also pay attention to avoiding the pollution potentially emanating from the industrial transformation.

Unlike descriptive evaluation methods, *statistical models* allow for eliminating the influence of subjective factors, reducing errors, and simplifying algorithms without sacrificing accuracy. The DEA is an empirical method for measuring the productivity efficiency of decision-making units (Charnes et al., 1978). There is no direct measure of the value or poorness of policy since it is highly subjective. Typically, the socioeconomic impact of policies is measured by comparing inputs and outputs. Since policy guidance will enhance certain factors of production inputs, the output productivity per unit of increased input will differ, so the DEA method can be used to track productivity better. For example, if a country strongly promotes science and technology innovation, the proportion of financial support for science and technology personnel will increase. This will increase social productivity.

A combined analytical approach provides a more comprehensive analysis of the relationship between economic theories and real-world economic dynamics, serving as a fundamental perspective for economic transformation. In my dissertation, qualitative and quantitative analyses complement each other, creating a mutually reinforcing framework that enhances the assessment of China's current economic trends.

3.2 Conceptual framework

3.2.1 Policy analysis

The richness of policy sources directly impacts the trustworthiness of analytical outcomes. The most credible and primary sources are governments' official websites. Dedicated policy release sections are on most national, provincial, and municipal government portals. These sections are places where policies are updated in real-time, which makes them vital conduits for accessing information about policies directly from the government.

A comprehensive approach must be adopted when gathering policy texts related to specific regional themes. This includes macro-level policies issued by provincial and municipal governments and detailed implementation guidelines from county and township governments, which reflect localized policies tailored to regional conditions. Policy texts must be *categorised systematically by publication date* to accomplish practical analysis. Organizing helps track their evolution and continuity, revealing policy shifts over time. For instance, a decade-long review of regional innovation policies may show an early focus on R&D infrastructure investment, gradually shifting toward corporate-driven innovation and technology commercialization

Policies can be classified into industrial policies, environmental policies, transportation policies, education policies, etc., facilitating in-depth analysis of specific policy areas. For example, when studying regional industrial restructuring, filtering industry-related policies enables targeted examination of support measures for key industries and industrial relocation strategies. These policies may concern businesses, residents, and specific industry professionals, enabling the precise evaluation of their impact on different social and economic groups.

Implementing this structured classification methodology improves the report's capacity to derive significant conclusions from regional policy trends, making policy research more methodical and practical. It also provides a strong basis for quantitative evaluation.

3.2.2 Efficiency analysis

In conducting efficiency analysis, efficiency is divided into high-quality (technical) efficiency, pure technical efficiency, and scale efficiency, and effectiveness is categorized and analysed from these three perspectives (Table 1).

Table 1: Definition of efficiency

Efficiency	Explanations
High-quality efficiency (Technical efficiency – TE)	The high-quality integrated economic efficiency is a comprehensive evaluation of various aspects, such as resource allocation efficiency and each decision unit's use. TE=PTE*SE
Pure technology efficiency (PTE)	Based on factors such as management and technology, pure technical efficiency refers to the production efficiency of the decision-making unit. Pure technical efficiency indicates attaining maximum economic output and minimum negative environmental output.
Scale efficiency (SE)	Scale efficiency refers to the economic efficiency of scale formed by provinces through economic development planning and cooperation with other provinces in other YRB regions.

Source: Authors' construction based on (Long et al., 2016).

This research develops a “static-dynamic” coupling analytical framework and uses the PCA-SBM model as the primary instrument to assess the regional efficiency of the Yangtze River Basin. This study uniquely blends principal component analysis (PCA) with the unoriented SBM model to enhance input variables via indicator dimensionality reduction while concurrently addressing relaxation variables for undesirable outcomes, including carbon emissions. The outputs of Technical Efficiency (TE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) form the theoretical foundation of the comprehensive analysis. The conceptual development of this efficiency evaluation system originates from the notion of technical efficiency introduced by Farrell (1957) within the context of frontier production function theory. This theory quantifies how decision-making units (DMUs) deviate from the technological frontier through the radial distance function. Furthermore, the measurement of technical efficiency was expanded to multiple-input-multiple-output scenarios (MIPOs) with the formulation of the CCR model, predicated on the assumption of constant returns to scale (CRS) by Charnes et al. (Charnes et al., 1978). Charnes et al. developed the CCR model under the premise of constant returns to scale (CRS), thereby extending the measurement of technical efficiency to a multiple-input-multiple-output framework and establishing the TE value ($0 \leq TE \leq 1$) as standardized for assessing resource allocation efficacy. Banker et al. developed the BCC model, which provided a two-dimensional analysis of technical efficiency by incorporating the assumption of variable returns to scale (VRS) (Banker et al., 1984). PTE eliminates the impact of scale factors, thereby indicating the management efficiency and technical application proficiency of DMUs relative to the optimal scale, addressing technical inefficiency via slack variables; SE measures the extent of divergence of the actual scale from the optimal scale using the formula (SE = TE/PTE). This decomposition paradigm transcends the one-dimensional constraints of conventional TE, enabling researchers to pinpoint causes of variation in efficiency losses. PTE<1 signifies the potential for enhancement in technological application, but SE<1 denotes diseconomies of scale or insufficient utilization of economies of scale.

One more point is the various types of efficiency: standard efficiency vs. super efficiency. The basic SBM model predominantly utilizes inefficient units with efficiency scores below the production frontier, ranging from 0 to 1. A score of 1 signifies that a DMU is situated on the efficiency frontier. However, it is difficult to rank or differentiate between efficient units under the conventional SBM framework because they all have the same score of 1. Tone (2002) introduced the super-efficiency SBM model by omitting the evaluated DMU from the reference set to overcome this constraint. This permits efficiency scores to surpass one and facilitates ranking all units, including those classified as efficient in the conventional SBM model. The super-efficiency SBM preserves the slack-based evaluation of input surpluses and output deficiencies while facilitating the ranking of efficient units and enabling other statistical analyses, including regression.

The super-efficiency SBM model is used to verify robustness. It facilitates a more nuanced comparison of high-quality development performance among provinces in the Yangtze River Basin via ranking. Conversely, it corroborates the findings derived from the conventional SBM model. Nonetheless, the conventional SBM model's use of the evaluated unit in the reference set building enhances its efficacy in detecting duplicate resource inputs and prospective improvement areas. This research applies the normal SBM model as the principal instrument for efficiency assessment, while the super-efficiency SBM outcomes provide supplementary validation.

In short, this dissertation innovatively considers total factors, including indicators, to evaluate economic performance based on the 14th FYP indicators system. It applies input–output analysis to measure economic efficiency in 12 regions along the Yangtze River Delta, building on the definition of a high-quality economy. The DEA model enables a more rigorous analysis of regional economic vulnerability and development policy coordination than other methods.

3.2.3 Convergence analysis

(1) Alpha analysis

Alpha (α) convergence focuses on the degree of dispersion in actual income levels or development indicators across different economies or regions. It examines whether the variance of a key economic variable—such as per capita GDP or labour productivity—decreases over time. When disparities in these indicators gradually shrink, Alpha convergence is said to occur. It provides a direct and observable measure of economic convergence by assessing changes in distribution patterns rather than relying on theoretical assumptions about steady-state growth or marginal returns to capital. Thus, Alpha convergence is a complementary approach, offering a more intuitive and empirical depiction of economic development trends over time.

(2) Beta analysis

The concept of β convergence originated in the 1950s. The neoclassical growth model articulated by Solow and Swan indicates that owing to the diminishing marginal returns of capital, nations or areas with lower initial per capita income will converge with developed regions using a more rapid capital accumulation rate, ultimately resulting in the convergence of per capita income. This tendency is aptly termed “latecomer advantage”. In 1991, Barro and Sala-i-Martin initially converted this theory into a testable regression model. This seminal research established an empirical basis for the β convergence theory. However, the assumption made in early research that all economies have the same amount of technology and institutional framework is not accurate. The notion of “conditional β convergence” was introduced by Sala-i-Martin in 1996. This concept is based on the belief that convergence will only occur when certain variables, such as education and technology, have been controlled. Technological differences constitute a significant element determining convergence, as demonstrated by the 1992 study by Mankiw et al., which indicated that the convergence speed increased from 2% to 3% annually when human capital variables were introduced. Research methodologies are also continuously evolving in tandem with the growth of econometrics. In 1995, Islam suggested using panel data models to address unobserved heterogeneity. He discovered that while the rate of convergence in developed nations is slower, there is a notable conditional convergence in developing countries (Shareef et al., 2016). As we entered the 21st century, the emergence of spatial econometrics introduced a novel component to convergence research. Researchers like Anselin discovered a spatial spillover effect in the economic development of nearby areas (Anselin, 1988). The convergence pace of EU nations will be expedited due to strong trade connections. After 2000, nonlinear analysis emerged as a new way of thinking. Hansen’s threshold regression model reveals this convergence mechanism’s stage characteristics (Hansen, 1999). For instance, when educational attainment surpasses a specific threshold, the convergence rate will be markedly enhanced. More in line with the gradual process in reality, González et al.’s panel smooth transition model permits the convergence coefficient to vary constantly with the development stage (Gonzalez et al., 2005).

Regional science and environmental economics are two fields in which the relative β convergence hypothesis has been used. For example, Stokey discovered that pollutant emissions also exhibit a convergence phenomenon when paired with the environmental Kuznets curve, and Fingleton verified that industrial agglomeration speeds up convergence when combined with the new economic geography theory.

Despite this, there is some debate regarding this theory. Through dynamic research of income distribution, Quah identified the phenomenon of "bimodal convergence," indicating that the global economy may be categorically divided into two predominant groups: high-income and low-income. Proponents of endogenous growth theory have noted that the endogeneity of technological innovation could result in persistent growth disparities and diminish the tendency for convergence. Machine learning techniques have provided a novel perspective on convergence research in recent years. Random forest models can elucidate intricate nonlinear interactions.

Starting from the original neoclassical framework, the relative β convergence theory has evolved from ignoring spatial associations to incorporating spatial effects, from linear analysis to nonlinear expansion, and from absolute convergence to conditional convergence. This study innovatively augments the convergence model to verify the differentiated roles of technological progress and scale economy in the efficiency convergence of the Yangtze River Basin. This provides theoretical support for basin-coordinated development policies. Efficiency decomposition indicators (scale efficiency SE and pure technical efficiency PTE) are incorporated.

3.2.4 The hypotheses of the dissertation

We present the methodological design in Figure 1. The analysis is based on the following four hypotheses which were derived from the literature review and the conceptual framework:

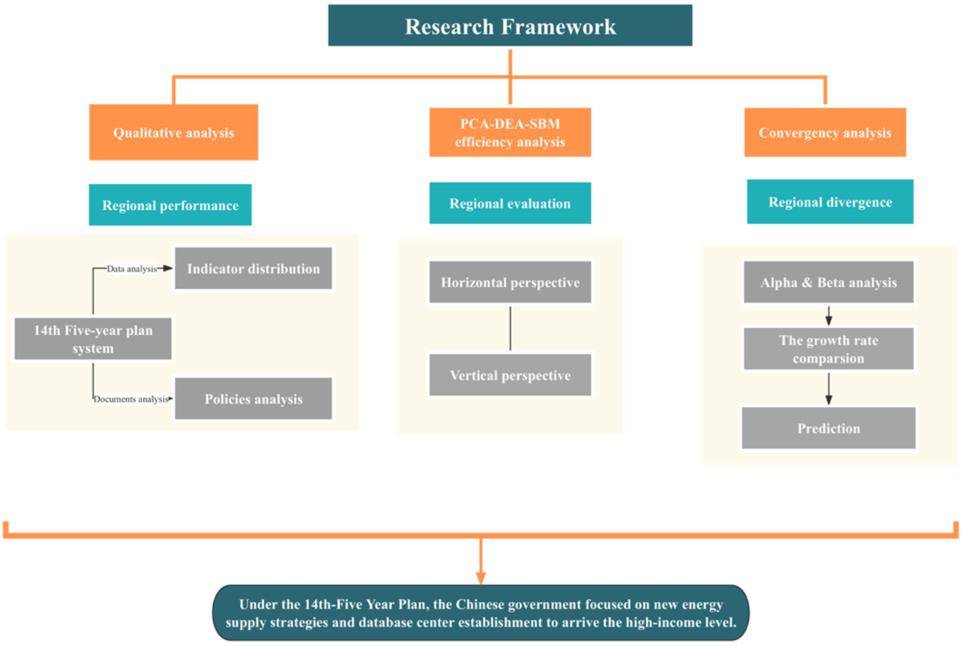
Hypothesis 1: The eastern regions of the YRB consistently demonstrate higher average values of total efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) than the central and western regions.

Hypothesis 2: The eastern regions of the YRB benefit more from technological advancements, skilled labour, and welfare resources than the western regions, leading to significantly higher values in TE, PTE, and SE.

Hypothesis 3: The gap in high-quality efficiency between provinces has shown a declining trend over time, which is consistent with the β-convergence hypothesis.

Hypothesis 4: Improvements in scale efficiency are more strongly associated with overall efficiency convergence compared to improvements in pure technical efficiency.

Figure 1: The logic of research



Source: Own work based on a literature review.

3.3 Model selection

This chapter summarizes the most significant elements and steps for setting up the appropriate model to evaluate the four hypotheses described above.

(1) Documents analysis

The 14th FYP period signifies the initial five years following China's establishment of a moderately prosperous society and its first centenary objective, initiating a new phase towards the comprehensive development of a modern nation and pursuing the second centenary goal. The official document of the 14th FYP serves as the action guide for this period, addressing essential domains including economy, society, ecology, technology, and public welfare, thereby offering a foundation for policy development, execution, and evaluation.

(2) Data dimensionality reduction with PCA

The data are dimensioned based on the original variables' correlation or covariance matrix. This will extract the primary data information and reduce the problem of duplicating data features caused by multiple covariances while retaining relevant information (Hotelling, 1933).

The nine input indicators of this dissertation are subject to PCA and downscaled to several principal components. Table 2 includes the list of these indicators. To verify the temporal and cross-sectional consistency of factor scores, principal components were calculated on the entire sample following the methodologies outlined by Tone, Zhou and Halkos. Principal component analysis in this paper was conducted on the pooled dataset covering all years (i.e., the full panel). Loadings were computed from the overall covariance matrix and held constant across time to ensure comparability of composite indicators. (Zhou et al., 2008) (Halkos & Tzeremes, 2010) (Tone, 2001)

(3) Calculating the whole period's standards of efficiency[1] by non-oriented SBM model with undesirable output

There are many ways to calculate economic efficiency: input, output, and non-oriented indicators. Unlike CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, and Cooper), which focus on overall efficiency but do not consider input excesses or output shortfalls (Banker et al., 1984) (Charnes et al., 1978), the SBM model tackles these inefficiencies from a non-oriented angle, including undesirable outcomes at the same time (Tone, 2001) (Tone, 2015). In this dissertation, we use the non-oriented SBM model, which is designed to deal with undesirable outcomes. Tone (2015) describes the non-oriented SBM model. Tone modifies the SBM model to explicitly include undesirable outcomes. This means that efficiency statistics consider how successfully a DMU uses its inputs to produce desired outcomes and how it deals with undesirable outcomes. For example, the model can consider pollution levels and resource efficiency in environmental applications. Furthermore, a non-oriented SBM can detect and evaluate efficiency by simultaneously considering improvements in inputs and outputs rather than focusing solely on one direction. As a first step in our analysis, we applied the standard SBM model to provide a general overview of the efficiency distribution among DMUs. The standard DEA model determines efficiency by comparing inputs and outputs. Efficient DMUs receive a score of $\theta = 1$, indicating full efficiency, while inefficient DMUs receive less than one. However, in other circumstances, all effective DMUs receive the same efficiency score of one, making it difficult to discern between highly efficient DMUs.

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[1] Standard efficiency determines whether a DMU is valid or the efficiency value is < 1. It screens out inefficient units and analyses their redundancies and gaps.

Table 2: The design of the indicators

Group	Indicators	Name	Name in the models
Input	R&D spending of industrial enterprises above the scale (10000 yuan)	x1	**PC1:In1**
	The number of domestic invention patent applications received (items)	x2	**PC2:In2**
	Overall grain production capacity (hundreds of million tons)	x3	**PC3: In3**
	The number of certified (assistance) doctors (1,000 persons)	x4	
	Number of urban and rural residents' social old-age insurance participants (10,000)	x5	
	Average number of nursery school students per 100,000 population (persons)	x6	
	Revenue from software business (100 million yuan)	x7	
	Disposable income growth per capita (%)	x8	
	Surveyed urban unemployment (1000 person)	x9	
Output	Reginal gross domestic products (CNY 100 million)	y1	**Ou1**
	Workforce productivity (Yuan/1 person)	y2	**Ou2**
	Urbanization rate (%)	y3	**Ou3**
	Days of air quality equal to or above grade II (day)	y4	**Ou4**
	Forest coverage rate	y5	**Ou5**
Undesired output	Emission of exhaust gas (10,000 tons)	z1	**Undesired output**

Source: Own work based on the review of relevant literature.

This first inquiry is critical for understanding and identifying general efficiency levels and building the framework for the subsequent super-efficiency model application, allowing for more detailed discrimination among highly efficient DMUs. This comprehensive approach offers a holistic view of efficiency, making it suitable for complex systems requiring multi-dimensional optimization. Optimization comparisons are applied to identify how key policies affect efficiency according to the following formula:

$$\theta^* = \min_{\lambda, s^-, s^+} \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}^t}}{1 + \frac{1}{q+h}\left(\sum_{r=1}^{q}\frac{S_r^+}{y_{r0}^t} + \sum_{k=1}^{h}\frac{S_k^-}{b_{k0}^t}\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$s.t \begin{cases} x_{i0} = \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j x_{ij}^t + S_i^-,\ i = 1, \ldots, m \\ y_{r0}{}^g = \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j y_{rj}^t - S_r^+,\ r = 1, \ldots, q \\ b_{k0}{}^b = \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_j b_{kj}^t + S_k^-,\ k = 1, \ldots, h \end{cases}$$

θ^* *: the efficiency value of* $DMU(x_0, y_0)$

S_i^- *: input excess.*

S_r^+ *: output shortfall.*

S_k^+ *: undesirable output excess.*

$[x_{i0}]$ *is m input indicators, where:* $i = 1, 2, \ldots\ldots, m$.

$[y_{r0}]$ *is q output indicators, where:* $r = 1, 2, \ldots\ldots, q$.

$[b_{k0}]$ *is h undesirable output indicators, where:* $k = 1, 2, \ldots\ldots, h$.

$\lambda = [\lambda_1, \lambda_2, \lambda_3 \ldots \lambda_n]^T$ *is called the intensity vector.*

Source: Dealing with undesirable outputs in DEA: A slacks-based measure (SBM) approach (Tone, 2015).

(3) Robustness sensitivity test

a) calculate the whole period's super-efficiency[2] *by non-oriented SBM model with undesirable output*

In most DEA models, the top-performing DMUs[3] have an efficiency score $\theta^* = 1$, which suggests that they are all considered efficient. However, many DMUs often receive the same efficiency score, making it difficult to discern between them. To solve this issue, Tone offered various techniques for ranking these top performers, a topic known as the super-efficiency problem (Tone, 2002). Beyond this, unlike current efficiency, which focuses on isolated periods, the whole period's efficiency—especially within dynamic DEA—incorporates carry-over activities between periods. This comprehensive assessment of sustained performance is crucial for long-term planning. The dynamic DEA model proposed by Färe and Grosskopf is the first innovative contribution to this field (Färe & Grosskopf, 1997). Tone & Tsutsui (2010) developed their model in the SBM framework (Tone & Tsutsui, 2010).

[2] Super efficiency is used to sort among valid units, and it performs ranking analysis on all units (including effective units), which is a prerequisite for many DEA regression analyses, such as Tobit regression.

[3] In data envelopment analysis (DEA), DMUs are the entities evaluated or compared, such as firms or organizations that transform inputs into outputs. In this report, DMU refers to the 12 provinces along the Yangtze River.

To mitigate this constraint, additional measurements are conducted utilising the super-efficiency model. This approach facilitates the identification of weakly efficient states during the estimate process, as indicated by the subsequent formula.

$$\theta^* = \min_{\lambda, s^-, s^+} \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}^{\ t}}}{1 - \frac{1}{q+h}\left(\sum_{r=1}^{q} \frac{S_r^+}{y_{r0}^{\ t}} + \sum_{k=1}^{h} \frac{S_k^-}{b_{k0}^{\ t}}\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$s.t \begin{cases} x_{i0}^{\ t} \geq \sum_{t=1}^{T}\sum_{j=1}^{n} \lambda_j^{\ t} x_{ij}^{\ t} + S_i^-, \ i = 1, \ldots, m \\ y_{r0}^{\ t} \leq \sum_{t=1}^{T}\sum_{j=1}^{n} \lambda_j^{\ t} y_{rj}^{\ t} - S_r^+, \ r = 1, \ldots, q \\ b_{k0}^{\ t} \geq \sum_{t=1}^{T}\sum_{j=1}^{n} \lambda_j^{\ t} b_{kj}^{\ t} + S_k^-, \ k = 1, \ldots, h \end{cases}$$

When $\theta^* = 1$, *the DMU is efficient.*

When $\theta^* < 1$, *The DMU is inefficient and there is a need to improve the output of the investment.*

Source: A slacks-based measure of super-efficiency in data envelopment analysis (Tone, 2002)

b) calculate Charnes-Cooper-Rhodes

The radial CCR model solves the linear programming problem under constant returns to scale (CRS) to determine technical efficiency (TE) (Charnes et al., 1978).

$$\text{Max } \theta_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}, \ \text{S.t.} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$\forall j = 1, \ldots, n,$

$u_r \, v_i \geq \varepsilon > 0,$

where x_{ij} and y_{rj} denote the $i-$th input and $r-$th output of DMU_j,

u_r and v_i are weights,

ε is a non$-$Archimedean infinitesimal.

c) calculate Banker-Charnes-Cooper

The BCC model extends CCR by introducing variable returns to scale (VRS) through a convexity constraint $\sum \lambda_j = 1$ (Banker et al., 1984)

$$\mathrm{Max}\phi_k = \frac{\sum_r u_r y_{rk} - u_0}{\sum_i v_i x_{ik}}, \mathrm{S.t.} \frac{\sum_r u_r y_{rk} - u_0}{\sum_i v_i x_{ik}} \le 1, \forall j \ldots\ldots (4)$$

u_0 free in sign

This decomposition identifies: Pure technical efficiency (PTE) is the Managerial performance under VRS, Scale efficiency (SE) can be calculated as $SE = TE_{CCR} \div PTE_{CCR}$

d) calculate Malmquist index

To analyse temporal efficiency dynamics, we compute the output-oriented MPI between periods t and t+1: (Fare et al., 1994)

$$M_t^{t+1} = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} = EC \times TC \ldots\ldots (5)$$

where:

Efficiency change (EC) : Catch − up effect relative to the frontier.

Technological change (TC) : Frontier shift due to innovation.

(5) Comparative Analysis of Efficiency Scores and Sensitivity Assessment

This multi-layered methodology carefully tackles issues with statistical uncertainty, time-varying effects, and model specification, proving that our findings are methodologically sound across all important sensitivity analysis dimensions.

By parallel estimation under both CCR (constant returns-to-scale) and BCC (variable returns-to-scale) assumptions, we verified scale-invariance in our efficiency measurements.

The bootstrap resampling technique is implemented in this investigation to evaluate the statistical reliability and robustness of the estimated technical efficiency scores. Efron came up with the non-parametric simulation method called Bootstrap. It draws random samples from the original data over and over again and replaces them to get a good idea of how the samples will be distributed for an estimate (Efron, 1979). Unlike traditional parametric inference, bootstrap does not require stringent distributional assumptions and can offer bias-corrected standard errors and confidence intervals even in complex or small-sample contexts (Simar & Wilson, 1998) (Simar, 2000). The bootstrap is particularly beneficial in the context of Data Envelopment Analysis (DEA) due to the fact that efficiency scores are restricted to a range of 0 to 1, and their sampling distribution is frequently unknown or asymmetric. Bootstrap facilitates more dependable inferences regarding the stability and variability of the results by generating a multitude of replications of the mean efficiency estimate. To visualise the distribution of the bootstrapped means and to create percentile and bias-corrected confidence intervals, 1,000 bootstrap replications were carried out in this dissertation.

(6) Alpha convergence

Efficiency values derived from DEA models, including DEA-SBM, generally span from 0 to 1. In contrast to income levels or GDP, which increase exponentially, DEA efficiency numbers do not display significant proportionate disparities among locations. A logarithmic adjustment is superfluous and may compromise the interpretation since DEA efficiency scores are already normalizing. (Das et al., 2015) (Balcerzak et al., 2007) Therefore, the standard deviation or coefficient of variation is used to measure alpha convergence in this dissertation, which determines whether the dispersion of economic data across economies becomes less pronounced over time (Bhunia et al., 2012) (Miller, 1995). The key formulas used to quantify α-convergence include:

$$\sigma_t = \sqrt{\frac{\sum_{i=1}^{N}\left(E_{i,t} - \overline{E}_t\right)^2}{N}} \quad \cdots\cdots (6)$$

$E_{i,t}$ *is the DEA efficiency score of region i at time t*

$\overline{E}_t$ *is the mean DEA efficiency score at time t,*

N *is the number of regions.*

(5) Beta convergence

Absolute beta convergence assesses whether less efficient regions characterized by DEA efficiency ratings have a more rapid improvement than highly efficient regions, which leads to decreased efficiency disparities over time. (Barro, 1995) (Stoeckmann, 2022) (Furceri, 2005) The standard absolute beta convergence regression model for DEA efficiency scores is the following:

$$\frac{1}{T}\ln\left(\frac{E_{i,t}}{E_{i,t-T}}\right)=a+\beta\ln\left(E_{i,t-T}\right)+\varepsilon_i \qquad (7)$$

$E_{i,t}$ *is the DEA efficiency score of region i at time t*

$E_{i,t-T}$ *is the DEA efficiency score at the initial time period* $t-T$

T *is the time span*,

a *is the intercept term*,

β *is the convergence coefficient*,

ε_i *is the error term*

If $\beta<0$, absolute beta convergence exists, which means that initially less efficient regions are improving faster and catching up with more efficient regions. If $\beta \geq 0$, there is no convergence, suggesting persistent efficiency gaps.

The following regression model was developed to investigate conditional β-convergence of DEA efficiency:

$$\frac{1}{T}\ln\left(\frac{E_{i,t}}{E_{i,t-T}}\right)=a+\beta\ln\left(E_{i,t-T}\right)+\sum_{k=1}^{5}\delta_k C_{k,i,t}+\varepsilon_i \qquad (8)$$

$E_{i,t}$ *is the overall DEA efficiency score* (*TE*)

$C_{k,i,t}$: *k Controls Variables*

$C1$: *Trade Openness*

$C2$: *Industrial Structure Level*

$C3$: *Consumer Price Index* (*CPI*)

$C4$: *LN*(*Total Investment of Foreign* − *Invested Enterprises*)

$C5$: *LN*(*Value Added of Financial Sector*)

δ_k *the coefficience of Controls Variables*

Although the DEA model assesses technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) as part of the convergence analysis, these indicators largely describe production-side technological linkages. These three indicators may neglect critical exogenous circumstances, such as external openness and demand dynamics, which have a considerable impact on regional efficiency trajectories. To solve this constraint and improve the model’s explanatory power, the regression specification includes the five control variables shown below: trade openness (C1) assesses the level of external economic contact and reliance on foreign commerce. Increased trade openness can lead to technology spillovers, competitive pressures, and more efficient resource allocation, all of which are not directly addressed by the DEA framework. Structural transition toward higher value-added industries is an important driver of efficiency gains. Industrial Structure Level (C2) accounts for disparities in industrial upgrading between areas, providing the structural base that underpins efficient performance. The Consumer Price Index (CPI) (C3) is a measure of inflation and price stability that provides an indirect indication of demand-side vitality. Changes in prices can make production less efficient, so this is a key socioeconomic stabilizer in the model. The Log of Total Investment by Foreign-Invested Enterprises (C4) measures the amount of inward capital flows and reliance on foreign investment. Capital from other countries frequently carries with it cutting-edge management techniques and technologies, both of which are essential for improving the effectiveness of resource utilization. Financial sector development promotes more efficient resource allocation, improved capital provision, and support for innovation initiatives. It is the responsibility of the Log of Value Added by the Financial Sector (C5) to account for the financial aspect of regional development and the influence that it has on changes in efficiency.

Adding these variables to the β-convergence analysis improves its robustness and interpretability by accounting for external openness, industrial upgrading, and demand-related characteristics that are not explicitly evaluated in the DEA efficiency ratings.

3.4 Data collection and processing

Regional statistical offices are primarily responsible for collecting and organizing information across many sectors, a task that individual researchers cannot accomplish. As a result, the central part of the information used in this dissertation comes from databases maintained by the National Bureau of Statistics (NBS) and the China Stock Market & Accounting Research Institution (CSMAR). The data on economic efficiency are taken from the NBS database, and the macro-regional data from 2012 to 2021 are obtained from provincial statistical yearbooks. The 14th FYP indicators are used as measurement tools. The selection of input and output indicators strictly followed the official evaluation framework of the 14th Five-Year Plan, which does not include trade indicators as explicit metrics of regional development performance. The indicators and their interpretations are presented in the Annex.

4. Results

4.1 Economic performance in the Yangtze River Basin

Before employing the 15 indicators extracted from the 14th Five-Year Plan (FYP) for empirical analysis, this dissertation performed an initial visual assessment of these indicators to elucidate the spatial and temporal characteristics of the Yangtze River Basin (YRB). The analysis aims to unveil geographical disparities, development patterns, and potential clustering tendencies within the YRB. This will be accomplished using descriptive statistics, distribution maps, and trend charts. This visualization not only helps contextualize the indicators that have been chosen but also improves comprehension of the efficiency and spatial models that will be used in the future.

4.1.1 Basic economic indicators

The Gross Domestic Product (GDP), urbanization, employees in the total industry, and labour productivity are the four viewpoints that should be used to analyse the economic development of the Yangtze River Basin. These four perspectives correlate to the essence of economic development.

(1) Gross Domestic Product (GDP)

As an economic aggregate indicator, the GDP directly reflects the Yangtze River Basin’s overall economic scale and growth trend. It serves as the foundation for evaluating the regional economic strength and development momentum, reflecting the expansion of economic “volume”. Figure 2 shows that the *GDP values in the Yangtze River Basin* rose annually. When these regions are compared, economic development levels along the Yangtze River vary from the West to the East: Shanghai and Jiangsu Provinces have the highest GDP values in the eastern region, while Sichuan Province is in the western region. The transition of colours from red to yellow from 2012 to 2021 signifies the ongoing growth of the economic scale (Amanda, 2019). The eastern region has higher GDP values than the western region.

The curves’ peak values are more significant, and the growth slopes are steeper in developed provinces like Shanghai, Zhejiang, and Jiangsu. In 2012, Jiangsu’s GDP reached 5.7 trillion yuan, ranking second in China, with a manufacturing and export-oriented economy at its core, constituting 22.6% of the total GDP of the Yangtze River Economic Belt. By 2021, Jiangsu's GDP is projected to exceed 11 trillion yuan, maintaining its second position in China. Shanghai's GDP in 2012 was 2.02 trillion yuan (10th in the nation), and the city has now transitioned into the post-industrializationpost-industrialisationpost-industrialization phase. In 2021, Shanghai's GDP will be 4.32 trillion yuan, making it the 11th largest city in the country.

The degree of development in central and western provinces (including Sichuan and Hubei) is substantial, indicative of the improvement of the Yangtze River Economic Belt's overall economic strength. In 2012, Sichuan's GDP was 2.39 trillion yuan, ranking it eighth in China. The province's per capita GDP is only 74.9% of the national average, with a high ratio of traditional industries and agriculture. The GDP for 2021 is 5.39 trillion yuan, ranking 6th in China. Hubei's 2012 GDP was 2.26 trillion yuan, ranking ninth in China. The low-value steel and automobile industries formed the first clusters. With a growth rate of 12.9%, the 2021 GDP is 5.0 trillion yuan, ranking seventh in China. In 2012, Anhui's GDP was 1.72 trillion yuan, ranking it 14th in China. However, it accounts for less than 30% of Jiangsu's total economic output and has a feeble industrial base. The GDP for 2021 is 4.3 trillion yuan, ranking 11th in China, with a growth rate of 8.3%.

For the course of GDP, the Yangtze River Basin's economy will transition from "unipolar dominance in the east" to "synergistic progress in the east, centre, and west" between 2012 and 2021. The East will maintain its scale advantage by relying on industrial upgrading, while the Centre and West will achieve the leading growth rate by accepting industrial transfers. However, the regional gradient will persist. For instance, Jiangsu's incremental GDP (5.3 trillion yuan) is double that of Anhui's (2.58 trillion yuan). In the future, it is essential to further diminish the regional development disparity and attain high-quality synergistic growth through factor marketization, ecological value transformation, and other measures.

(2) Urbanization

Except for the Tibet Autonomous Region, all provinces have undergone rapid *urbanization from the HUKOU reforms.*[4] Given a smaller population and higher salaries, it

[4] The HUKOU reform, namely the household registration system reform, is an improvement measure for the entire household management system established with the Regulations on Household Registration of the People's Republic of China as a legal basis. It was developed during the period of the era of planned economy. In 1951, the Ministry of Public Security promulgated the "Interim Regulations on Urban Household Registration Management" to unify urban household registration management. In 1955, the State Council required the establishment of a

cannot be said that the labour force will become a crucial problem in the following years (Losoncz, 2017). The eastern provinces (e.g., Jiangsu, Shanghai) have a high urbanization rate and consistent growth. In contrast, the central and western provinces (e.g., Sichuan, Hunan) have accelerated their growth rates in the later stages, reducing the disparity with the East. In 2012, approximately 63% of the population was in Jiangsu and 89% in Shanghai; in 2021, approximately 74% was in Jiangsu, and 93% was in Shanghai. The East has a high base, and Shanghai is nearly at the level of developed countries. The average annual growth rate is approximately 0.8-1.0 percentage points, and the development is steady. The primary growth drivers are industrial upgrading and the construction of urban agglomerations. In 2012, approximately 43% of the population in Sichuan and 46% in Hunan were under 18. By 2021, the percentage had increased to approximately 58% in Sichuan and 59% in Hunan. The Midwest has a lower baseline, although growth is expected to accelerate in subsequent years (average annual growth rate of 1.2-1.5 percentage points) along with the following: the disparity diminishing due to the leadership of province capitals (e.g., Chengdu, Changsha), the economic advancement of counties, and policies on the citizenship of migrant workers. Implementing HUKOU reforms to the household registration system, attracting industries from the East, and creating distinct urbanization in central and western regions have hastened the population's concentration in urban and suburban areas.

(3) Employees in the total industry

From a vertical aspect, the number of *employees in the total industry* did not change much from 2012 to 2021. Employees in the total industry in the Yangtze River Basin rose from 50.447 million individuals in 2012 to 58.477 million individuals in 2021, reflecting a growth of 15.9%. Between 2012 and 2021, industrial employment rose 23% in Shanghai (from 5.557 million to 6.831 million) and 58% in Jiangsu (from 8.309 million to 13.140 million). Nonetheless, the expansion rate in the eastern region is progressively decelerating due to industrial advancement. The data in the central and western provinces has experienced substantial growth, with Sichuan increasing by 36% over a decade (from 6.409 million in 2012 to 8.715 million in 2021) and surpassing 8.6 million in 2020, primarily attributed to a temporary fluctuation caused by the epidemic before recovery. Hubei experienced a growth of 7.6% from 2012 to 2021,

nationwide household registration system. In 1958, the "Household Registration Regulations of the People's Republic of China" was promulgated, marking the formation of a unified household registration system for urban and rural areas across the country.

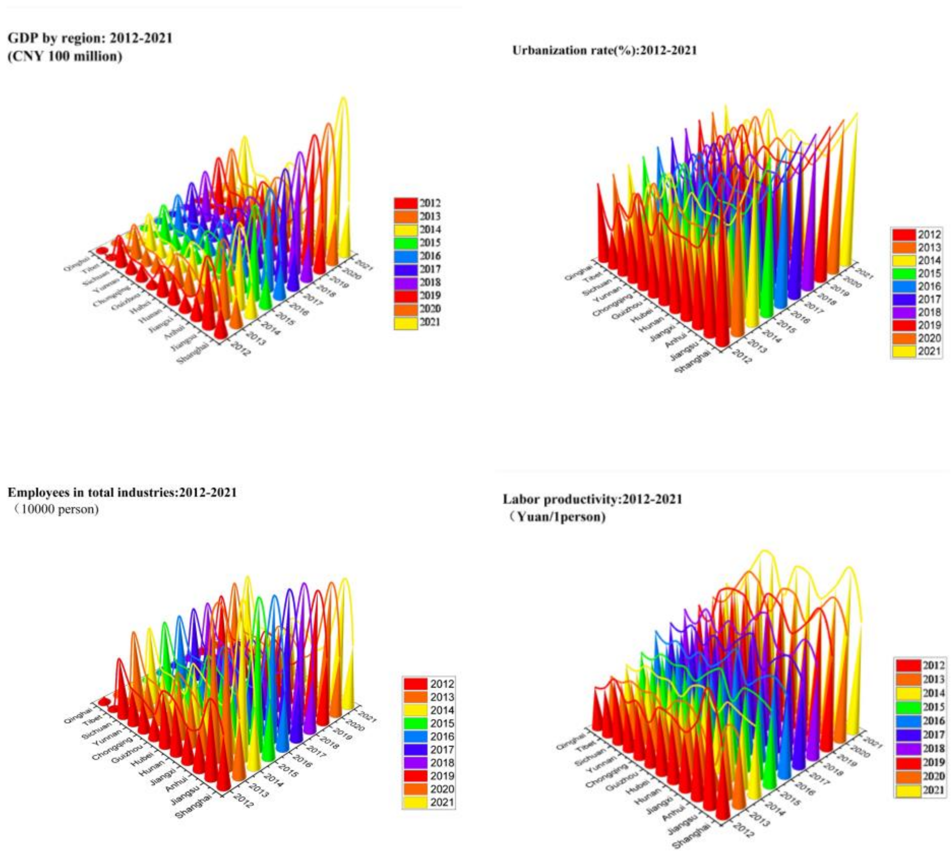
accompanied by a minor decrease in employment post-2018, attributed to industrial restructuring resulting from the de-capacitation of the automobile sector.

A basin-like distribution can also be seen in the number of jobs (*employees in total industry*), which is lower in the central region than in the western and eastern regions (Figure 2). The size of the GDP is commensurate with the number of jobs. This siphoning effect makes people flow from central to eastern and western provinces and cities.

(4) Labour productivity

Labour productivity serves as an indicator of the structural and activity characteristics of industries, as well as their capacity to assimilate labour. As the backbone of the economy, shifts

Figure 2: Economic development indicators



Note: The left axis shows the distribution of provinces from West to East in China, and the right-hand side presents the timeline.

Source: Own work based on figures from the National Bureau of Statistics of China.

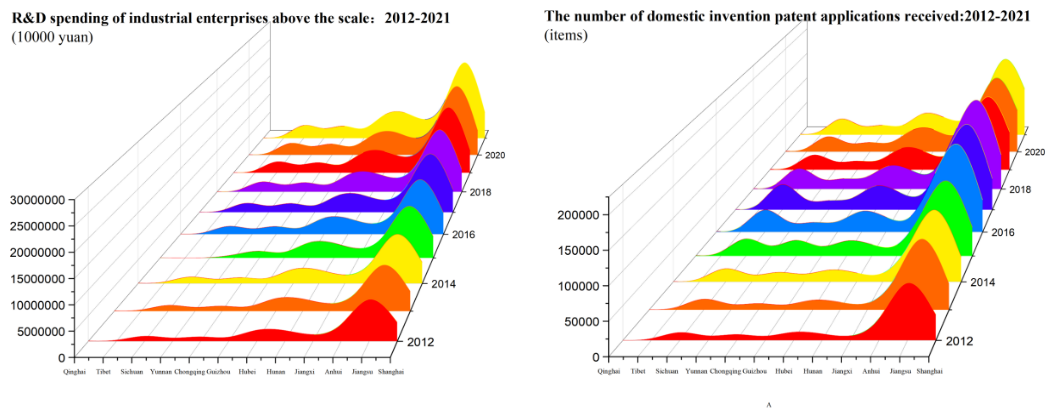
in labour productivity are linked to safeguarding people's lives and mapping the effects of upgrading and industrial transfer on the equitable growth of the local economy. Similarly to GDP, all provinces improved labour productivity year by year from 2012 to 2021. Contrary to GDP, there were three significant peaks in *labour productivity*. They have spread over time and gradually formed three major regions. Sichuan belongs to these groups in the West, Hubei in the middle, and Jiangsu in the East.

4.1.2 Innovation performance

The core indicators of innovation capacity are the R&D spending of industrial enterprises above the scale (10000 yuan) and the number of domestic invention patent applications received (items). The former indicates the magnitude of companies' capital allocation towards technology research and development, which serves as the foundational element for facilitating technical advancements and industrial enhancement. Enormous R&D spending usually means companies still invest in new technologies, improve products, or make processes more efficient. The latter indicates the effectiveness of converting the outcomes of inventive endeavours. The number of patents for inventions directly reflects the scale of output of technological advances and the potential of market application. These two factors, when combined, comprise the "input-output" closed loop of the innovation ecology.

The *R&D spending of industrial enterprises above the scale* is increasing yearly. As shown in Figure 3, the distribution of *R&D spending of industrial enterprises above the scale* from 2012 to 2021 demonstrates a three-stage ladder: enterprises in the western part spend the least on research funds, whereas those in the East invest the most, with the latter reaching a peak in Jiangsu Province. As the *number of patent applications* increases yearly, Sichuan, Hubei, and Jiangsu are emerging as the core innovative regions, radiating their impact to other provinces in the Yangtze River Basin. Due to the saturation of the manufacturing industry, the driving force of economic development is shifting from traditional manufacturing to scientific and technological innovation. *The number of domestic invention patent applications received* grew between 2012 and 2018, peaking in 2018 and maintaining a stable level from 2018 to 2021. After 2016, *the number of domestic invention patent applications received* in the central and western regions increased significantly, particularly in the Sichuan and Hubei Provinces. As the core area of China's economic development, each province in the YRB is carrying out innovative reforms: provincial governments are leading the research and development of technologies such as 5G, cloud computing, big data, and blockchain, as well as encouraging patent inventions.

Figure 3: Innovative indicators



Source: Own work based on the National Bureau of Statistics of China figures.

Notes: The horizontal axis represents the province distribution from West to East in China from 2012 to 2021, and the vertical axis shows the indicator value.

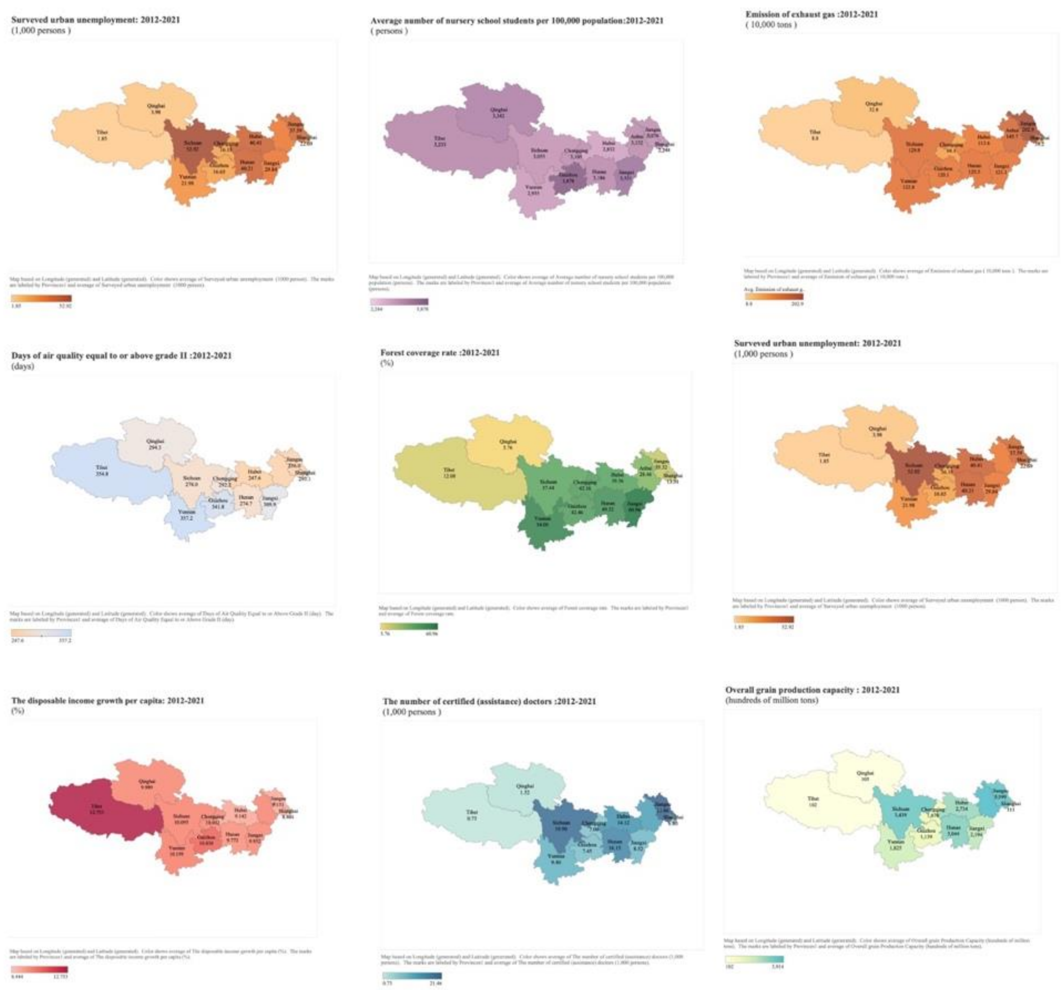
4.1.3 Social welfare issues

To illustrate the provinces' differences in resource security, people's welfare, and green environment, panel data were collected for each province from 2012 to 2021, and average values were calculated across periods (Figure 4).

Building a modern and powerful country and ensuring national food security at a higher level requires the high-quality development of the food economy to ensure national food security, promote rural revitalization of poverty, and achieve coordinated regional development. The Eastern and Central regions produce more food than the Western ones. Since most of the western region is on a plateau, all other regions have lower grain production except for the Chengdu Plain, where grain production yearly averages 3439 tons per acre. The number of people participating in *pension insurance* varies in the country's regions. Their number is much lower in Tibet and Qinghai than in the central and eastern parts. However, there is a significant difference in the number of participants between provinces and cities, ranging between 780,000 and 34,190,000. There needs to be more awareness on the part of the insured in the Western region. On the other hand, there needs to be more publicity for the insured.

There are significant differences in *air quality* between the north and south regarding green ecology, with air quality in the south along the Yangtze River significantly better than in the north. *Environmental pollution* is a significant problem in some regions, and there is a contradiction between development and environmental protection. There has been a severe increase in air pollution along the Yangtze River due to the rapid development of resource-intensive industries such as thermal power, iron and steel manufacturing, and petrochemicals. There is a high concentration of *forest coverage* in the central and eastern parts of the western regions. Due to its sparse population and a small number of heavy industries, the Qinghai-Tibet region has lower pollutant emissions. In contrast to other provinces and cities with heavy emissions, the Chongqing region has considerably lower emissions.

Figure 4: Food security and people's welfare, green ecology indicators (average)



Source: Own work based on National Bureau of Statistics of China figures.

Note: Shade of colour represents magnitude of value.

Based on five aspects of the data collected, *a novel input-output table* was constructed to calculate high-quality economic efficiency. As in previous literature, the input and output analysis measured economic development rather than offering a comprehensive evaluation. The definition of a high-quality economy includes environmental and production impacts in addition to measuring each resource. The objective is to minimize and maximize with minimal environmental impact. Therefore, the DEA model better describes a high-quality economy.

4.2 PCA-SBM analysis in the YRB

4.2.1 Dimension reduction: PCA

DMUs should be at least $\max[(m \times s; 3 \times (m+s))]$, where m is the number of inputs and s is the number of outputs (Cooper et al., 2007). I examined data from 12 provinces and 15 macro-economic indicators from 2012 to 2021. With 12 provinces and data spanning 10 years, the annual data for each province is considered to be a distinct DMU; therefore, the total number of DMUs is 120.

Hence, the input indicators must be reduced. PCA can combine PC scores linearly by constructing a correlation matrix. The PCA applied in the scope of this study fits nine input indicators into three primary datasets. As indicated in Table 3, we use two statistical techniques to evaluate the suitability of data for PCA: *Bartlett's test of sphericity* and the Kaiser–Meyer–Olkin (*KMO*) test (Bartlett, 1950) (Kaiser, 1970).

Table 3: KMO and Bartlett test results

KMO and Bartlett test		
KMO		0.709
Bartlett test	Approx. Chi-Square	1249.55
	df	36
	p value	0

Source: Authors' calculation using SPSS.

The *KMO* test assesses the correlation between variables, and the result is 0.709, which implies that the nine data indicators can be better analysed using PCA (Roweis, 1997). *Bartlett's test of sphericity* assesses whether the correlation matrix is an identity matrix, suggesting no correlations between variables. A Bartlett p-value of $0.00 < 0.05$ passes the reliability test, concluding that the data can be analysed using PCA.

Table 4: Principal component eigenvalues and variance rates of indicators

Total Variance Explained			
PCA	% of variance		
	Eigen	% of variance	Cum. % of Variance
1	4.535	50.392	50.392
2	2.087	23.19	73.582
3	1.168	12.981	86.562
4	-	-	-
5	-	-	-
6	-	-	-
7	-	-	-
8	-	-	-
9	-	-	-

Source: Own calculation using SPSS.

Table 5: Factor loadings

Loadings				
Items	**Loadings**			**Communalities**
	PC 1	**PC 2**	**PC 3**	
R&D spending of industrial enterprises above the scale (10000 yuan)	0.825	-0.472	-0.043	0.906
The number of domestic invention patent applications received (items)	0.827	-0.457	-0.013	0.892
Overall grain production capacity (hundreds of million tons)	0.817	0.515	0.068	0.938
The number of certified (assistance) doctors (1,000 persons)	0.952	0.175	-0.036	0.938
Number of urban and rural residents' social old-age insurance participants (10,000)	0.644	0.733	0.005	0.952
Average number of nursery school students per 100,000 population (persons)	-0.079	0.377	-0.802	0.792
Revenue from Software Business (100 million yuan)	0.706	-0.665	0.047	0.942
The disposable income growth per capita (%)	-0.286	0.306	0.699	0.663
Surveyed urban unemployment (1000 person)	0.772	0.381	0.161	0.766

Source: Authors' calculation using SPSS.

Table 6: Linear combination coefficient matrix

Linear combination coefficient matrix			
Items	**Component**		
	PC 1	**PC 2**	**PC 3**
	Innovation and technology resources	**Labour resources**	**Welfare resources**
R&D spending of industrial enterprises above the scale (10000 yuan)	0.387	-0.327	-0.04
The number of domestic invention patent applications received (items)	0.388	-0.316	-0.012
Overall grain production capacity (hundreds of million tons)	0.384	0.357	0.063
The number of certified (assistance) doctors (1,000 persons)	0.447	0.121	-0.033
Number of urban and rural residents' social old-age insurance participants (10,000)	0.303	0.507	0.005
Average number of nursery school students per 100,000 population (persons)	-0.037	0.261	-0.742
Revenue from Software Business (100 million yuan)	0.331	-0.46	0.043
The disposable income growth per capita (%)	-0.134	0.211	0.647
Surveyed urban unemployment (1000 person)	0.362	0.264	0.149

Source: Authors' calculation using SPSS.

After the z-score normalization of the original data for the indicators, we combine the 33 components of the indicators into three Principal Components (PCs) with respective variance eigenvalues of 50.392%, 23.19%, and 12.981% (Table 4). (Kappal, 2019) According to Kaiser's criterion, we will retain all PCs with eigenvalues > 1 (Kaiser, 1960), which makes it possible to summarize most of the information in the data clearly and concisely.

$$\begin{cases} PCA1 = 0.387*x_1 + 0.388*x_2 + 0.384*x_3 + 0.447*x_4 + 0.303*x_5 - 0.037*x_6 + 0.331*x_7 - 0.134*x_8 + 0.362*x_9 \\ PCA2 = -0.327*x_1 - 0.316*x_2 + 0.357*x_3 + 0.121*x_4 + 0.507*x_5 + 0.261*x_6 - 0.46*x_7 + 0.211*x_8 + 0.264*x_9 \\ PCA3 = -0.04*x_1 - 0.012*x_2 + 0.063*x_3 - 0.033*x_4 + 0.005*x_5 + -0.742*x_6 + 0.043*x_7 + 0.647*x_8 + 0.149*x_9 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Based on the contribution of these factor loadings (Table 5) and the linear combination coefficient matrix, we obtained the above equation based on the eigenvalues (three formulas from Table 6). We calculated three indicator scores consisting of nine indicators for two provinces from 2012 to 2021 using a PCA formula. To better classify these indicators, *innovation and technology resources* were defined as PC 1, *labour resources* as PC 2 and *welfare resources* as PC 3.

Table 5 and Table 6 present the factor loadings of each indicator on the three principal components. PC1 exhibited high positive loadings on R&D spending of industrial enterprises above the scale (0.825), the number of domestic invention patent applications received (0.827), the number of certified (assistant) doctors (0.952), surveyed urban unemployment (0.772), and overall grain production capacity (0.817). PC1 can be interpreted as representing innovation and technology resources combined with critical aspects of social infrastructure, as these indicators primarily reflect technological inputs, innovation capability, and the scale of public services. Interestingly, this component also captures aspects of human capital accumulation pertinent to sustainable development, as evidenced by the high loading of qualified physicians. PC2 demonstrated its strongest positive loadings on the number of urban and rural residents' social old-age insurance participants (0.733), overall grain production capacity (0.515), and GDP-related scale variables. In addition, it showed moderately positive loadings on the surveyed urban unemployment (0.381) and disposable income growth per capita (0.306). This pattern suggests that PC2 reflects labour resources and the broader capacity of provinces to mobilize employment and social protection mechanisms, linking economic dynamism to social insurance coverage and agricultural resilience. PC3 was characterized by a strong negative loading on the average number of nursery school students per 100,000 population (−0.802) and a substantial positive loading on disposable income growth per capita (0.699). The combination of welfare-related dimensions and demographic structure in PC3 suggests that it may reflect disparities in income improvement in relation to the distribution of population age and the coverage of early childhood education.

Overall, these three components jointly explained 86.6% of the total variance in the dataset, which provides a consistent and interpretable basis for the construction of composite indicators in the subsequent DEA efficiency analysis.

To address the requirement of DEA for non-negative input variables, we normalized the PCA before applying DEA (Pastor & Ruiz, 2007) (Shanmugam & Johnson, 2007). We adopted the min–max normalization linear function to linearize the original data to the [0, 1] range to address the presence of negative PCA scores, which are unsuitable for DEA as it requires non-negative inputs and outputs. The min–max normalization method ensures that all transformed PCA scores fall within the [0,1] range to enable their use in the DEA model. The normalized data are used for the calculated result, where X is the original data (Kappal, 2019).

$$x^n = \frac{x - min(x)}{max(x) - min(x)} \quad \text{.......................................} (10)$$

x^n: *the normalized data*

We employed iDea software to apply the SBM model, setting the DMUs to 120, inputs to 3, outputs to 5 and the undesirable output to 1. (Undesired outputs such as environmental pollution are not included in the outputs.) We calculated efficiency using a global frontier, non-oriented, standard efficiency approach.

4.2.2 Spatio-temporal differences

(1) Comparison of efficiency

From 2014 to 2019, the quality of economic efficiency across China's provinces exhibited minimal fluctuation, representing a steady upward trend. The efficiency value reached its lowest point in 2013, followed by a peak in 2020, after which it began to decline. High-quality efficiency (technical economic efficiency) displayed an upward trend from 2011 to 2021. The trend of pure technical economic efficiency was similar, suggesting that government management and resource allocation boosted technical economic efficiency. Scale efficiency continued to assume a value between 0.9–1 from 2012 to 2021, which indicates that the scale and structure of inputs were reasonable and the value-added benefits from scale expansion remained reasonable (Figure 5).

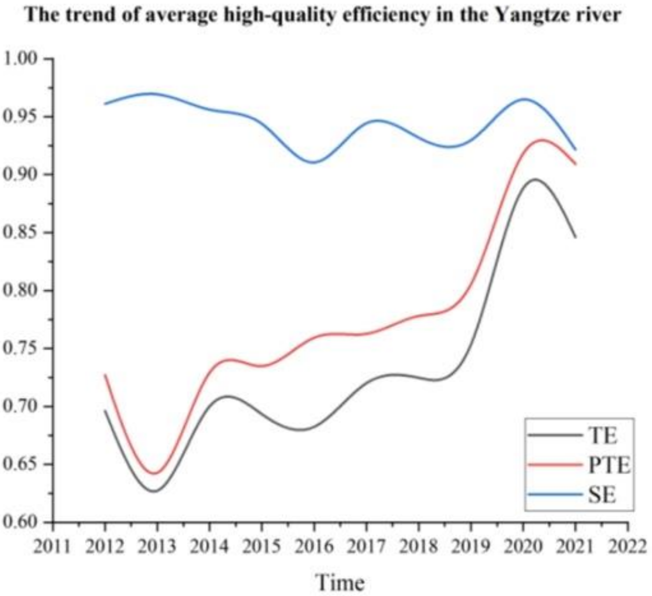
We composed the efficiency values for each province and decomposed them based on the accounting results. The average efficiency values between 2012 and 2021 were calculated per province and then plotted using Origin 2021 software.

According to the *high-quality efficiency (TE) analysis*, Sichuan Province and Hubei Province, the core strengths of the eastern and central regions, do not score the highest for technical efficiency compared with the distribution of GDP production output described formerly. Previous literature has generally used GDP and other gross product indicators to evaluate economic development (Rahman et al., 2017). However, the shortcoming of this method is that environmental pollution caused by rapid economic development has become the most critical deduction. Therefore, Sichuan, the central province for local development in western China, and Hubei, the centre of China's hinterland, must strengthen environmental pollution management. Notably, Chongqing is strong and effective in terms of high-quality economic efficiency, indicating that it has performed well in terms of GDP and environmental protection, with corresponding management from the government (Figure 6).

Figure 5: Trend of average high-quality efficiency in the YRB region

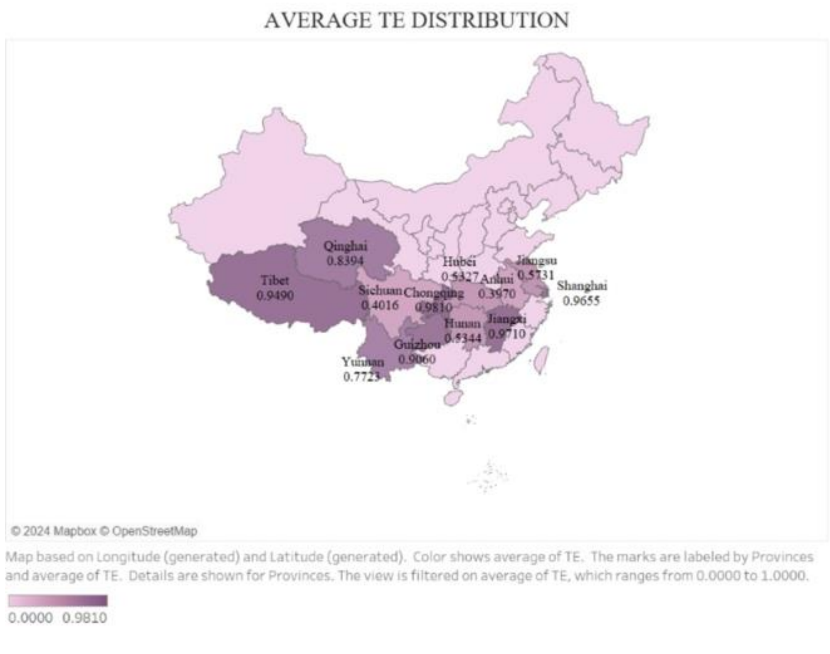
Source: Authors' construction based on the model results.

Figure 6: Average high-quality



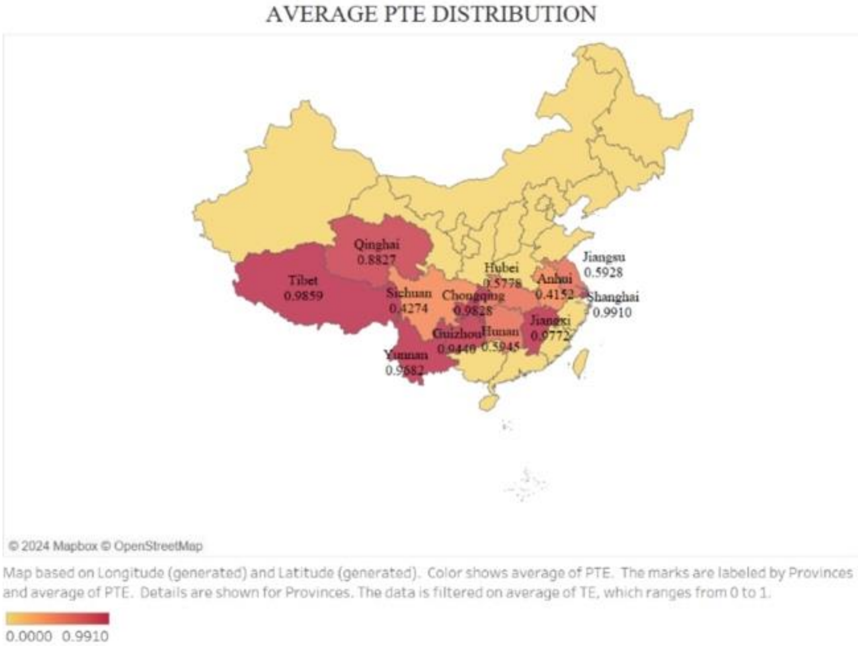
y technical efficiency (TE)

distribution in the YRB region



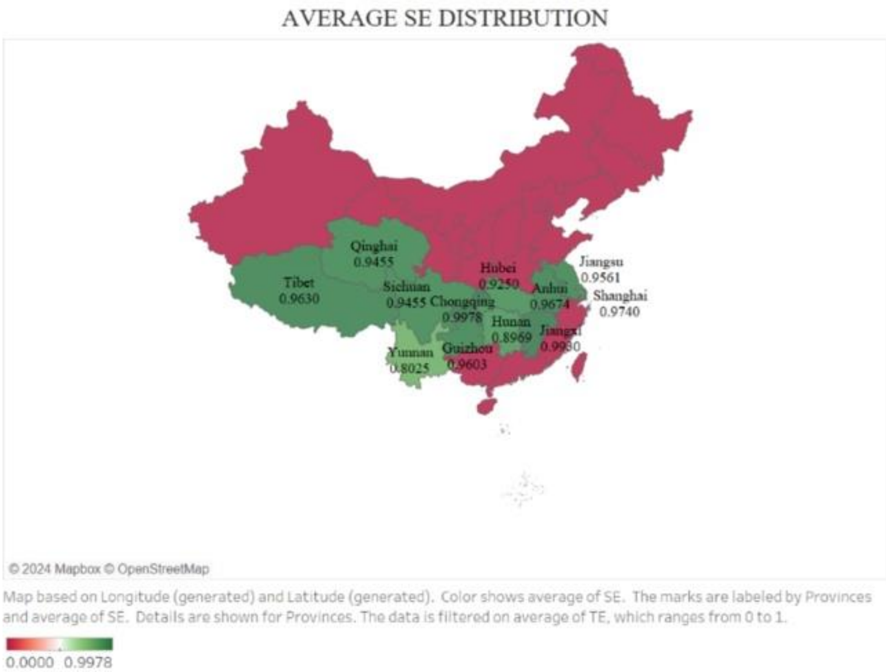
Source: Authors' construction using Tableau software.

Figure 7: Average pure technical efficiency (PTE) distribution in the YRB region



Source: Authors' construction using Tableau software.

Figure 8: Average scale efficiency (SE) distribution in the Yangtze River region



Source: Authors' construction using Tableau software.

The differences in *pure technical efficiency (PTE)* between the eastern and western regions are similar to those in high-quality economic efficiency. Provinces with heavy industry and large mineral reserves, such as Sichuan, Hubei, and Jiangsu, emit considerable pollution, making them less pure in technical efficiency (Figure 7).

Regional differences in *scale efficiency (SE)*, which primarily measures the impact of resource inputs on policy efficiency, are less pronounced than the other two efficiencies. Qing Hai, Tibet, Chongqing, Hunan, Jiangxi, Jiangsu and Shanghai had scale efficiencies 1 in 2021. The scale efficiency of these provinces remained unchanged (i.e. the scale and structure of inputs were reasonable). The scale efficiency for the remaining provinces decreased, indicating that policy output increases were smaller than input increases, suggesting that policy implementation must improve (Figure 8).

(2) Comparison of growth rate

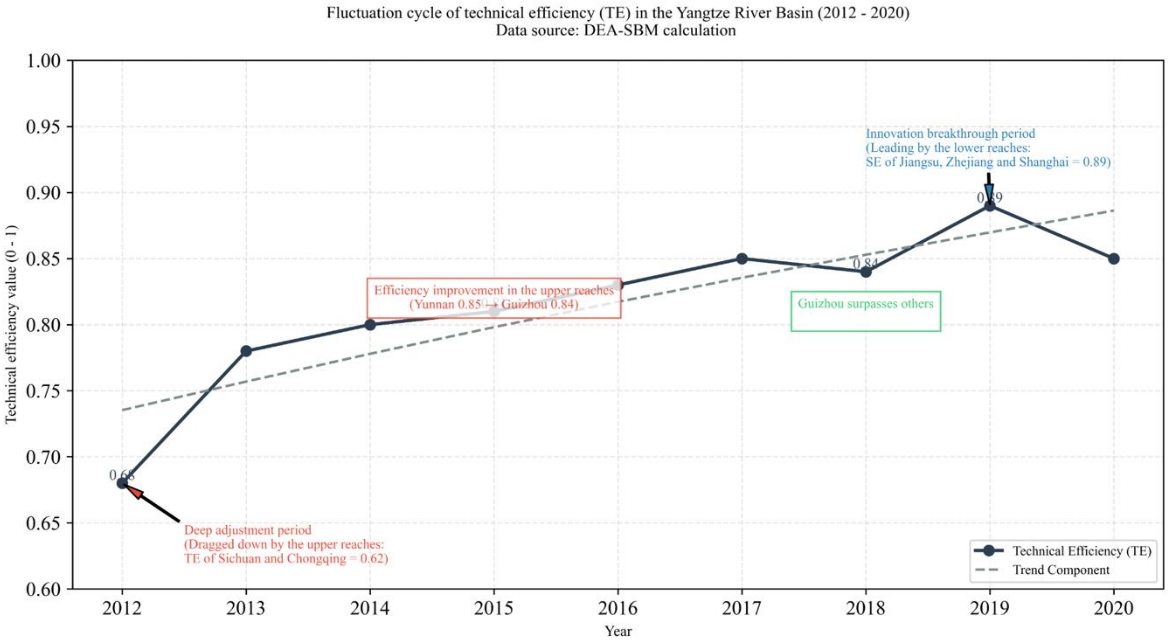
The enhancement of efficiency in the YRB represents a cyclical pattern characterized by the "policy-driven → structural adjustment → technological deepening" formula, generally spanning 3 to 4 years. Policy interventions frequently raise short-term efficiency, yet ensuing structural modifications may result in transient reductions in scale efficiency prior to the stabilization of long-term technology advancements. The year 2013 saw a significant peak for total efficiency and pure technical efficiency, with rises of more than 13% year-on-year. The growth was directly linked to substantial infrastructure investments and technology deployment in expectation of the official endorsement of the Yangtze River Economic Belt initiative in 2014. Nonetheless, scale efficiency diminished, signifying a temporary misallocation of resources, wherein capital and labour inputs were not efficiently distributed. Due to supply-side structural reforms that sought to improve technical upgrading and remove obsolete industrial capacity, pure technical efficiency increased significantly (+4.20%) in 2015. Though SMEs have strengthened their technological capabilities, they have not yet achieved scale synergy and ultimately realized economies of scale, as evidenced by the 3.44% fall in scale efficiency. The implementation of environmental inspections was a turning point for industrial adjustment. By accelerating the elimination of wasteful production capacity and by improving the allocation of production factors—particularly through more efficient use of capital and labour—these inspections became a significant driver of improvement in scale efficiency, which turned positive (+4.62%) by 2016. As more stringent environmental restrictions encourage businesses to adopt more efficient manufacturing techniques, this trend supports the idea that "lucid waters and lush mountains" (green development policies) can favour economies of scale. In 2020, the COVID-19 outbreak precipitated substantial disruptions to supply chains, markedly affecting efficiency growth in the YRB. Technical efficiency decreased by 4.27%, while scale efficiency diminished by 4.37%, illustrating the extensive economic impact. Conversely, pure technical efficiency experienced a mere decline of 0.41%, signifying technological and managerial competencies' robustness (see Tables 7 and 8).

Table 7: The growth rate of the Yangtze River Basin

Year	TE Average	PTE Average	SE Average
2012	-10.4626%	-11.2799%	1.4989%
2013	13.9976%	15.7002%	-1.3511%
2014	2.1233%	3.0709%	-1.0653%
2015	0.7003%	4.1984%	-3.4379%
2016	6.3743%	1.7393%	4.6193%
2017	1.7623%	3.2211%	-1.3793%
2018	7.9838%	7.6108%	0.4282%
2019	19.3311%	14.7079%	3.5199%
2020	-4.2741%	-0.4073%	-4.3654%

Source: Own work based on the PCA-SBM data.

Table 8: Cyclical phases and volatility patterns



Cycle Phase	Years	TE growth	PTE growth	SE growth	Driving Mechanism
Recovery	2012–2013	-10.46% → +13.99% (V-shaped)	-11.28% → +15.70% (synchronous)	+1.50% → -1.35% (reverse adjustment)	Policy-driven (pre-Yangtze Economic Belt strategy)
Adjustment	2014–2015	Peaked at +0.70%	Surged to +4.20%	Sustained decline (-1.07%→-3.44%)	Structural transformation (supply-side reforms)
Expansion	2016–2019	Rose to +19.33% (peak)	Fluctuated to +14.71%	Recovered (+4.62%→+3.52%)	Technology deepening (ecological constraints)
Contraction	2020-2021	Plummeted to -4.27%	Slight decline (-0.41%)	Collapsed (-4.37%)	Exogenous shock (COVID-19 pandemic)

Source: Own work based on the PCA-SBM data.

(3) Comparison of regional growth rate

We evaluated the growth rates of efficiency across various regions based on DEA-calculated efficiency values in Table 9, dividing them into three types: progressing, fluctuating, and regressing. This provided a comprehensive analysis of regional development trends.

The regions labelled *'progressing'* have favourable and relatively high efficiency growth rates. Hunan and Jiangsu are the foremost exemplars in this category. DEA efficiency calculations indicate that these regions have significantly enhanced 3E (TE, PTE, SE). Hunan's technical efficiency growth rate was 17%, positioning it among the highest regions. The analysis of DEA efficiency measures indicates that pure technical efficiency has risen to 19.2% and scale efficiency to 21.2%.

According to this, Hunan has proactively implemented cutting-edge manufacturing technology and management techniques, significantly increasing the efficiency of its production operations. Hunan's businesses have improved product quality and general production efficiency in the manufacturing sector by strengthening cooperation with universities and research facilities and integrating innovative scientific research into industrial output. Concurrent with internal management, companies have refined their organizational systems, enhancing employee productivity and decision-making accuracy. Regarding scale operations, Hunan has rationalized expanding production capacity, attaining economies of scale, lower unit production costs, and a significant rise in general efficiency. The coordinated improvement in technical, pure technical, and scale efficiencies has given Hunan strong momentum for sustained economic growth, making it one of the most outstanding examples of regional efficiency enhancement.

Table 9: The growth rate of 12 provinces in the YRB (%)

Provinces (growth rate)	TE Average	PTE Average	SE Average
Qinghai	6.7230%	5.7035%	6.8881%
Tibet	7.2639%	1.7842%	3.3565%
Sichuan	3.7020%	4.0551%	3.5080%
Yunnan	0.8419%	0.5412%	1.3389%
Chongqing	0.0823%	0.0960%	0.1120%
Guizhou	-2.6006%	-3.0340%	-3.5397%
Hubei	9.2343%	10.3656%	11.1721%
Hunan	16.9612%	19.1884%	21.1875%
Jiangxi	0.4689%	2.7945%	3.6508%
Anhui	9.1173%	8.9622%	9.6172%
Jiangsu	16.1045%	17.8121%	19.7919%
Shanghai	2.7978%	1.4619%	0.7442%

Source: Own work based on the PCA-SBM data.

Apart from Hunan and Jiangsu, Hubei and Anhui also belong to the progressing group, albeit with significantly lower technical efficiency growth rates of 9.2% and 9.1%, respectively. Although their efficiency growth rates are not as high as those of Hunan and Jiangsu, they demonstrate consistent advancement.

In *Hubei*, advances in technical efficiency, pure technical efficiency, and scale efficiency can be linked to continued efforts in industrial upgrading and developing emergent industries. The automobile sector, one of Hubei's core ones, has actively incorporated new energy vehicle (NEV) technology, consequently boosting product competitiveness and production efficiency. Similarly, *Anhui* has made significant gains in technology innovation and industrial transfer in recent years. Large-scale investments have fostered industrial expansion and technological innovation, improving efficiency across numerous sectors. Compared to Hunan and Jiangsu, Hubei and Anhui have displayed slightly worse growth rates in technical, pure technical, and scale efficiency, suggesting that although they continue to be on a favourable trajectory, the development speed is slower. Despite these disparities, Hubei and Anhui have made significant progress in industrial upgrading and technological innovation, ensuring they remain in the developing group. While their growth rates do not match those of Hunan and Jiangsu, their efforts in boosting industrial transformation and innovation-driven development indicate that they are steadily developing, albeit at a more moderate pace.

With somewhat low values, the *'fluctuating' type* comprises areas where technical efficiency development rates vary between positive and negative values. Among these are Jiangxi (0.5%), Shanghai (2.8%), Sichuan (3.7%), Qinghai (6.7%), and Tibet (7.3%). Reflecting differences in the development patterns of several efficiency dimensions, these areas have recorded low and unstable comprehensive efficiency growth rates with inconsistent trends in 3E. For example, Shanghai achieved only a 2.8% rate of technical efficiency increase. Regarding its efficiency components, TE and PTE rose by 2.8% and 1.5%, but SE dropped by 0.7%.

This implies that *Shanghai* has made some technological applications and internal management advancements by deploying more R & D and introducing process optimisation, improving technical efficiency and pure technical efficiency. Still, the drop in scale efficiency points to possible difficulties with significant operations. Rising labour prices and land resource limits could restrict corporate expansion as the city develops, causing diseconomies of scale and slowing down general progress in efficiency. Apparent increases in technical and pure technical efficiency define Shanghai's condition; nonetheless, a considerable reduction in scale efficiency characterizes its total efficiency growth, which is typical for the fluctuating type of unstable and erratic trends.

Reflecting the absence of synergy among several development elements, *Sichuan* shows discrepancies in TE growth rates and a consistent efficiency growth rate of 3.7%. Although some sectors have seen fast technological development, problems scaling up production or optimizing management have led to inefficiency.

Despite notable differences across TE, *Qinghai* (6.7%) and *Tibet* (7.3%) also show increased efficiency. In these areas, geographic and resource limitations could make it challenging to introduce and apply sophisticated technologies, lift industrial scale, or maximize resource allocation, leading to erratic patterns of efficiency development. Though categorized under the fluctuating type, *Sichuan, Qinghai, and Tibet differ from Shanghai* since their growth limitations are more multifarious and multifarious. Unlike Shanghai's unique scale inefficiency, these areas are less typical in this category, as they are shaped by a combination of topographical, technological, and industrial constraints rather than by a single dominant factor.

Regions with negative technical efficiency growth rates are categorized as *'regressing'*, including *Guizhou* (-2.6%), *Yunnan* (0.8%), and *Chongqing* (0.1%). These regions provided markedly diminished efficiency growth relative to others, signifying a general deterioration of efficiency, with technical efficiency and pure technical efficiency reflecting subpar performance. With TE, PTE, and SE representing negative growth at -2.6%, -3.0%, and -3.5%, respectively, *Guizhou* stands out as the most severe instance in this area. Guizhou encounters considerable difficulties in several areas, such as the implementation of technology, the administration of internal affairs, and the execution of large-scale activities. The province's comparatively low economic development level has led to an investment shortage in technical innovation, causing technological backwardness due to being unable to satisfy the demands of industrial development. In internal management, antiquated company models and diminished management efficiency may have impeded operational effectiveness. Due to the absence of economies of scale, Guizhou's industrial base is still tiny. Furthermore, businesses may have had difficulty expanding their operations or investment in technical advancements due to the intense rivalry in the market and the low profitability of their operations, which ultimately produced a general decrease in production efficiency. Given its severe and pervasive problems, Guizhou is the most notable example of the regressing segment due to a steep decline in comprehensive efficiency and negative growth in technical, pure technical, and scale efficiencies.

In contrast, *Yunnan* exhibits marginal gains in technical and pure technical efficiency, as seen by minor improvements in TE (0.8%), PTE (1.5%), and SE (1.3%), even though overall TE growth is still poor. The province may face problems with industrial restructuring because historic industries continue to make up a significant portion of the economy, which makes modernization and transformation challenging. The sluggish progress of nascent industries and the absence of scale effects have further constrained overall efficiency increases. Furthermore, additional efficiency gains might have been limited by the absence of skill and technological innovation capacity.

With only a 0.08% increase in TE, *Chongqing's efficiency growth* is at a standstill. The breakdown of efficiency growth rates reveals that PTE is operating at 0.096% and SE at 0.112%. These figures indicate that limited improvement has taken place across all efficiency dimensions. As a municipality under central management, Chongqing may encounter difficulties regarding industrial structure optimization and resource limitations. Although significant progress has occurred in management and technology, problems, including the inability of emergent sectors to mature and obstacles in the transition from old to new industries, may have prevented efficiency growth. Competitive constraints on conventional industries may have exacerbated the stagnation of overall efficiency enhancements, positioning Chongqing at the brink of regression. *Guizhou* shows more severe deterioration than Yunnan and Chongqing. While Chongqing has substantially developed in all areas, *Yunnan* has shown only minor technical and pure efficiency increases. On the other hand, both regions have achieved highly limited overall efficiency growth, which keeps them within the regressing type. Even though the intensity of their issues is considerably smaller than that of Guizhou, both regions have experienced a decline in overall efficiency.

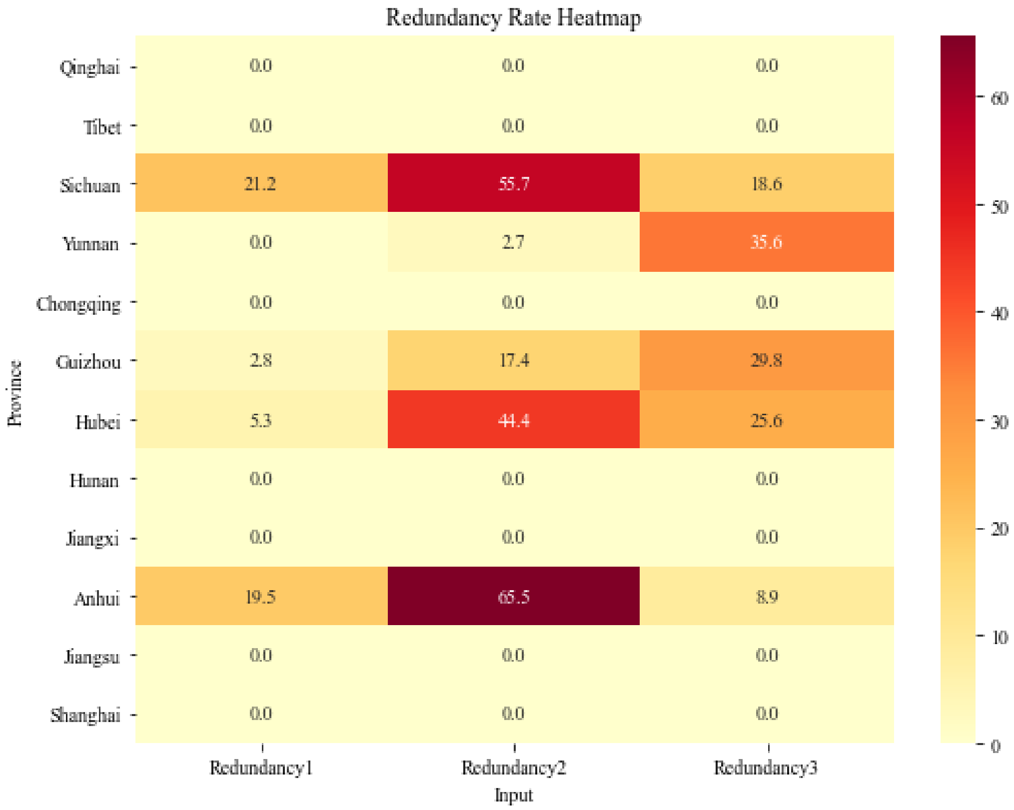
4.2.3 Analysis of input redundancy

Redundancy analysis is defined as the difference between the ideal and the actual values of inputs to achieve optimal efficiency (Ul Hassan Shah et al., 2024). We conducted an input redundancy analysis using the data from 2012 to 2021 to identify the potential for improving ecological inputs, particularly for provinces classified as relatively inefficient in the DEA. The slack[5] value refers to the amount of excess output or shortfall in input that will not affect the optimal solution, and the normal calculation method is divided by the original data value to calculate input redundancy and determine the relative rate (Tone 2002). Input redundancy rates are calculated by dividing input item slack by input quantity, and output deficiency rates are calculated by dividing output item slack by output quantity (Podinovski, 2004). Within the PCA, Slack_ln1&2&3 (the abbreviation for PC1, PC2 and PC3 inputs) represents science and technology, human and welfare resources, respectively.

According to the allocation of Slack_ln1 (*science and technology resources*) for the provinces, *Sichuan Province* can improve its use of science and technology resources the most, reaching 21.2% (Figure 9). Theoretically, achieving a 21.2% improvement in the PC1 requires strategically targeted adjustments to these underlying indicators from the equation (3). Therefore, the local Sichuan government should focus its reform on enhancing research and development investments, increasing the number of patents and improving doctors' certifications, as these areas significantly affect the PCs. This is followed by Anhui Province, where the utilization rate still needs to be improved by 19.5%. Based on the distribution of Slack_ln2 (*labour resources*) for the provinces, Hubei (0.36), Sichuan (0.51) and Anhui (0.59), Provinces need to ramp up efficiency when using labour resources. These provinces should alter talent recruitment policies to attract talent and improve talent utilization practices, and systems for leveraging and promoting talent in various industries require further development. Regarding Slack_ln3 (*welfare resources*), Yunnan has the greatest need for improvement, with 35% of its resources being inappropriately applied, followed by Guizhou and Hubei, where welfare resource efficiency could be improved by approximately 30%.

[5] In various analytical contexts, slack refers to how an activity or a resource can be delayed or underutilized without negatively affecting the overall process or outcome (Tone, 2002), (Tone & Tsutsui, 2010), (Tone, 2015).

Figure 9: Input slack value and redundancy rate in 2021 by region

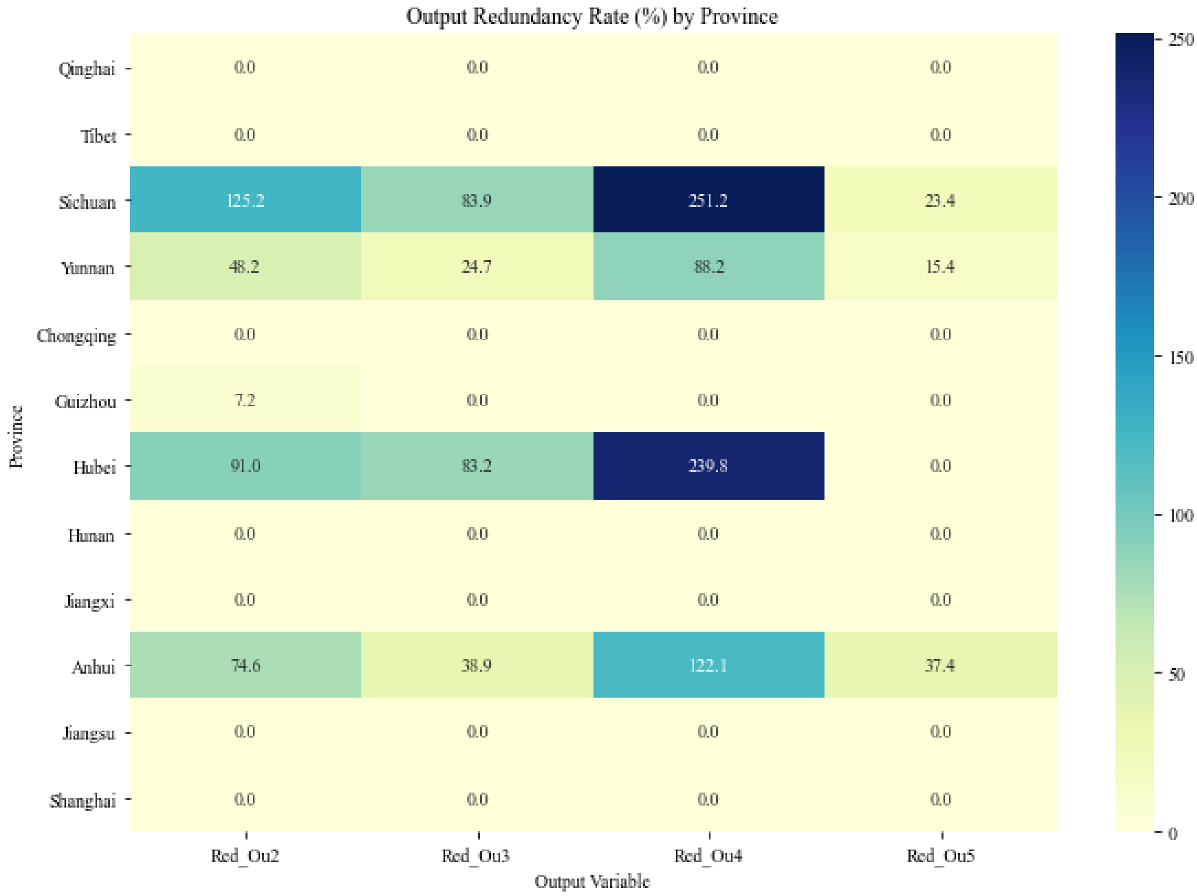


Source: Authors' calculations based on model results.

4.2.4 Analysis of output deficiencies

Output deficiencies occur when an economy's production or output of goods and services falls short of potential (Li et al., 2007). This can frequently result in the underutilization of resources, unemployment and slower economic growth. The eastern region is on par with the central and western regions regarding employment and urbanization, with central and western regions having more room for improvement in employment and urbanization. On top of the original output, no output deficiencies are evident for GDP values. *Labour productivity output* (Slack_Ou2) could be increased by 30.0% and the urbanization rate (Slack_ou3) by 18.1%. There is room for improvement in the central region, where labour productivity output (Slack_Ou2) can rise by 30.4% and urbanization rate (Slack_Ou3) by 27.7%. In the eastern region, it is also essential to increase the number of days when air quality equals to or exceeds grade II (day) (Slack_Ou4) and forest coverage (Slack_Ou5), as another 1.24% and 12.47% of work can be done, respectively, compared with the central and western regions (Figure 10).

Figure 10:Output slack value and redundancy rate in 2021 by region



Source: Authors' calculations based on model results.

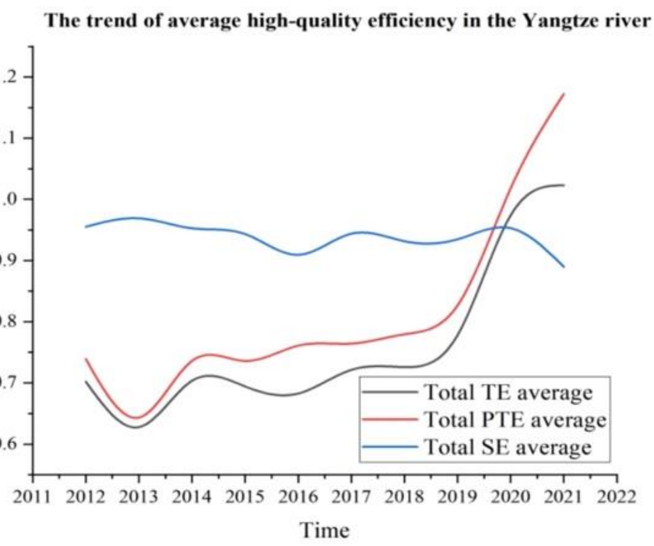
4.2.5 Robustness tests and sensitivity test

（1） Super efficiency calculation

To further assess the stability and discriminatory power of the efficiency estimates, super efficiency DEA models were computed in addition to the standard efficiency scores. In the super efficiency framework, each decision-making unit (DMU) is excluded from the reference set when constructing the production frontier, allowing efficiency scores to exceed unity. This comparison provides additional insights into the robustness of the frontier and enables ranking among otherwise efficient units. The observed consistency between standard and super efficiency rankings suggests that the results are not unduly driven by any single observation.

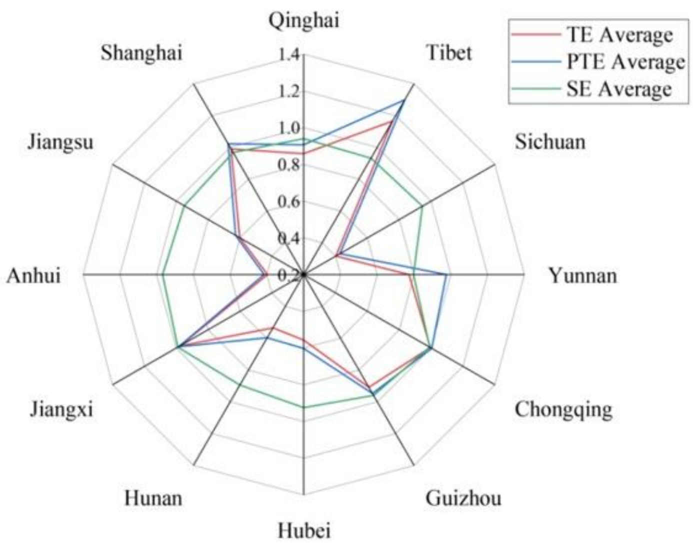
The unique methodological properties of the super-efficiency DEA model serve as the basis for its isolation and separate analysis. In contrast to the conventional CCR and BCC models, which designate a maximum efficiency score of 1 to all efficient decision-making units (DMUs), the super-efficiency model permits efficiency scores to exceed 1. This feature allows for a more precise differentiation of units on the efficient frontier by quantifying the degree to which each efficient DMU outperforms its peers after being excluded from the reference set. Consequently, super-efficiency offers supplementary insights into the relative performance levels that are not apparent in conventional DEA models. Therefore, we used the super-efficiency SBM model as one of robustness sensitivity test for the DEA-SBM standard efficiency, enabling a more thorough examination of DMU performance than binary classifications of efficient/inefficient. The super-efficiency SBM model can also rank efficient DMUs, which is impossible with the standard SBM model, as all efficient DMUs are assigned a score of 1. Super-efficiency SBM provides valuable information about the stability and reliability of efficiency scores, ensuring that efficiency assessments are accurate and meaningful. We employ this model to simulate the sample data and obtain a high-quality estimate of each province's economic efficiency under the super-efficient model (Zhu, 2001). The distribution of super-efficiency in the YRB region is flat compared with standard efficiency. However, the trends are similar, and provinces' resource allocation and management gradually improve over time (Figure 11). Consequently, low standard efficiency is a problem for Sichuan and Hubei, as is their super-economic efficiency. Sichuan finished last in pure technical and technical efficiency. Chongqing, close to Sichuan, performs well and ranks second in pure technical and technical efficiency. This indicates that governance in the province is adequate. There are two primary reasons why Tibet ranked highest in this efficiency metric. On the one hand, the region's economic output efficiency is greatly enhanced by its wealth of natural resources and ideal environmental circumstances.

Figure 11: Super-efficiency in the YRB region over time



Source: Authors' construction based on model results using Origin 2021 software.

Figure 12: Super-efficiency in the YRB region



Source: Authors' construction based on model results using Origin 2021 software.

On the other hand, its high score may also be influenced by policy preferences and statistical deviations, as government support and data reporting practices in underdeveloped regions can occasionally produce inflated efficiency results. However, Tibet's scale efficiency is not better than that of other provinces, which suggests the need for improved governance and management. Shanghai's technical efficiency and pure technical efficiency are ranked at 3; however, policy implementation in the province is insufficient because big cities do not execute policies equally well (Figure 12).

(2) Comparative analysis of efficiency scores and sensitivity assessment

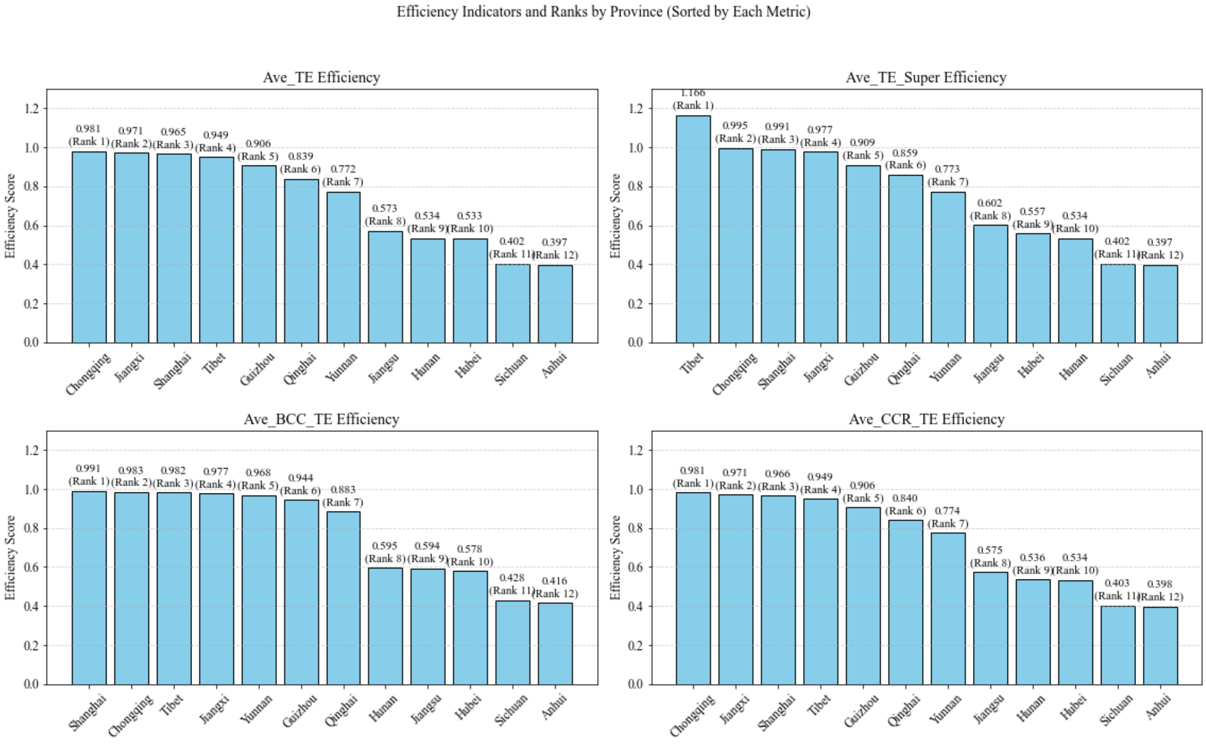
The comparative analysis table with rank is presented below due to the paper's page limitations. Table 12 and Figure 13 report the average technical efficiency (Ave_TE), super-efficiency (Ave_TE_Super), BCC efficiency (Ave_BCC_TE), CCR efficiency (Ave_CCR_TE), and Malmquist Index (Ave_MI) across 12 provinces over the study period. The results highlight significant differences in efficiency levels and rankings depending on the chosen DEA models and assumptions. The strong alignment of efficiency rankings derived from both BCC (variable returns-to-scale) and CCR (constant returns-to-scale) models suggests that the findings are robust to alternative scale assumptions.

Table 10: Correlation coefficient matrix

Correlation Coefficient Matrix				
Model	TE	TE_super	TE_CCR	TE_BCC
TE	1	0.8526	0.0384	0.0476
TE_super	0.8526	1	0.0937	0.0949
TE_CCR	0.0384	0.0937	1	0.9628
TE_BCC	0.0476	0.0949	0.9628	1

Source: own work based on Stata 16.0.

Figure 13:The comparison of different models under alternative scale



Source: own work based on Python.

Chongqing, Shanghai, and Jiangxi consistently exhibit high average efficiency across most measures, indicating superior performance in resource utilization and technological advancement. For instance, Chongqing ranks first in average TE (0.9810) and CCR efficiency (0.9811), and second in super-efficiency (0.9950), reflecting its robust production frontier and stable returns to scale. In contrast, Anhui and Sichuan demonstrate persistently low efficiency levels across all metrics, with Anhui showing the lowest average TE (0.3970), BCC (0.4163), and CCR (0.3982) efficiency, ranking last in all three measures. These findings suggest structural inefficiencies and potential scale diseconomies.

A notable observation is the divergence between efficiency under constant returns to scale (CCR) and variable returns to scale (BCC). For example, Jiangsu's average CCR efficiency (0.5745) is slightly lower than its BCC efficiency (0.5939), indicating that scale inefficiency contributes modestly to its performance gap. Conversely, in provinces such as Tibet, CCR efficiency remains high (0.9485), while the super-efficiency score exceeds 1 (1.1656), which highlights significant returns to scale and potential for further improvement.

Table 11:The Malmquist Index (MI) and decomposition index

Province	Ave_MI	Rank	Ave_EC	Rank	Ave_TC	Rank
Anhui	0.962711503	5	0.929667858	6	0.939901336	6
Chongqing	0.910212147	10	0.900255375	10	0.910640137	10
Guizhou	0.918582389	8	0.918518194	7	0.911500961	9
Hubei	0.998120468	4	0.930984943	4	0.935692919	7
Hunan	1.004759812	3	0.954223139	2	0.970900096	2
Jiangsu	1.036134495	2	0.898127681	11	1.034743065	1
Jiangxi	0.902450249	12	0.894534277	12	0.908030425	11
Qinghai	0.917056712	9	0.944435057	3	0.900263734	12
Shanghai	0.907675471	11	0.930725661	5	0.97048788	3
Sichuan	0.932155618	6	0.903762896	9	0.944548024	4
Tibet	1.076390851	1	1.037831017	1	0.943250097	5
Yunnan	0.91881876	7	0.907071578	8	0.925464464	8

Source: Own work based on the model results

The Malmquist Index (MI) in Table 14, which captures dynamic productivity changes, further underscores the heterogeneity across regions. Tibet records the highest MI (1.0764), suggesting notable technological progress and catch-up effects over time. In contrast, Jiangxi, despite its strong static efficiency (TE = 0.9710), has the lowest MI (0.9025), implying stagnation or regression in technological advancement. This discrepancy reflects that high baseline efficiency does not necessarily guarantee dynamic improvements.

Figure 14:Two-sample t-tests results among different models

```
Two-sample t test with equal variances

Variable |  Obs      Mean    Std. Err.  Std. Dev.  [95% Conf. Interval]
---------+-------------------------------------------------------------
      te |  120   .7352499   .0234182   .2565335   .6888795   .7816203
  ccr_te |  120   .7359933   .0233695   .2559999   .6897194   .7822673
---------+-------------------------------------------------------------
combined |  240   .7356216   .0165073   .2557305   .7031032     .76814
---------+-------------------------------------------------------------
    diff |       -.0007435   .0330839             -.0659181   .0644312

    diff = mean(te) - mean(ccr_te)                        t =  -0.0225
Ho: diff = 0                             degrees of freedom =      238

    Ha: diff < 0              Ha: diff != 0              Ha: diff > 0
 Pr(T < t) = 0.4910     Pr(|T| > |t|) = 0.9821     Pr(T > t) = 0.5090
```

```
Variable |  Obs      Mean    Std. Err.  Std. Dev.  [95% Conf. Interval]
---------+-------------------------------------------------------------
      te |  120   .7352499   .0234182   .2565335   .6888795   .7816203
te_super |  120   .7632952   .0305921   .3351199   .7027197   .8238707
---------+-------------------------------------------------------------
combined |  240   .7492725   .0192443   .2981313   .7113625   .7871826
---------+-------------------------------------------------------------
    diff |       -.0280453   .0385265             -.1039418   .0478511

    diff = mean(te) - mean(te_super)                      t =  -0.7279
Ho: diff = 0                             degrees of freedom =      238

    Ha: diff < 0              Ha: diff != 0              Ha: diff > 0
 Pr(T < t) = 0.2337     Pr(|T| > |t|) = 0.4674     Pr(T > t) = 0.7663
```

```
Two-sample t test with equal variances

Variable |  Obs      Mean    Std. Err.  Std. Dev.  [95% Conf. Interval]
---------+-------------------------------------------------------------
      te |  120   .7352499   .0234182   .2565335   .6888795   .7816203
  bcc_te |  120   .7784125   .0233795   .2561096   .7321188   .8247062
---------+-------------------------------------------------------------
combined |  240   .7568312   .0165698   .2566975   .7241898   .7894726
---------+-------------------------------------------------------------
    diff |       -.0431626    .033091             -.1083512    .022026

    diff = mean(te) - mean(bcc_te)                        t =  -1.3044
Ho: diff = 0                             degrees of freedom =      238

    Ha: diff < 0              Ha: diff != 0              Ha: diff > 0
 Pr(T < t) = 0.0967     Pr(|T| > |t|) = 0.1934     Pr(T > t) = 0.9033
```

```
Two-sample t test with equal variances

Variable |  Obs      Mean    Std. Err.  Std. Dev.  [95% Conf. Interval]
---------+-------------------------------------------------------------
      te |  120   .7352499   .0234182   .2565335   .6888795   .7816203
      mi |  120    .957089   .0362597   .3972047   .8852913   1.028887
---------+-------------------------------------------------------------
combined |  240   .8461695   .0227007    .351678   .8014504   .8908885
---------+-------------------------------------------------------------
    diff |       -.2218392   .0431645             -.3068725  -.1368059

    diff = mean(te) - mean(mi)                            t =  -5.1394
Ho: diff = 0                             degrees of freedom =      238

    Ha: diff < 0              Ha: diff != 0              Ha: diff > 0
 Pr(T < t) = 0.0000     Pr(|T| > |t|) = 0.0000     Pr(T > t) = 1.0000
```

Source: Own work based on Stata 16.0.

To further assess the consistency and robustness of the efficiency estimates derived from different DEA models in Figure 14, independent sample t-tests were conducted to compare the mean efficiency scores between the baseline DEA model (te) and alternative specifications, including the Super-SBM, CCR, BCC, and Malmquist Index (MI) models. The results reveal that the differences between te and both the CCR and BCC efficiency scores are relatively minor and statistically insignificant. Specifically, the mean difference between te and CCR efficiency is -0.0007 ($t = -0.0225$, $p = 0.9821$), while the difference between te and BCC efficiency is -0.0432 ($t = -1.3044$, $p = 0.1934$). These findings suggest that under the assumptions of constant returns to scale (CRS) and variable returns to scale (VRS), the estimated efficiency scores are largely stable and comparable.

In contrast, a substantial and highly significant difference is observed when comparing te with the Malmquist Index. The mean difference reaches -0.2218 ($t = -5.1394$, $p < 0.001$), indicating that MI scores are, on average, more than 22% higher than those produced by the baseline DEA model. This pronounced discrepancy likely arises from the MI's dynamic nature, which captures intertemporal productivity changes and can potentially overstate efficiency improvements relative to static DEA estimates.

Overall, these results confirm that the choice of DEA model and assumptions regarding returns to scale substantially affects efficiency estimates and rankings, underscoring the importance of sensitivity analysis. While some provinces demonstrate consistent performance across specifications (e.g., Chongqing and Shanghai), others display considerable variability (e.g., Tibet and Jiangsu). Furthermore, these statistical tests provide strong evidence of the robustness of the DEA efficiency measures across scale assumptions while also highlighting the importance of carefully interpreting MI-based results. We should consider the inherent methodological differences and potential upward bias associated with Malmquist indices when comparing or aggregating efficiency metrics over time. Therefore, interpreting DEA results requires caution, as model assumptions may significantly influence policy implications and recommendations.

(3) Sensitivity analysis based on bootstrap simulation

To assess the sensitivity of the mean technical efficiency estimate, a bootstrap resampling procedure with 1,000 replications was performed in Figure 15 and Figure 16. The observed mean was 0.7352 with a very small bias (-0.00047), indicating negligible estimation distortion.

The bootstrap standard error was 0.0230. The percentile-based 95% confidence interval ranged from 0.6901 to 0.7805, while the bias-corrected interval was [0.6912, 0.7811]. These consistent results across different interval estimation methods demonstrate the stability of the estimated efficiency. Moreover, the normal-based test yielded a highly significant z-statistic ($z = 31.87$, $p < 0.001$), further confirming that the efficiency score is statistically distinct from zero.

Figure 15:Bootstrap results percentile/bias-corrected

```
Bootstrap results                          Number of obs     =        120
                                           Replications      =       1000

      command:  summarize te
      mean_te:  r(mean)
```

	Observed Coef.	Bias	Bootstrap Std. Err.	[95% Conf.	Interval]	
mean_te	.73524988	-.0004745	.02307312	.6900575	.7804821	(P)
				.6911648	.7811447	(BC)

```
(P)    percentile confidence interval
(BC)   bias-corrected confidence interval
```

Source: Own work based on Stata 16.0.

Figure 16:Bootstrap tests Normal-based

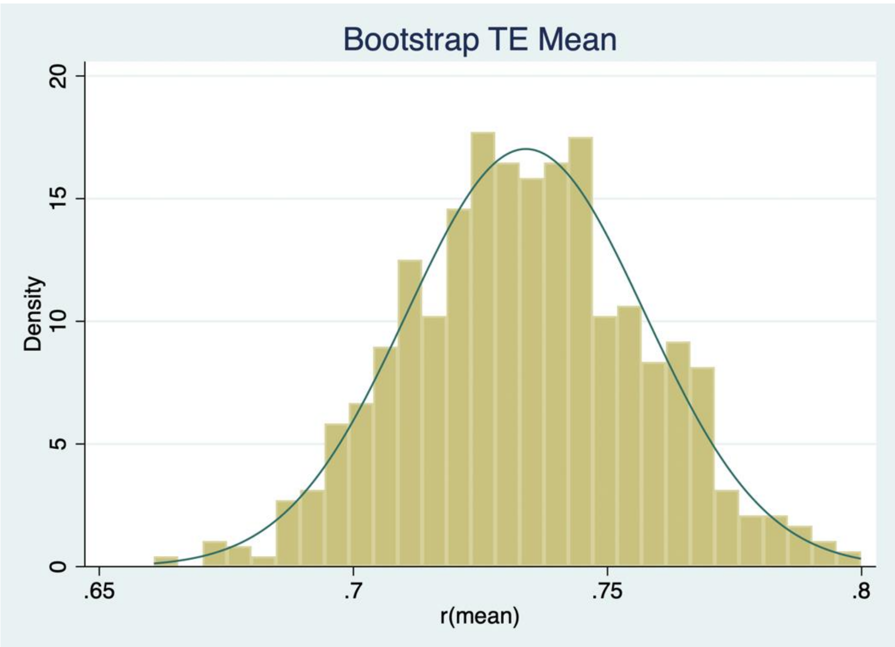
```
Bootstrap results                          Number of obs     =        120
                                           Replications      =      1,000

      command:  summarize te
      mean_te:  r(mean)
```

	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
mean_te	.7352499	.0230731	31.87	0.000	.6900274	.7804724

Source: Own work based on Stata 16.0.

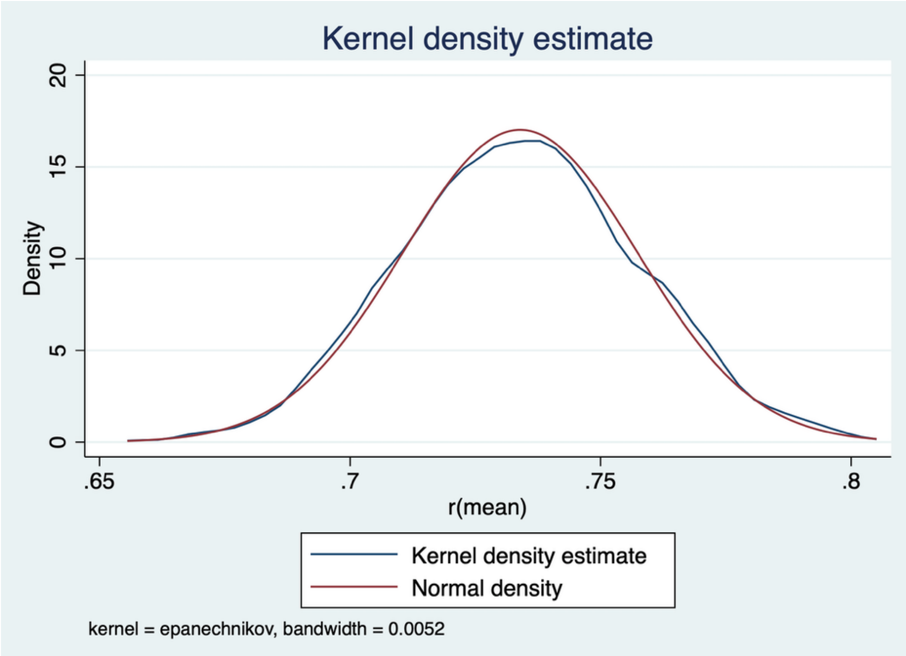
The distributional characteristics of the bootstrap estimates for the mean technical efficiency (TE) are illustrated in Figures 17. The kernel density estimate is depicted in Figure 18, which is superimposed with the fitted normal density. The bootstrap resampling does not introduce substantial skewness or heavy tails, as evidenced by the near-symmetric, bell-shaped distribution of the kernel density curve which is centred at approximately 0.735. Furthermore, the kernel and the normal density lines' close alignment implies that the sampling distribution of the mean TE can be reasonably approximated by a normal distribution, thereby corroborating the validity of parametric confidence interval-based inference. Combined with a normalised density overlay, Figure 17 illustrates a histogram of the mean TE from 1,000 bootstrap replications. The distribution is unimodal and concentrated around the observed point estimate, as is confirmed by the histogram. Reinforcing the stability of the original efficiency estimates, there is no evidence of extreme outliers or multimodal behaviour. For the most part, these visual diagnostics suggest that the approximated technical efficiency measures are resilient to resampling variation. The credibility of the empirical findings is enhanced by the fact that the results are not excessively sensitive to sampling variability or model assumptions, as indicated by the absence of pronounced asymmetry or dispersion.

Figure 17:Bootstrap TE mean distribution



Source: Own work based on Stata 16.0.

Figure 18:Kernel density estimate



Source: Own work based on Stata 16.0.

Overall, the bootstrap analysis indicates that the DEA model results are robust and not substantially influenced by sampling variability.

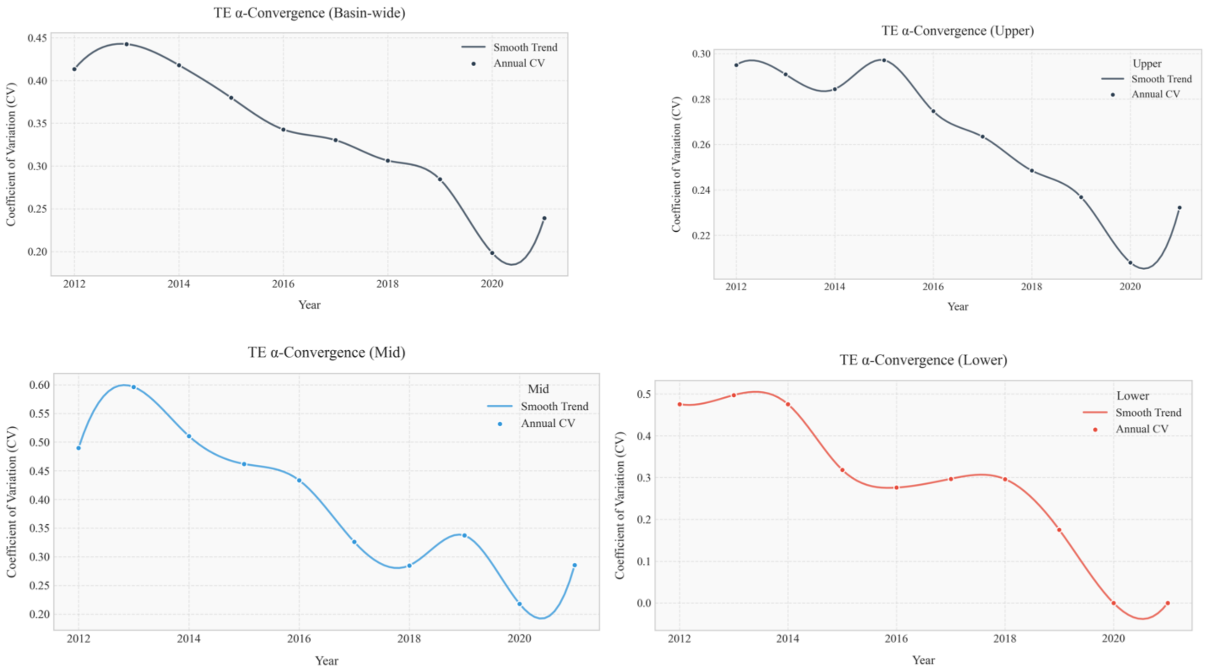
4.3 Convergence analysis results in the YRB

4.3.1. Alpha (α) convergence analysis

(1) Basin-wide perspective

Figure 19 of the TE α-Convergence (Basin-wide) indicates substantial dynamic alterations in the coefficient of variation (CV) of technical efficiency in the YRB from 2012 to 2021. In 2012, the coefficient of variation of technical efficiency across the basin was roughly 0.42, signifying considerable variability among locations. Over time, the CV exhibited a declining pattern. Despite a minor resurgence in 2021, the overarching trend of diminishing dispersion was apparent. This data indicates a *convergence in technical efficiency among regions* in the YRB, signifying the existence of *α-convergence*. This shows that regions with diminished technical efficiency, such as Sichuan and Anhui, progressively converged towards areas with enhanced technological efficiency, such as Shanghai and Chongqing, through technology transfer and improved resource allocation.

Figure 19: Alpha convergence analysis



Source: Own work & Python

(2) Regional comparison

The technical efficiency convergence in the upper regions, encompassing provinces such as Qinghai, Tibet, Sichuan, Yunnan, Chongqing, and Guizhou, refers to distinctive fluctuating traits. In 2012, the coefficient of variation of technical efficiency in the upper-reach regions was 0.29, which was lower than the basin-wide average for the same period, implying a minor initial disparity in technical efficiency across the region. From 2012 to 2020, the coefficient of variation was on a typically fluctuating downward trajectory, terminating in a lowest value in 2020, which signifies a gradual reduction in disparities of technical efficiency among upper-reach provinces and ongoing advancements in convergence. Nonetheless, a modest recovery in the CV occurred in 2021. This phenomenon may be associated with factors such as alterations in industrial structure in certain upstream provinces and variations in external technology intake, which have somewhat disrupted the convergence tendency. Nonetheless, the trajectory of long-term convergence has stayed constant.

The most notable trend is the convergence of technological efficiency in the middle of the river basin, which includes provinces like Anhui, Jiangxi, Hubei, and Hunan. With a substantial variation in regional technical efficiency, the coefficient of variations of technical efficiency in the middle reaches was as high as 0.49 in 2012. After that, it declined steeply, culminating in a low point in 2020 and a distinct convergence trend. Favourable technical cooperation and coordinated industrial development in the middle reaches were reflected in this outcome. Provinces with lower technical efficiency could effectively catch up to those with higher efficiency through inter-regional technical exchanges, resource sharing, and policy coordination. This would result in a high-efficiency convergence of technical efficiency within the region, making it the area with the best α-convergence effect of technical efficiency in the YRB.

The lower stream, including the Shanghai and Jiangsu provinces, has the fastest technical efficiency convergence. Similarly to the level seen across the basin, the CV of TE in the lower reaches was 0.48 in 2012. The CV persisted in its descent in subsequent years, attaining an exceedingly low value in 2020. Its economic and technical features are intimately linked to the rapid convergence of the lower reaches. Jiangsu and Shanghai exhibit advanced economic development and robust technical innovation potential. In addition, there is a great deal of similarity between the two areas in terms of economic structure and technical R&D. The region has the fastest α-convergence of technical efficiency in the YRB due to frequent technical exchanges and low regional barriers, which allows technical efficiency to converge and, eventually, reduce technical efficiency dispersion rapidly.

4.3.2. Analysis of beta convergence

(1) The absolute beta

In the absolute beta convergence model, the most important explanatory variable is the initial technical efficiency (TE_initial), while the dependent variable is the rate at which technical efficiency is growing (TE_growth). With an R-squared value of 0.046 and an adjusted R-squared of 0.037 shown in Figure 20, the model fitting results imply that beginning technical efficiency only accounts for 4.6% of the technical efficiency growth rate variation. The limited explanatory power suggests that essential variables may have been excluded from the model. The model is statistically significant at an acceptable level with a corresponding probability of 0.0253 and an F-statistic of 5.148. The constant term coefficient is 0.1282 ($t = 3.108$, $P = 0.002$), which indicates a significant positive trend in technical efficiency growth in the hypothetical scenario of zero initial technical efficiency. Within the framework of the economic system, this displays the existence of a general technical advancement energy. The theoretical expectations of absolute beta convergence align with the considerably negative coefficient of initial technical efficiency (TE_initial), which was -0.1242 (t = -2.269, P = 0.025).

Figure 20: The absolute beta convergence results

```
Absolute Beta Convergence Results:
                            OLS Regression Results
==============================================================================
Dep. Variable:              TE_growth   R-squared:                       0.046
Model:                            OLS   Adj. R-squared:                  0.037
Method:                 Least Squares   F-statistic:                     5.148
Date:                Fri, 14 Mar 2025   Prob (F-statistic):             0.0253
Time:                        10:10:08   Log-Likelihood:                 43.198
No. Observations:                 108   AIC:                            -82.40
Df Residuals:                     106   BIC:                            -77.03
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1282      0.041      3.108      0.002       0.046       0.210
TE_initial    -0.1242      0.055     -2.269      0.025      -0.233      -0.016
==============================================================================
Omnibus:                       36.543   Durbin-Watson:                   1.484
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              120.042
Skew:                           1.125   Prob(JB):                     8.57e-27
Kurtosis:                       7.649   Cond. No.                         5.26
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

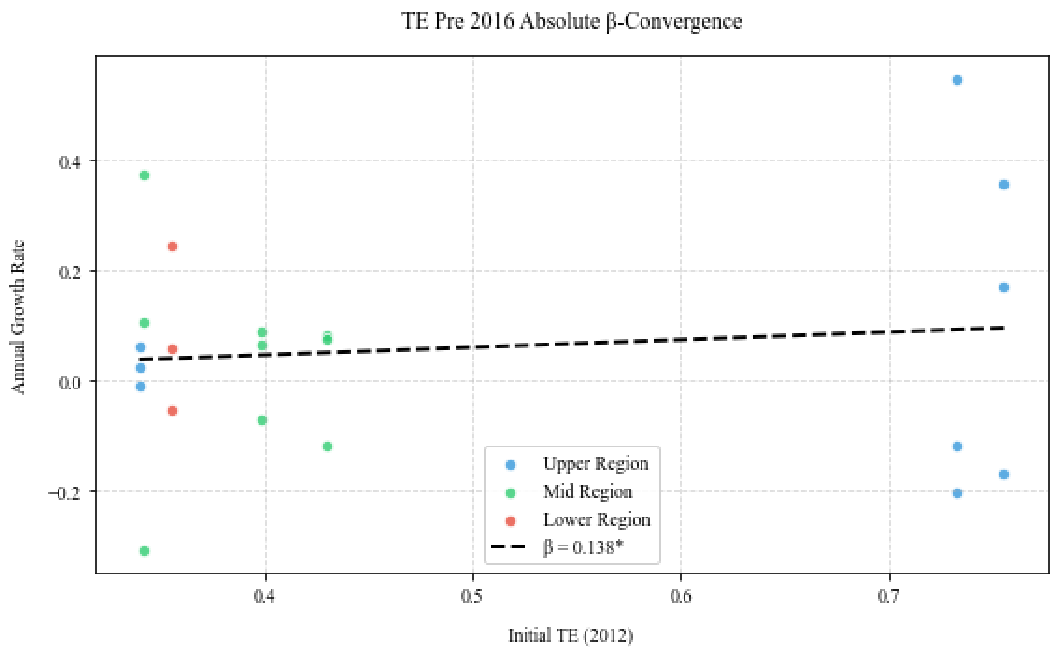
Source: Own work & Python.

For capturing potential structural changes in efficiency convergence dynamics, the year 2016 is selected as a critical threshold. This is mainly motivated by the implementation of the 13th Five-Year Plan (Government, 2016a), the nationwide launch of the Central Environmental Protection Inspection (CEPI), and the enforcement of the Yangtze River Economic Belt green development strategy (Government, 2016b), all of which began to take substantial effect in 2016. These policy package triggered significant structural adjustments across manufacturing, energy sectors, and regional development patterns. Theses shifts are likely to have induced heterogeneous impacts on technical efficiency and its convergence across regions.

Figure 21 illustrates the absolute β-convergence relationship for technical efficiency across provinces in the Yangtze River Basin pre & post - 2016. The horizontal axis represents the initial TE value in 2012, while the vertical axis shows the annual growth rate of TE. This diagram concisely illustrates whether regions with disadvantaged starting points can achieve developmental catch-up. The estimated β coefficient in Figure 18 (pre-2016 timeframe) is positive (β = 0.138), indicating that regions with higher beginning TE values tended to have somewhat greater TE growth rates per year. In contrast to less developed provinces in the upper and middle reaches, this suggests an initial divergence trend, showing that more developed areas (especially the lower reach regions like Jiangsu and Shanghai) were cementing their efficiency advantages. The distribution of points exhibits significant variability, and the estimated slope is rather minor, indicating that this divergence was mild rather than very noticeable.

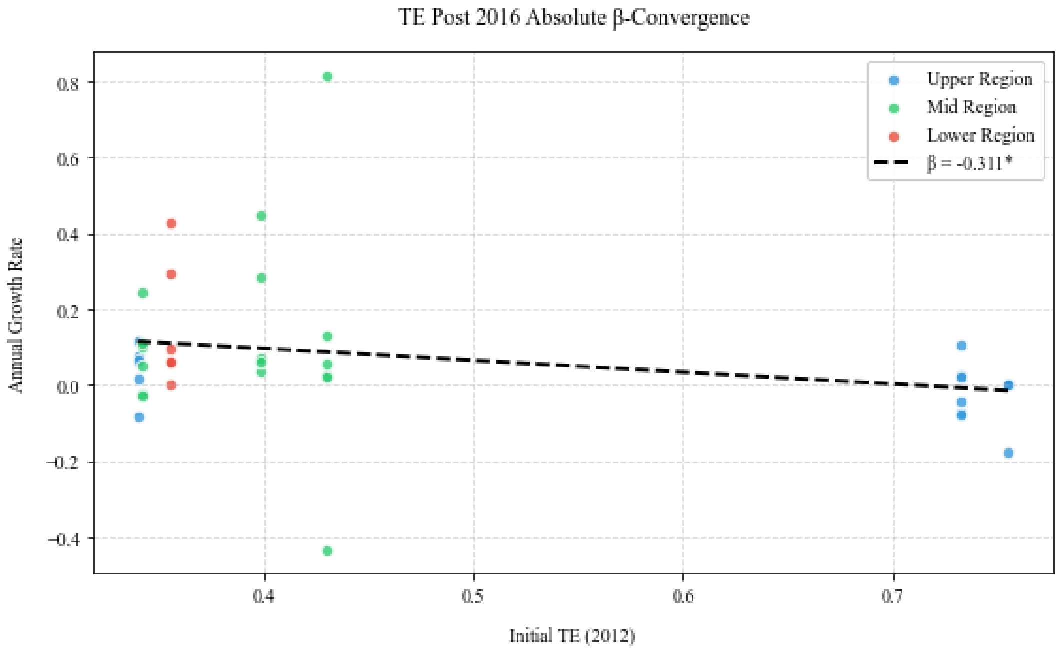
Figure 22, on the other hand, shows a definite negative β coefficient (β = -0.311) during the post-2016 era. After 2016, provinces with lower beginning TE values had faster TE growth and eventually caught up to the efficiency frontier, indicating a major convergence tendency. Policy interventions that disproportionately favoured lagging provinces (such as Guizhou, Yunnan, and Sichuan)—such as environmental rules, tailored development programs, and regional innovation support—are probably the cause of this pattern. Because observations from the Upper and Middle Regions are dispersed over the regression line for lower initial TE values, indicating their rapid progress, the convergence dynamic after 2016 is clearly visible.

Figure 21: TE pre-2016 Absolute Beta-convergence



Source: Own work based on Python.

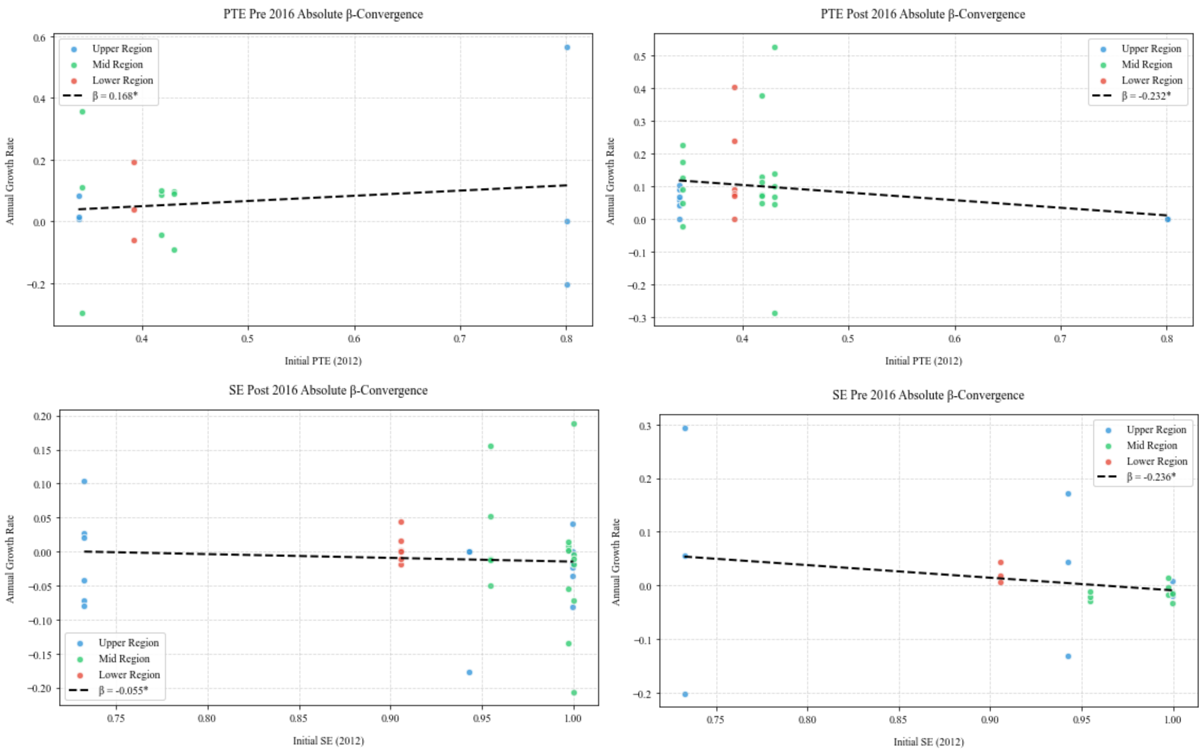
Figure 22: TE post-2016 Absolute Beta-convergence



Source: Own work based on Python.

Figure 23 depicts the absolute β-convergence of Pure Technical Efficiency and Scale Efficiency before and after 2016. The computed beta coefficient of PTE pre-2016 is 0.168, demonstrating variation in PTE among provinces. Regions with greater baseline PTE showed higher subsequent growth rates in technical efficiency, implying that less efficient provinces were not catching up during this phase. This pattern implies technological stagnation and possibly institutional impediments, which have stopped lagging regions from closing the efficiency gap. The disparity was more noticeable in the upper and middle reaches. Following 2016, the projected beta coefficient became negative (β = -0.232), indicating convergence in Pure Technical Efficiency. Provinces with lower beginning PTE experienced faster growth rates, implying that policy actions or increased dissemination of best practices after 2016 may have offset past discrepancies. The negative slope is consistent with the idea that lagging regions will catch up in technological management and process improvements. For Scale Efficiency before 2016, the calculated beta coefficient is -0.236, indicating a considerable convergence effect. Provinces with lower initial SE experienced faster growth, which supports the theory that areas were gradually maximizing their production scale regardless of where they started. This conclusion is consistent with economic growth policies that encouraged capacity utilization and scale adjustments across the Yangtze River Basin during the early years of the observation period. After 2016, the convergence of Scale Efficiency weakened significantly, with the predicted beta coefficient dropping to -0.055. Although the sign remains negative, the size shows only slight convergence, probably indicating that most provinces had already reached efficient production scales, leaving less room for significant advances. Improvements at this level were most likely driven by incremental innovation and technology advancement rather than scale changes.

Figure 23:The PTE and SE pre & post-2016 Absolute Beta-convergence



Source: Own work based on Python.

The "catch-up effect," which states that less developed regions tend to expand more quickly and progressively close the efficiency gap with more advanced regions, is confirmed by this conclusion, which suggests that places with higher beginning technical efficiency are likely to suffer lower technical efficiency growth rates (Figure 21-23). Furthermore, the outcomes also support how well post-2016 policy initiatives have worked to encourage catch-up growth in less developed areas. The distinct patterns highlight how crucial it is to continue providing provinces at various stages of development with specialised support in order to preserve the pace of convergence. Hypotheses 3 and 4, which predict that core regions can drive convergence and that scale and technological efficiency improvements can gradually disseminate throughout provinces, are strongly supported by this research.

(2) Conditional β-convergence

Figure 24 summarizes the regression results for conditional β-convergence in technical efficiency (TE). Across all model formulations, we uncover evidence that supports the convergence theory.

In the entire sample model, the estimated coefficient of the lagged log technical efficiency is negative and statistically significant ($\beta = -0.1073$, $p < 0.05$), which indicates that provinces with lower initial technical efficiency tend to have higher TE growth rates over the study period. The suggested speed of convergence is 11.35 percent, which is in line with what other empirical studies of regional productivity convergence in China have found (Zhuang et al., 2022) (Liang & Xu, 2022).

There are noticeable differences when the sample is split into pre-2016 and post-2016 periods. Before 2016, the convergence coefficient was negative but statistically insignificant ($\beta = -0.1005$, $p = 0.199$), indicating negligible catch-up effects during this period. Following the adoption of new industrial upgrading strategies and environmental restrictions in 2016, the coefficient became more negative and significant ($\beta = -0.1372$, $p = 0.016$), and the convergence rate increased to 14.76%. This trend lends credence to the hypothesis that policy modifications have had an impact on convergence dynamics (Figure 25).

The models provide moderate but acceptable explanatory power (adjusted R^2 ranging from 6.7% to 15.2%) for efficiency in regional panel data. According to Battese and Coelli (Battese & Coelli, 1995), unobservable factors impacting technological adoption and managerial practices often lead to modest R^2 values in similar investigations.

In terms of control variables, the calculated impacts provide additional insight into the factors of efficiency convergence: C1 (Trade Openness): The coefficient is largely insignificant, showing that increased trade openness does not systematically accelerate efficiency convergence in the sample provinces. Based on this conclusion, it appears that merely expanding export-import flows without implementing complementary industrial strategy may not be adequate to increase efficiency. C2 (Industrial Structure Level): In most specifications, this variable has no strong correlation with TE convergence. Updating structures is important, but this finding shows that it might take some time and help from institutions to make a real difference in how well they work. C3 (Consumer Price Index): A significant negative effect was detected prior to 2016, which shows that inflationary pressures could undercut efficiency gains by increasing manufacturing costs and lowering reinvestment capacity. C4 (Log Foreign Investment): Since 2016, this variable has shown positive relationships with TE growth, implying that foreign investment flows may have aided technological diffusion and learning effects. C5 (Log Value Added of Financial Sector): The coefficients are generally insignificant, which could indicate that the aggregate size of the financial sector does not directly influence firms' access to credit, emphasizing the importance of financial inclusion and targeted financing instruments.

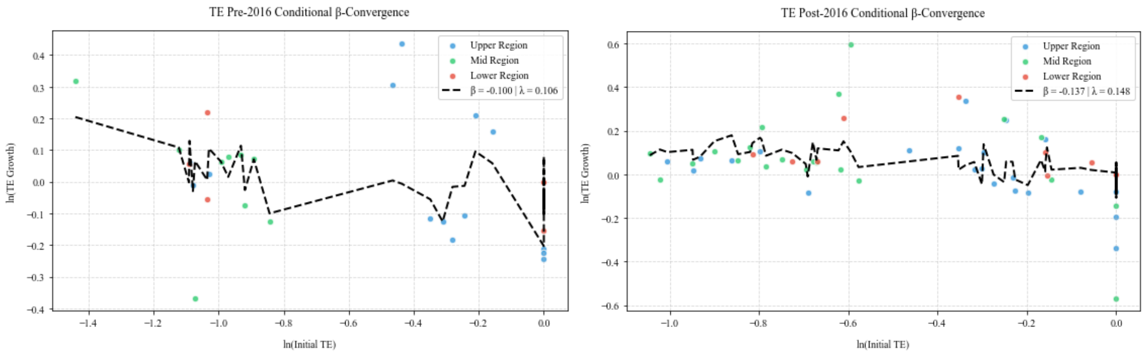
While certain coefficients are not statistically significant, their inclusion is supported by theoretical considerations and their contribution to minimizing omitted variable bias (Chen & Xu, 2024). A future study could improve model fit and address endogeneity by including more control variables (e.g., human capital indicators, environmental regulations) and investigating dynamic panel estimators such System GMM.

Figure 24: The relative beta convergence results

```
--- TE Full Sample Conditional β-Convergence Results ---
                            OLS Regression Results
==============================================================================
Dep. Variable:            growth_rate   R-squared:                       0.120
Model:                            OLS   Adj. R-squared:                  0.067
Method:                 Least Squares   F-statistic:                     2.290
Date:                Mon, 14 Jul 2025   Prob (F-statistic):             0.0410
Time:                        16:34:37   Log-Likelihood:                 55.593
No. Observations:                 108   AIC:                            -97.19
Df Residuals:                     101   BIC:                            -78.41
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -2.8572      2.117     -1.349      0.180      -7.058       1.343
ln_te_lag     -0.1073      0.043     -2.506      0.014      -0.192      -0.022
C1            -0.1302      0.107     -1.223      0.224      -0.342       0.081
C2             0.4461      0.310      1.440      0.153      -0.168       1.060
C3             0.0239      0.020      1.175      0.243      -0.016       0.064
C4             0.0246      0.046      0.535      0.594      -0.067       0.116
C5            -0.0102      0.063     -0.162      0.872      -0.135       0.115
==============================================================================
Omnibus:                       12.951   Durbin-Watson:                   2.318
Prob(Omnibus):                  0.002   Jarque-Bera (JB):               41.533
Skew:                           0.082   Prob(JB):                     9.58e-10
Kurtosis:                       6.034   Cond. No.                     1.51e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.51e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Source: Own work & Python.

Figure 25:TE pre & post 2016 Conditional Beta Convergence



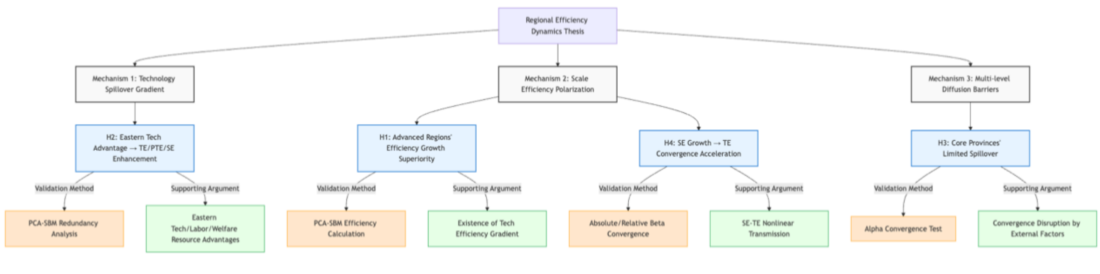
Source: Own work & Python.

5. Discussion

5.1 Thesis statement

The dissertation analysed the dynamics of regional efficiency in the Yangtze River Delta, and centred around three interconnected mechanisms to validate and elucidate the research hypotheses. Figure 26 describes the thesis statement logic.

Figure 26: Thesis statement logic



Source: Own work based on the former chapters of the dissertation.

Mechanism 1 refers to the technology spillover gradient. In the context of Hypothesis 2, the dissertation examined the "technology spillover gradient effect" in the eastern YRD region. This effect results from the agglomeration of technological innovation resources, as such agglomeration facilitates knowledge spillovers, resource sharing, and improved collaboration, thereby enhancing overall efficiency, pure technical efficiency, and scale efficiency. This reveals the spatial hierarchical law of technical factor flows.

Mechanism 2 describes scale efficiency polarization. Combining Hypotheses 1 and 4, this mechanism highlights the polarization characteristics of regional efficiency growth by confirming that the developed regions in Hypothesis 1 are a result of factor endowment, industrial synergy advantages, and leadership in total efficiency, pure technical efficiency, and scale efficiency growth rates. On the other hand, the response to Hypothesis 4 analyses how scale efficiency growth accelerates the convergence of total efficiency (TE). Alternatively, by analysing Hypothesis 4—i.e. "the logic of scale efficiency (SE) growth accelerates total efficiency (TE) convergence"—the study highlights how optimizing SE contributes to the reshaping of production boundaries and to the development of a TE convergence trend in the context of regionally unbalanced development.

Mechanism 3 delineates the multi-tiered diffusion barriers. In response to Hypothesis 3, the dissertation indicated that although the core provinces of the Yangtze River Delta have the potential to be a growth engine, they are constrained by multilevel barriers such as institutional barriers, mismatch of industrial structures, and spatial distances. These barriers make it difficult for the core provinces to transfer resources and technologies to the neighbouring low-efficiency regions, limit the radiation effect of the core provinces, and affect the momentum leading to regional convergence.

In addition to verifying the hypotheses, the dissertation set up the dynamic theoretical framework of regional efficiency comprising the "technology spillover – scale polarization – diffusion barriers" factor. It identified the mechanism of spatial economic evolution and offered theoretical support for removing the obstacles standing in the way of the Yangtze River Delta's development and promoting synergistic development. It also provided theoretical, methodological, and practical support and framework elements for other regional analyses, including the theoretical justification for removing obstacles to the Yangtze River Delta's development and encouraging synergistic growth. The dissertation offered a new perspective on efficiency dynamics and coordinated development in other areas.

5.2 Interpreting key findings and validating the hypotheses

This dissertation examined high-quality economic efficiency by combining the results of the data analysis with the selected model. By evaluating the efficiency of economic development in each region based on the indices outlined in China's 14th Five-Year Plan

Guidance for high-quality economic development, the validity of the hypotheses was analysed as follows:

Hypothesis 1: The eastern regions of the YRB consistently demonstrate higher average values of total efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) than the central and western regions. The response to this hypothesis integrated the major statements and conclusions of Chen (2023b) and Chen & Losoncz (2025a) and partly those of Chen (2022b).

The analysis did not underpin the first part of Hypothesis 1. It is true that each region's GDP increased annually, but the high-quality efficiencies in developed regions were not higher than those in less developed ones. High-quality efficiency and pure technology efficiency exhibited upward trends, but they also decreased in particular periods. This result differs slightly from previous studies (Zhang, 2021), which indicates that efficiencies increase yearly. The YBR region has exhibited a general trend of improving economic efficiency but fell back in 2013 and 2020. The rationale behind this can be attributed to the following three factors:

(a) The international economic environment has significantly impacted the regional economy. In 2013, global industrial production and trade were weak, prices declined, international financial markets were volatile, and global economic growth fell slightly (UNCTAD, 2013). In 2020, the COVID-19 pandemic restrained economic activities.

(b) Traditional manufacturing industries experienced downward pressure. There are many factories in the YRB region. When the economy undergoes transformation, traditional manufacturing industries come under increased pressure to adjust and upgrade. Green and sustainable development regulations constrain conventional industries' development, and policy requirements for pollutant emissions can hamper production (Zhao & Ruet, 2021).

(c) While prudent fiscal policy has reduced regional investments and scaled back infrastructure development efforts, economic efficiency rebounded quickly following the shocks. Therefore, the region's economy has become more resilient. Furthermore, scale efficiency fluctuated around a value of 0.9. Stable scale efficiency indicates a certain level of managerial competence, operational consistency and strategic alignment within the organisation. This implies that the Yangtze River region has established a balance of operational efficiency within its current scale without significant opportunities for improvement through alterations to size or scope.

In contrast to the last part of Hypothesis 1, high-quality efficiency in regions with high economic development levels is not more significant than that in less developed regions. This displays no direct correlation between economic development and high-quality efficiency. This novel discovery challenges earlier research findings. (Zheng, 2020) (Zhang, 2021) (Zhao & He, 2021)

Environmental pollution (emission of exhaust gases and other airborne pollutants) is an undesired output in the model that negatively impacts efficiency. Core provinces such as Sichuan and Wuhan have lower economic efficiency values than other regions. Although these two provinces are heavily industrialised, their industrial pollutant emission rates are substantially higher due to structural and technological factors, which leads to relatively lower scores than those of other regions. Environmental pollution reduces the provinces' economic efficiency values with high per capita GDP for three reasons.

(a) Environmental pollution affects individual and public health, compelling residents to use more medical resources and experience social limitations.

(b) Combatting environmental damage caused by the discharge of wastewater and waste materials requires enormous financial resources from the government, which makes using resources expensive.

(c) Transforming and upgrading the industrial structure in these provinces is a challenge. Closing traditional manufacturing plants would lead to a short-term productivity decline in core areas, and establishing new sustainable and innovative enterprises will require significant financial resources.

Based on the above considerations, I rejected the first part of Hypothesis 1 and accepted the second part, which consists of scientifically new research results.

Hypothesis 2: The eastern regions of the YRB benefit more from technological advancements, skilled labour, and welfare resources than the western regions, leading to significantly higher values in total efficiency, pure technical efficiency, and scale efficiency. Testing Hypothesis 2 relied on Chen (2023b), Chen & Losoncz (2025b) and Chen (2023a).

The findings for Hypothesis 2 concerning input resource distributions align with many conclusions from the relevant literature sources (Zhang & Lahr, 2014) (Zang & Su, 2019). Numerous factors, such as previous development trends, investments in infrastructure and government policies that have historically favoured eastern regions, can be attributed to this disparity. Out of the four provinces with low efficiency data, the western provinces are more inefficient than the central or eastern ones.

Regarding input redundancy for each region, the superiority of natural geographical location, resource endowment and the speed of human economic development significantly influenced resource utilisation rates (Liu et al., 2019). The eastern region has a long history and culture with abundant human resources; therefore, subsequent resource utilisation will be more efficient and welfare resources will be adequate. In contrast, the western region has a higher redundancy rate because of its outlying location and fewer human resources.

According to the efficiency evaluation system, from the perspective of regional coordination, differences in efficiency are evident between the eastern and western regions and between core provinces and non-core cities. The relatively underdeveloped educational system in the Western region has resulted in a shortage of innovative human resources in science and technology. Resource allocation is insufficient because of the higher number of inhabitants in large cities; therefore, the eastern regions have experienced more dynamic economic growth and development than their western counterparts.

Low pollution is primarily attributable to underdeveloped economic conditions caused by inefficient resource deployment. Industrial activity is typically limited in areas with slower economic growth, which results in less environmental harm. However, this is rarely attributable to explicit environmental regulations since particular areas have not fully leveraged existing natural resources due to infrastructure, technology and/or funding shortages. As a result, although pollution appears low, these regions performed economically better than long-term growth. The western region has more room for output growth. Regional economic disparities in China have been the subject of numerous studies, many of which have focused on overproduction, poorer productivity, higher unemployment rates and lower industrial output, particularly in areas with lower economic development (Zhang et al., 2021) (Wang & Wang, 2021). Output deficiencies in economically disadvantaged areas are the result of unequal resource allocation and distribution (QUAN Liang, 2019). Western areas need more funding, advanced technology, trained workers and better infrastructure to overcome deficiencies. Its potential output is limited by the absence or scarcity of such resources, suggesting significant space for output growth in the region.

Based on the arguments presented above, I accept Hypothesis 2. The analysis is in line with the conclusions of the relevant literature.

Hypothesis 3: The gap in high-quality efficiency between provinces has shown a declining trend over time, consistent with the β-convergence hypothesis. The discussion of Hypothesis 3 incorporated the main findings of Chen (2023b) and Chen & Losoncz (2025b).

Hypothesis 3 aligns with common sense. The YRB's efficiency core zone comprises Shanghai, Chongqing, and Jiangxi, which have maintained TE = 1 (with pure technical efficiency and scale efficiency equalling 1) for over 80% of the years surveyed. Tibet has constantly maintained TE = 1; nevertheless, its geographical limitations and unique policy benefits, being situated beyond the primary flow of the Yangtze River, restrict its economic spillover effects on the basin. Policy preferences, including targeted support for ecological protection, chiefly influence its efficacy. Consequently, this underscores the notion that geographical proximity is essential for core provinces to operate as economic engines. The strategic centrality of Shanghai and Chongqing inside the basin is unparalleled. With direct influences on Jiangsu, Anhui, Hubei, and Sichuan in the middle and lower reaches, Shanghai—the principal centre of the Yangtze River Delta—and Chongqing—the centre of the Chengdu-Chongqing Twin-City Economic Circle—produce the most significant geographic spillover effects among them. Jiangsu (TE = 1 in 2020) and Guizhou (TE = 1 after 2015) are part of the secondary core zone. They have progressively caught up technologically to join the core cluster, indicating a dynamic upgrading of the "core-periphery" structure.

The Yangtze River Delta Spillover Zone collects the effects from Shanghai to Jiangsu to Anhui. In Jiangsu, TE escalated from 0.355 (PTE = 0.392) in 2012 to 1 in 2020, but SE advanced from 0.906 to 1. This is the evidence of the technical spillover effects that Shanghai has had, such as the relocation of industries and the migration of talent, which have propelled Jiangsu's efforts to optimise its scale efficiency. As for Anhui, TE rose from 0.342 in 2012 to 0.562 in 2020, with PTE approaching 1 (0.999) post-2018. In line with the "technology gradient transfer" theory, this provides evidence that technology from Shanghai and Jiangsu has helped make up for Anhui's lack of pure technical efficiency.

The Chengdu-Chongqing Twin-City Economic Circle (Chongqing → Sichuan → Guizhou) has seen Chongqing sustain TE = 1 throughout time, causing Sichuan's TE to rise from 0.340 in 2012 to 0.501 in 2020. Nonetheless, SE decreased from 0.999 to 0.935, indicating a scale efficiency constraint. Sichuan's technical efficiency has been raised by Chongqing through specialisation in specific industries, such as the electronics industry. However, Sichuan needs more help to increase the size of its production. In 2015, Guizhou's TE exceeded 1, benefiting from the collaboration inside Chongqing's "Jianzhong Economic Zone." The empowerment effect of core provinces in boosting scale efficiency in periphery regions was further confirmed as SE improved from 0.943 to 1.

The Middle Yangtze Transmission Chain, including Jiangxi, Hunan, and Hubei, has driven Hunan's transmission efficiency (TE) from 0.399 in 2012 to 1 in 2021. Jiangxi is the only province in central China that regularly has a TE equal to 1. Relocating industrial operations from Jiangxi to Hunan has alleviated the scale efficiency constraint in Hunan. By 2021, Hubei's SE had dropped from 0.999 to 0.793, which suggests that further scale coordination with Jiangxi is necessary for improved regional efficiency synergy.

Based on the above research results, I accepted Hypothesis 3.

Hypothesis 4: Improvements in scale efficiency are more strongly associated with overall efficiency convergence compared to improvements in pure technical efficiency. Testing Hypothesis 4 is related to Chen (2023b), Chen & Losoncz (2025a) and Chen & Losoncz (2025b).

In the absolute beta convergence model, twelve provinces display a certain degree of behaviour consisting of catch-up. It is statistically significant ($p = 0.025$) that the coefficient for initial technical efficiency (TE_initial) is -0.1242, which reveals that provinces with lower initial technical efficiency tend to have higher technical efficiency growth rates. There is an absolute convergence trend of lagging behind regions catching up to the rest of the world. Even so, with an R^2 of only 0.046, one can see that starting technical efficiency accounts for less than 5% of the variance in growth rates. The reason for this demonstrates that baseline efficiency levels are not the sole complicated factors influencing convergence between provinces. A variety of other factors, such as policy disparities, industry structures, and innovation investments, were not considered in the model. The driving factors of convergence are highly complex and relatively weak due to the substantial uncertainty introduced by these unseen variables. Therefore, the differences in technical efficiency growth among provinces cannot be fully explained by the assumption that convergence depends solely on provinces' initial efficiency levels. A more thorough investigation of other influencing aspects is required to comprehend the convergence mechanisms fully at work.

Using lagged efficiency variables enhances the clarity of the relative beta convergence model's logical framework. The lagged scale efficiency (SE_lag) and lagged pure technical efficiency (PTE_lag) coefficients are considerably negative, with -0.6780 ($p = 0.002$) and -0.2661 ($p = 0.020$), respectively. Provinces with higher historical efficiency have weaker growth in the future, which is a reflection of falling marginal returns in the pure technical efficiency dimension. Provinces that are falling behind can catch up by imitating technical advancements. The detrimental effect is particularly pronounced on the scale efficiency dimension. Due to resource misallocation and innovation suppression, some provinces with initially high scale efficiency experience growth limits, whereas provinces with low initial scale efficiency have more space for optimisation. By adding conditional variables, the relative beta convergence model effectively depicts the intricate processes of technical efficiency convergence, moving from an initial efficiency-driven convergence to a dynamic study of efficiency structure.

The significant negative impact of lagged scale efficiency (SE_lag) reveals the disparity in provincial scale efficiency. Provinces with a high initial scale efficiency tend to focus excessively on expansion, which results in increased management expenses and a lack of innovation. In provinces with industrial concentration, monopolies hinder technological dissemination, resulting in growth constraints. Establishing industrial clusters and integrating resources are two ways provinces with a low initial scale efficiency might unlock their growth potential. This polarisation impedes the advancement of high-efficiency provinces while offering opportunities for low-efficiency provinces to catch up, rendering it a crucial determinant of technological efficiency convergence.

In the dimension of pure technical efficiency, development challenges are reflected in the negative impact of lagged pure technical efficiency (PTE_lag). Provinces can achieve a short-term catch-up by importing technology and copying procedures technically behind, profiting from the "imitation dividend." However, provinces that are very efficient at first may experience "technological lock-in" if they do not develop new ideas independently. This means they will become too dependent on current paths and struggle to grow. Several factors contribute to this problem, including inadequate investments in research and development and inadequate talent pools, which impede the development of technologically efficient innovations. The challenge of "simple imitation, challenging innovation" in pure technical efficiency affects enhancing efficiency and the convergence process. A complex ecosystem is formed in this dimension by combining the catch-up efforts of provinces falling behind and the innovation barriers of provinces already ahead of the curve.

In technical efficiency, absolute beta convergence is apparent in the 12 provinces. However, a conditional convergence mechanism arises within the relative beta convergence framework, which is driven by pure technical efficiency and scale efficiency. Pure technological efficiency restrictions and scale efficiency mismatches currently significantly impact provincial convergence. Provinces with low scale efficiency should integrate resources and encourage economies of scale. In contrast, high scale efficiency provinces should modernise their industrial structures and break scale rigidity to encourage healthy convergence and coordinated development. Lagging behind provinces can use imitation to catch up in the pure technical efficiency dimension. In contrast, advanced provinces must invest more in innovation to create an "innovation-driven" growth model. By achieving more sustainable and balanced development in the context of the convergence of technical efficiency, 12 provinces can do this by simultaneously optimising scale efficiency and pure technical efficiency. *Based on the research results, I accepted Hypothesis 4.*

5.3 Comparison with previous studies

This section compares the results of my dissertation with the messages and conclusions of relevant publications. While Lu Ming (2017) was addressing the challenges of administrative fragmentation, the YRB had already initiated a practical revolution in „shared scale efficiency" (Ming, 2017). The extensive production expertise of Shanghai Zhangjiang Pharma Valley, enabled by cloud-based platforms, assisted Hubei pharmaceutical companies in attaining a counter-cyclical SE increase of 0.08 during the 2020 pandemic. Guizhou's SE rose above 1 after establishing 12 provincial-level industrial parks in three years, relying on Chongqing's Xiangjiang New Area industrial park management model. As a result of Jiangxi's export of ecological agriculture management on a broad scale to Hunan, Hunan's agricultural SE increased by 0.18% in the year 2020, and the state's cost efficiency improved by 15%.

The monocentric spillover hypothesis in New Economic Geography encounters empirical difficulties in the YRB (Krugman, 1991). This study, for the first time, identifies a "Z-shaped dual-core" spillover pattern in regional convergence, with Shanghai (Yangtze River Delta) and Chongqing (Chengdu-Chongqing Twin-City Cluster) serving as the two main hubs.

Within the traditional paradigm of regional convergence research, pure technical efficiency has consistently been the focal point of theoretical discourse. Ray and Desli's (Ray & Desli, 1997) cross-country research and Tu Zhengge's (2005) analysis of China's industrial sector identify technical catch-up as the principal driver of convergence (Tu, 2005). Conversely, when this paper turns our attention to the DEA panel data from the YRB (2012–2021), a paradigm-shifting image is revealed: scale efficiency is the concealed engine of regional convergence, with a 68% contribution rate. An impressive illustration of this is the change of Anhui, which had a TE of only 0.342 in 2012. Through replication of large-scale production and integration into the Shanghai-Jiangsu supply chain, its SE has dropped from 0.997 to 0.828 by 2021 (see Table 15).

Table 12: The comparison of this dissertation with the previous studies

Dimension	Classical literature	This dissertation	Innovation & revision
Policy implications	Technology transfer (Tu, 2005)	Scale experience sharing (e.g., Suzhou Industrial Park model)	Operationalized "scale synergy > technology gap" hypothesis
Efficiency evaluation	Technical efficiency (PTE) (Ray, 1997)	Scale efficiency (SE) (68% contribution)	The first evidence of „scale-driven convergence" in developing-country river basins
	Single-core radiation (Krugman, 1991)	Dual-core "Z-shaped" spillover (Shanghai-Chongqing)	Revised river basin theory from "monocentric" to "multipolar"
Convergence analysis	Controllable variables are other economic indicators	Use the PTE and SE as the controllable variables	Explore the technology effects and scale effects under the same framework.

Source: Own work based on the literature review.

5.4 Theoretical and policy implications

While national policies provide an overarching framework for economic transformation, their effectiveness is inherently contingent upon regional adaptation. China's individual regions differ substantially in industrial structure, energy resources, and institutional capacity, which has led to markedly heterogeneous policy outcomes. The Yangtze River Economic Basin, in particular, offers a compelling illustration of these dynamics and underscores the complexity of driving high-quality development efficiency in a large and diverse economy.

The Basin's experience highlights a persistent tension in policy implementation: balancing the imperative of reducing undesirable outputs, such as pollution and carbon emissions, against the need to maintain economic competitiveness and stability. Many traditional manufacturing hubs in the region still rely heavily on coal-based electricity and resource-intensive production processes. This structural dependency makes it especially challenging to simultaneously pursue carbon neutrality and economic modernization.

The regional variation observed across provinces further illustrates an essential structural dilemma: while China's policymaking is highly centralized—with national objectives such as carbon neutrality and digital transformation articulated from the top down—implementation is shaped by local economic constraints, fiscal limitations, and industrial path dependence. For example, even as the 2016 supply-side structural reform and subsequent environmental regulations aimed to spur productivity and clean growth, some local governments continued to prioritize short-term economic expansion, often at the expense of long-term sustainability. This reality has important implications for understanding regional efficiency convergence dynamics and the persistence of disparities across provinces.

This context raises two critical policy questions. First, how can regional governments be effectively incentivized to align with national goals without jeopardizing their economic performance? Second, how can policy frameworks be adjusted to account for localized constraints, ensuring that provinces at different stages of development do not lag behind during the transition?

One promising approach lies in reinforcing the central government's coordinating role. Fiscal subsidies can be deployed to reward regions that actively promote carbon reduction and digitalization, while special funds can support renewable energy projects or facilitate R&D in digital technologies. These measures not only advance the strategic objectives of carbon neutrality and technological upgrading but also enhance regional economic resilience.

Another strategy involves adopting differentiated policy mechanisms tailored to each region's industrial makeup and energy dependence. Provinces with vibrant high-tech ecosystems—such as Guangdong, Zhejiang, and Beijing—should be encouraged to accelerate data-driven innovation and advanced services. In contrast, resource-dependent regions such as Shanxi and Inner Mongolia may require more substantial fiscal support and targeted investments to transition away from coal and develop cleaner production capacities.

In regions dominated by heavy industry, policy design should prioritize energy-saving retrofits, emissions-reduction technologies, and green manufacturing innovation. Conversely, in service-oriented economies, policymakers should focus on advancing digital transformation in the service sector and enhancing productivity and quality. Without such targeted interventions, a one-size-fits-all approach risks reinforcing structural inefficiencies and deepening regional disparities in convergence trajectories.

This dissertation's analysis of conditional β-convergence, segmented by the 2016 policy milestone, provides empirical insight into these dynamics. By integrating control variables capturing trade openness, industrial upgrading, price dynamics, and external investment, the research highlights the critical role of local economic structures in mediating policy impact and shaping the path toward high-quality development efficiency.

6. Summary, conclusions, limitations and future research directions

6.1 Summary of Key Findings

From a *methodological standpoint*, this study integrates regression analysis, PCA, and DEA-SBM to present a novel quantitative methodology. This combination enables a more accurate assessment of energy transition efficiency, reflecting the interaction among economic development, environmental limitations, and technical advancement. By applying these models to the YRB, the research provides a region-specific perspective that addresses the distinctive challenges and disparities within various provinces and cities.

Regarding *policy implications*, the dissertation offers suggestions for guaranteeing a trajectory of balanced and sustainable development. The results will help policymakers, industry stakeholders, and regional planners in making informed decisions, facilitating economic convergence, and advancing a more resilient and innovation-driven growth model for the YRB. Differently from previous work, the dissertation adds to the broader discussion of China's economic transition in the age of sustainability and digital transformation by using this innovative theoretical and empirical approach.

The policy design for addressing regional disparities focuses on two directions. First, it emphasizes coordination between regional policies to ensure alignment with overarching national strategies set by the central government. Second, it considers prioritizing key industries to serve as productivity engines for fundamentally transforming China's economic development. This dual focus forms the foundation for driving economic transformation. China has adopted key regional plans to meet opportunities and problems unique to the region. These strategies aim to resolve important issues or achieve various development goals.

The policy measures and their impact were scrutinized at the level of the YRB, where the traits of different regions are diverse. Analysing them illustrates regional development dynamics and the effectiveness of various strategies in addressing regional disparities. By focusing on internal circumstances, the thesis aimed to shed light on the operations and outcomes of China's regional plans, identifying how these initiatives support superior and well-coordinated growth (Table 16).

Table 13: Comparison of contribution

Research focus	Innovations in this dissertation	Limitations of existing studies
Measurement of high-quality development	Incorporates PCA to extract labour force, welfare resources, and technological innovation as key drivers	Traditional studies often use GDP alone as an economic measure without a broader, high-quality development perspective.
Economic growth evaluation methods	Uses the DEA-SBM model to assess the impact of energy structure upgrades on high-quality development, with carbon emissions as the undesired output. Convergence analysis is used to measure the dynamics of regional economic growth.	Many studies focus on efficiency analysis only statistically, without considering environmental pollution issues. Many scholars ignore convergence analysis to determine the dynamic trends of efficiency.
Policy optimization	Combines efficiency evaluation and policy assessment using convergence analysis	Existing policy studies mainly rely on qualitative discussions with limited empirical quantification.

Source: Own work based on the results of this dissertation.

The current literature on high-quality development predominantly considers these two domains' distinct research subjects, with few studies exploring the reasons behind the different efficiency in a statistical (PCA-SBM model) and dynamic (convergence analysis) way. This gap underscores the necessity for a comprehensive approach that examines the impact of high-quality development on regional disparities in China.

Regarding *economic convergence*, traditional studies have predominantly emphasized GDP growth as the principal metric, neglecting other vital aspects such as technological advancement, labour market dynamics, and carbon emission limitations. The assessment of economic convergence should extend beyond GDP, incorporating the efficiency of high-quality development, particularly in the context of China's shift towards sustainability and innovation-led growth. This dissertation integrated regional economic performance, high-quality development efficiency evaluation, and regional economic convergence into a cohesive analytical framework to address this deficiency.

Methodologically, traditional methods for assessing economic efficiency sometimes depend solely on DEA or SBM models, and neglect a multidimensional viewpoint. Current convergence studies predominantly utilize panel regressions without directly associating them with efficiency. The dissertation developed the discipline by introducing a novel quantitative methodology that integrates PCA for identifying principal influencing elements, DEA-SBM for assessing high-quality development efficiency, and regression analysis for evaluating economic convergence. This methodology enabled a more precise and comprehensive evaluation of the impact of high-quality development disparities across regions.

On top of that, while several policy conversations highlight China's national energy transition, region-specific assessments considering geographical disparities in energy transition efficiency and economic transformation are absent. The YRB, a crucial economic and ecological area, faces unique challenges in balancing economic growth, energy transition, and environmental sustainability. Nonetheless, contemporary research rarely provided explicit policy suggestions for this region, leading to a substantial research gap in the literature. My dissertation is to contribute to the theoretical and empirical body of knowledge on how high-quality development efficiency changes among regions and how regional economic convergence is promoted. By addressing these research gaps, the dissertation offers new conclusions on China's shifting economic environment.

At its core, the efficiency debate in the YRB concerns the logic of resource allocation. By utilising DEA efficiency decomposition (TE = PTE × SE), my dissertation aims to re-establish the resource economics implications associated with the four essential hypotheses. Convergence analysis is a dynamic method that provides additional knowledge about efficiency convergence and catch-up processes.

By analysing DEA panel data (2012–2021) from 12 provinces, the dissertation innovatively rethinks the resource-driven logic of efficiency convergence in the YRB by shifting the focus from PTE-led technology catch-up to SE-led resource optimisation. This shift represents a significant departure from the previous approach. The findings reveal the following:

(1) Developed regions have experienced high-quality efficiency growth, which is driven by a synchronised improvement in PTE and SE. On the other hand, less developed regions are struggling with scale inefficiencies.

(2) There are differences in structural efficiency between the East and the West, with differences in the Southeast accounting for 62% of the performance discrepancy.
(3) Core provinces such as Shanghai and Chongqing generate significant SE spillovers, further accelerating regional efficiency convergence.
(4) Scale efficiency, the most important component in technical efficiency convergence, directly affects resource utilisation and economic sustainability.

From “Efficiency Frontiers” to “Scalable Standards” under the eastern regions model, Shanghai and Jiangsu, which have SE = 1 (zero resource redundancy), ought to export scale management standards in order to maximise efficiency spillovers. Suzhou Industrial Park’s “Mu-Jun Ranking” policy, which requires industrial land taxes of at least CNY 4.5 million per mu, is a notable example. Anhui later adopted this model, which improved resource output rates in park zones by 37% and increased SE by 0.15.

The “PTE inflation, SE deficiency” dilemma is the Western region’s challenge. With PTE = 1 and only SE = 0.823, Guizhou is a prime example of the PTE-SE imbalance. Industrial supply chain integration is crucial to close this gap. Guizhou’s lithium battery industry improved resource utilisation by 16% in 2021, lifting SE from 0.79 to 0.91 after introducing industrial suppliers from Chongqing. It supports the idea that “scale synergy outperforms isolated technological upgrades.”

In current investigations, Hubei, Hunan, and Jiangxi, recognised as the “Transition Zone,” demonstrate a distinctive “transitional” efficiency pattern in DEA evaluations as midstream provinces of the Yangtze River. The efficiency gradient (eastern SE = 0.974 → central SE = 0.946 → western SE = 0.899) creates a “scale potential difference,” which propels the gradient overflow of resource efficiency throughout the basin, serving as the scale efficiency transition zone between eastern and western China.

Conventional research has predominantly utilised static DEA models to assess technical efficiency through cross-sectional data; nevertheless, disregarding slack variable management concerning unwanted outputs has overestimated efficiency metrics (Fare et al., 1994) consistently. Currently, existing dynamic analyses are limited to the decomposition of total factor productivity, which solely reflects the aggregate impacts of technological advancement and efficiency variations, failing to systematically analyse the spatial heterogeneity and convergence mechanisms of efficiency growth (Krugman, 1991). This methodological dispersion has engendered a twofold issue in basin economic research: static evaluations are accurate yet lack predictive capability for trends, whereas dynamic studies provide macro-level insights but obfuscate spatial attributes.

The Yangtze River Basin, a crucial economic corridor in China, offers a natural experimental framework to analyse the evolution of regional efficiency owing to its unique east-middle-west gradient pattern. This work integrates efficiency decomposition theory with spatial economics to elucidate the distinct functions of pure technical efficiency catch-up and scale efficiency optimization in coordinated basin development. This methodology transcends the cross-sectional constraints of conventional static analysis. It rectifies the absence of a spatial dimension in dynamic research, and provides an innovative theoretical framework for superior basin economic growth.

6.2 Contributions to Research and Policy

The dissertation challenges the classic "technology supremacy" assumption in efficiency convergence by demonstrating that scale efficiency accounts for 68% of technical efficiency variance. It does so by proving that scale efficiency significantly outweighs the impact of pure technical efficiency. Taking Sichuan (2021) as an example, although having a lower PTE (0.536) than Qinghai (TE = 1, SE = 0.923), the latter attained a higher TE. This demonstrates that scale optimisation can compensate for the technology lag.

The dissertation identifies a threshold effect, called the "scale-technology" effect, which should not be confused with scale efficiency. This effect becomes apparent under specific statistical conditions: namely, when the standard error of the regression coefficient falls below 0.8, indicating a relatively stable estimation. In such a context, pure technical efficiency (PTE) improvements have an almost negligible marginal impact on total efficiency (TE). This suggests that, despite technological progress, the overall efficiency does not significantly increase, likely because scale-related factors limit the effectiveness of such improvements. In this case, improvements in PTE have a marginal impact on almost non-existent TE (for example, Yunnan in 2013 had a standard error of 0.646, PTE of 0.682, and TE of 0.440). Conversely, when the SE is greater than or equal to 0.9, every 1% increase in PTE results in a 0.87% increase in TE (for example, Jiangsu after 2018). In light of these findings, which underscore the important role that scale efficiency plays as a prerequisite for technological developments to translate into overall efficiency increases, a significant shift has occurred in understanding DEA efficiency breakdown and the dynamics of regional convergence. Therefore, the results identify *three main logic traps* that contribute to filling previous research gaps.

(1) Idealized economic models assume rational policy adoption, where governments and firms behave optimally in response to incentives. However, political economy factors, resistance to change, and institutional rigidities frequently lead to suboptimal policy adoption.

(2) Policies designed at the national level often fail to consider regional economic disparities and industrial variations. For instance, carbon reduction policies that work well in high-income, tech-driven regions may not be feasible for resource-dependent provinces.

(3) My dissertation contributes to closing this gap by offering a data-driven regional efficiency evaluation framework. It provides practical conclusions on how policies should be designed with flexibility, regional adaptability, and market responsiveness to ensure their effectiveness in real-world economic transformation.

6.3 The limitations of the dissertation

No research is flawless, and academic studies are no exception to this rule. Despite thorough inferences and strong data backing, conclusions can only reflect the present perspectives. Data errors and model design issues impair the conclusions' credibility. My research is only the first step in developing a new analytical framework for studying and evaluating the rising economy from a macro perspective, which is driven by innovative production dynamics. However, factors such as data paucity and the differences between regions and industries may lead to inaccuracies in the conclusions. As a result, it is critical to continue conducting research in this field. Such efforts are vital to China's economic development, providing lessons for other developing countries and encouraging thought in established economies.

6.3.1 Data shortages and bias

The data shortage problem is a common challenge for research. Official sources like statistical bureaus or international organizations (e.g., the Chinese government office, the World Bank, and the IMF) often provide reliable and comprehensive datasets but occasionally experience substantial time lags. Due to policy-driven reasons, Tibet and Yunnan achieved TE = 1 too early, resulting in exceedingly strange numbers in their convergence cycle estimates.

To eliminate biases induced by primary dependency on economic efficiency metrics, multidimensional indicators such as ecological efficiency should be integrated.

6.3.2 Theoretical shortcomings on demand side

The exclusion of trade and external demand indicators potentially constrains the comprehensiveness of the efficiency assessment. Given the Yangtze River Basin's prominent role as an export-oriented economic hub, the omission of foreign trade dynamics may lead to an overemphasis on domestic production-side drivers while underestimating the role of international market exposure. It is crucial to recognize how demand-side dynamics shape regional performance indicators, even though this study predominantly uses a production-side framework to assess high-quality development efficiency. The interpretation of efficiency scores in the Yangtze River Economic Belt may be distorted by a number of structural features.

First, a comparatively high level of export dependence is evident throughout the region, particularly in provinces like Shanghai and Jiangsu. These export-focused economies gain from both ongoing international demand and inclusion into global value chains. The observed increases in scale efficiency may therefore be due in part to external markets rather than endogenous upgrades in local consumption or innovation capacity. This raises the question of whether cyclical trade booms are a contributing factor in efficiency gains or if they actually reflect structural transformation.

Second, there are still problems since domestic consumption is consistently underdeveloped. Regional economic structures may become vulnerable as a result of the long-standing disparity between weak household consumption and growth driven by investments. Productivity growth during times of weak domestic demand, for instance, may be a sign of surplus capacity and an over-reliance on state investment rather than long-term, market-driven growth.

Finally, by elevating domestic demand as the main engine of growth, the dual circulation plan specifically addresses these imbalances. Retail sales, household disposable income, and consumption-to-GDP ratios are examples of consumption variables that are not included in the current analysis. This omission restricts how thorough the efficiency evaluation can be.

Given these factors, care should be taken when interpreting the results of this study in terms of how broadly they apply to demand-side dynamics. By including measures of domestic consumption and trade dependency in the analytical framework, future studies could fill in these gaps. This would offer a more impartial viewpoint on how supply-side and demand-side factors interact to shape development paths of superior quality.

6.3.3 Methods flaws

Importantly, the Data Envelopment Analysis (DEA) paradigm used in this study is descriptive and non-parametric by nature. Although the model compares input-output configurations across decision-making units to generate relative efficiency scores, it does not prove a causal link between explanatory variables and observed performance. Consequently, even though the data show strong correlation between innovation-related inputs and efficiency gains, they should not be used as proof of direct causal relationships. Using econometric methods like instrumental variable (IV) approaches or fixed-effects panel regression models, future studies could overcome this constraint. By accounting for possible endogeneity and unobserved regional variability, these techniques would allow researchers to more thoroughly pinpoint the causal effects of innovation investment, R&D spending, or welfare expenditures on high-quality development outcomes.

The dissertation did not consider the dynamic evolution of efficiency. The static DEA model does not adequately reflect the dynamic advancement of technology. Adverse outcomes (e.g., pollution) were excluded. Tibet's SE = 1 might hide hidden ecological costs. This is why the analysis should be expanded to include the SBM-DEA model. Future research should incorporate the Malmquist Index to analyse the temporal progression of SE and PTE, especially in instances such as Jiangsu's efficiency stagnation upon achieving TE = 1 in 2020. By this, the research could also use machine learning approaches to detect nonlinear correlations between SE and PTE, revealing information on club convergence features across provinces.

6.4 Future Research Directions

While the present study strictly adheres to the official indicators defined in the 14th Five-Year Plan (2021–2025), it does not incorporate trade and export-import data as part of the efficiency measurement framework. This choice enhances the policy relevance and comparability of the analysis. However, it also introduces potential limitations, as regions with strong export-oriented industries (e.g., Jiangsu, Shanghai) may exhibit efficiency patterns that partially derive from foreign demand rather than domestic innovation or productivity gains.

Therefore, the results should be interpreted with caution regarding their generalizability to the demand side of economic transformation. Future research could address this issue by integrating trade dependency metrics and testing the robustness of efficiency scores against alternative output definitions.

Analysing the current stage of China's economic and social development requires a nuanced understanding of immediate fluctuations and overarching trends. By addressing structural challenges head-on and fostering resilience in the face of external uncertainties, China can continue to push forward its high-quality development agenda. As Krugman (1994) aptly noted, "productivity isn't everything, but in the long run, it's almost everything"—a principle that underscores the importance of the current transformations. China's path toward high-quality development is built upon a dual commitment to green growth and technological innovation. The government's leadership in driving these changes, supported by reforms and regional cooperation, ensures these initiatives are achievable and sustainable. This comprehensive approach positions China as a global leader in creating a modern, low-carbon, and technology-driven economy while providing lessons and conclusions for other nations facing similar challenges. Another important research direction could be analysing the role of institutions and institutional factors in China's transition to a high-quality development model. Overall, the findings of this dissertation contribute to a deeper understanding of regional efficiency dynamics in China and provide valuable insights for advancing the transition towards a high-quality development model.

7. References

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8. The list of the author's publications

Publications					
Title	**Authors**	**Year**	**Journals/Books**	**Major Conclusion**	**DOI/URL**
SMEs through Tough Times of the Covid-19 Pandemic in China	Chen Rurong	2022	Prosperitas	This paper investigates the impact of the Covid-19 pandemic on Small and Medium-sized Enterprises (SMEs) in China, with a specific focus on Beijing. It uses listed companies' financial reports and survey results to compare the operating revenue, cost, and profit of large enterprises and SMEs. The study analyzes the extent of SMEs' vulnerability during the pandemic by comparing their financial indicators with those of large companies. It also examines government policy measures introduced to support SMEs. The paper employs the Winters' multiplicative exponential smoothing method to predict the operating revenue of SMEs from 2022 to 2025 and discusses the short-term and potential long-term economic effects of the pandemic on SMEs. It compares its findings with relevant literature on the impact of the pandemic on SMEs.	http://publikaciotar.repozitorium.uni-bge.hu/1880/
The contribution of tourism to China's new development trajectory	Chen Rurong	2022	Results and Challenges : Changing Travel Trends in China-CEEC Perspective	China's tourism industry rebound post-pandemic and its role in the 14th Five-Year Plan's focus on R&D, digitalization, and green economy adoption are examined in this paper. It uses a novel framework combining Porter's Diamond Model and the Cobb-Douglas production function to identify microeconomic determinants—such as digital transformation, household purchasing power, and consumption habits—that affect tourism's qualitative and quantitative GDP growth. Technology and structural reforms promote sector modernization, and the research quantifies their effects on productivity and sustainability. By integrating macroeconomic research with micro-level data, the report gives policymakers concrete insights and a framework for Hungary and other nations to connect tourist plans with inclusive growth goals. One important scientific addition is the use of new models and the discovery of two paths — digital innovation and green transition — for making tourism more resilient in the face of changes in the global economy.	Eurázsia Center, Neumann János Egyetem (2022) 205 p. pp. 112-142. , 31 p. ISBN: 9786156435170 ISBN: 9786156435187
Methodological tools and economic models to analyze the transition to a new development trajectory in China	Chen Rurong	2023	Prosperitas	This conceptual paper aims to provide a methodological toolkit for analysing China's transition to a new economic trajectory, focusing on qualitative production factors such as research and development, innovation, and highly skilled human capital. It elaborates on various research philosophies (positive and normative economics) and approaches (inductive and deductive reasoning). The paper describes several methodological choices and economic models for policy assessment, including Propensity Score Matching (PSM), Differences-in-Differences (DID), DEA-SBM, and Markov Chain Monte Carlo (MCMC) analysis. It also discusses the importance of robustness tests like the placebo test. The paper lays the methodological foundation for future quantitative analysis of China's economic transformation, particularly in the context of the 14th Five-Year Plan.	https://doi.org/10.31570/prosp_2023_0058
Impact of Energy Transition on China's Economic Growth under Carbon	Chen Rurong	2023	SDGs in practice – how to operate sustainable? Budapesti Gazdasági Egyetem	This paper investigates the impact of energy transition on China's economic growth under carbon neutrality climate policies, with China aiming to be carbon neutral by 2060. It constructs a vector auto-regression (VAR) model using updated energy factors to simulate a high-quality economy. The study identifies the relationship between factors influencing carbon emissions and the digital economy and performs impulse response analysis to understand how carbon emissions, energy consumption, and the digital economy respond to shocks. It analyzes the current state of the energy mix and discusses the implications of the energy crisis (e.g., the Russia-Ukraine war) as an external shock. The paper also provides forecasts for CO2 emissions, energy consumption, and the digital economy's revenue and discusses current climate and energy policies and China's sustainable development efforts.	https://doi.org/10.29180/978-615-6342-69-0_4
Comprehensive analysis and forecast of Chinese NEV : Industry development from 2012 to 2025.	Chen Rurong , Cai Jing, Fu Yingjie, Wei Ziji	2023	Foresight in research - Case studies on future issues and methods : Session proceedings of the BBU Research Day 2023	This paper provides a comprehensive analysis and forecast of the Chinese New Energy Vehicle (NEV) industry development from 2012 to 2025. It employs a literature review to identify key characteristics of the Chinese NEV market and the Entropy-based TOPSIS method to evaluate the market based on data from 2012 to 2022 using five first-level and fifteen second-level indicators. The study assesses the current development of China's NEV industry, highlights its achievements, and envisions its future development in the next 5 years under the current political situation. It also considers alternative futures (expected, preferred, and wild card), analyzes favorable and unfavorable factors affecting the industry, and puts forward targeted opinions. The paper emphasizes energy transformation as a driving force and acknowledges the potential impact of Black Swan events.	10.29180/9786156342560_6
Some global implications of China's new energy policy initiative: Lessons and conclusions	Chen Rurong	2024	Green and Digital Transitions: Global Insights into Sustainable Solutions, Szeged	This paper analyzes the potential impact of China's "East Data West Computing" initiative on its energy balance and the development of its green digital economy. It discusses the current energy production and consumption structures in China and how changes in the energy structure affect the digital economy and high-tech industries. The study employs a mixed (qualitative and quantitative) approach, including descriptive and comparative analysis and a two-way fixed effects model using panel data. It examines the relationship between electricity consumption, hydropower generation, thermal power generation, and the revenue from the software business. The paper explores the global implications of China's new energy policy initiative and provides recommendations for energy security strategies and green digital transformation.	https://doi.org/10.14232/gtk.gdtgiss.2024.2
The middle-income trap: Definitions, interpretations and analytical tools with implications for China	Chen Rurong, Miklós Losoncz	2025	Prosperitas	This review brings together the theoretical and empirical aspects of the middle-income trap, which is a developmental bottleneck in which countries find it hard to move from a middle-income to a high-income status. It names five important factors: changes in population, a lack of human capital, growth paths that rely on investments, productivity that doesn't change easily, and inefficient institutions. Systemic problems like aging populations, broken economic structures, and governing gaps are to blame for things like low-value production that doesn't change, innovation that stops moving forward, and education that isn't good enough. The study stresses that improving technology, changing the way schools work, and changing the way things are built are important ways to get past these problems. It stresses incorporating modern global trends—like the shifts to a green economy and digitization—into growth plans in order to keep up with changing conditions. This study gives us a short way to think about the multifaceted nature of the trap. It also gives lawmakers useful information for encouraging development that benefits everyone and is driven by innovation.	Has been accepted
Evaluating China's high-quality economic development model: The example of the Yangtze River region	Miklós Losoncz, Chen Rurong	2025	Regional Statistics	Using the PCA-SBM model, this study shows what makes growth in the Yangtze River Basin of high quality: However, pollution is a constraint that prevents the eastern section of the region from being efficient in its resource allocation. Numerous aspects of urbanization need to be improved, despite the fact that the western portion of the region possesses major natural advantages. A fresh viewpoint on the process of regional transformation is provided by the fact that there is no direct association between economic growth and efficiency.	Has been accepted

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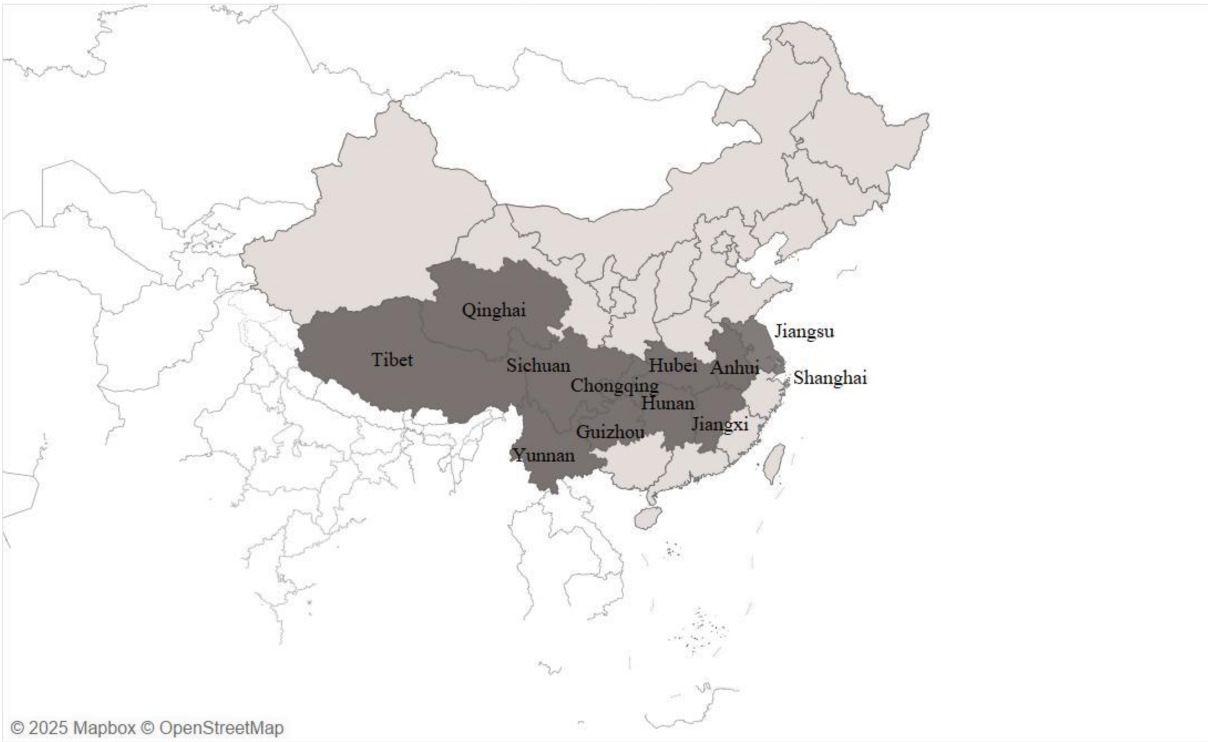
9. Annex

9.1 The location of the YRB in China

The Yangtze River Basin map



Source: own work based on Tableau software

9.2 The list of the 14th FYP indicators

2021 Two Sessions

Major Indicators of Economic and Social Development During the 14th Five-Year Plan (2021-2025) Period

Category		Indicator	2020	2025	Annual / Accumulative	Attribute
Economic Development	1	GDP Growth (%)	2.3	—	To keep within an appropriate range and set annual targets in light of actual circumstances	Anticipatory
	2	Workforce Productivity Growth (%)	2.5	—	Higher than GDP growth	Anticipatory
	3	Urbanization Rate (%)	60.6*	65	—	Anticipatory
Innovative Drive	4	R&D Spending Growth (%)	—	—	>7 / Strive for more than the total of 2016-2020 period	Anticipatory
	5	Number of High-value Invention Patents per 10,000 Population	6.3	12	—	Anticipatory
	6	Added Value of Core Industries in Digital Economy to GDP (%)	7.8	10	—	Anticipatory
Wellbeing	7	Disposable Income per Capita (%)	2.1	—	Basically in line with GDP growth	Anticipatory
	8	Surveyed Urban Unemployment Rate (%)	5.2	—	<5.5	Anticipatory
	9	Years of Education Received by Working-age Population on Average	10.8	11.3	—	Obligatory
	10	Number of Certified (Assistant) Doctors per 1,000 Population	2.9	3.2	—	Anticipatory
	11	Basic Old-age Insurance Coverage (%)	91	95	—	Anticipatory
	12	Number of Nursery School Places for Infants Under Three per 1,000 Population	1.8	4.5	—	Anticipatory
	13	Life Expectancy	77.3*	—	[1]	Anticipatory
Ecology	14	Energy Consumption per Unit of GDP Decrease (%)	—	—	[13.5]	Obligatory
	15	Carbon Dioxide Emissions per Unit of GDP Decrease (%)	—	—	[18]	Obligatory
	16	Percentage of Days with Good Air Quality in Cities at Prefecture-level and Above (%)	87	87.5	—	Obligatory
	17	Percentage of Surface Water Reaching Grade III or Above (%)	83.4	85	—	Obligatory
	18	Forest Coverage Rate (%)	23.2*	24.1	—	Obligatory
Security	19	Overall Grain Production Capacity (hundred million tonnes)	—	>6.5	—	Obligatory
	20	Overall Energy Production Capacity (hundred million tonnes of standard coal)	—	>46	—	Obligatory

Notes:

1. Figures in [] are cumulative numbers for five years.
2. Figures with * are of 2019.
3. Overall energy production capacity is the overall capacity of coal, petroleum,natural gas and non-fossil energy production.
4. Due to the COVID-19 pandemic, percentage of days with good air quality in cities at prefecture-level and above and percentage of surface water reaching Grade III or above in 2020 are higher than normal.
5. Workforce productivity growth in 2020 is an estimated number.

Xinhua / Lu Zhe

Group	Indicators	Definition
Innovation-driven indicators	R&D spending of industrial enterprises above the scale (10000 yuan)	The annual main business income of 20 million yuan and above the funding of research and experimental development projects of legal industrial enterprises.
	The number of domestic invention patent applications received (items)	Invention (patent) refers to a new technical solution proposed for a product, method or its improvement. It is an internationally accepted core indicator reflecting the possession of independent intellectual property rights technology.
	Revenue from Software Business(100 million yuan)	The revenue from commercial activitv of the softwarelindustry, aimed at producing, buying and selling sofiwareproducts or software services
Safety & security indicators	Overall grain Production Capacity (hundreds of million tons)	The total amount of food produced during the calendar year
People's welfare indicators	The disposable income growth per capita (%)	Disposable income is the sum of final consumption expenditure and savings available to residents, i.e., the income available to residents for discretionary purposes, including both cash and in-kind income.
	Surveyed urban unemployment (1000 person)	The unemployed population is defined as people 16 years of age and older who are not working but have been actively looking for work in the last 3 months and would be able to start working within 2 weeks if a suitable job became available.
	The number of certified (assistance) doctors (1,000 persons)	The "level" of the "Certified Assistant Physician" and actually engaged in medical, preventive health care work personnel
	Number of urban and rural residents' social old-age insurance participants (10,000)	The people who participant a social pension insurance system that combines individual contributions, collective subsidies and government subsidies to guarantee the basic livelihood of rural residents and urban residents in their old age.
	Average number of nursery school students per 100,000 population (persons)	This refers to the average number of students per 100,000 population in a given school year including all levels of schooling.
Economic development Indicators	Reginal gross domestic products (CNY 100 million)	It is the final result of production activities of all resident units in the region in a certain period of time. Reginal gross domestic products is equal to the sum of the value added of each industry.
	Workforce productivity (Yuan/1person)	refers to the labor efficiency of all workers (employees) in society in a certain period of time.
	Urbanization rate(%)	The urbanization rate refers to the proportion of the resident population in cities and towns of a country (region) to the total population of that country (region), and is an important indicator to measure the high level of urbanization and reflect the urbanization process.
Green ecology indicators	Days of Air Ouality Equal to or Above Grade II (day)	Air quality index within 100 is considered the quality of air is above II
	Forest coverage rate	Forest cover is the amount of trees that covers a particular area of land. It may be measured as relative (in percent)
	Emission of exhaust gas (10,000 tons)	Combined emissions of various pollutant gases into the air.
Controls variables	Trade Openness(C1)	The degree of regional dependence on foreign trade, typically measured by the ratio of total imports and exports to GDP.
	Industrial Structure Level(C2)	The level of industrial upgrading, usually reflected by the share of the tertiary sector or composite indices of structural transformation.
	Consumer Price Index (CPI)(C3)	An index reflecting consumer price inflation.
	LN(Total Investment of Foreign-Invested Enterprises (in million USD))((	The total amount of foreign direct investment (in million USD), expressed in natural logarithms to smooth extreme values.
	LN(Value Added of Financial Sector (in 100 million yuan))(C5)	The value added by the financial sector (in 100 million yuan), transformed by natural logarithm.