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Influencing factors on green innovation efficiency of Specialized, Refined, Peculiar, and Innovative enterprises

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ABSTRACT

Evaluation index system of green innovation input-output of Specialized, Refined, Peculiar, and Innovative (SRPI) enterprises is constructed to assess how internal factors affect green innovation efficiency, using Ningbo as the research object. Based on the data of SRPI enterprises in Ningbo from 2017 to 2022, green innovation efficiency of SRPI enterprises is evaluated by DEA model, with input-output index selected across green and innovation dimensions. The Systematic Generalized Method of Moments (GMM) Dynamic model is applied to evaluate how internal variables enhance eco-innovation effectiveness. First, comprehensive technical efficiency, pure technical efficiency, and scale efficiency of SRPI enterprises in Ningbo are not optimized, with variations observed in green innovation efficiency across different city regions; second, internal factors, including market credit, internal capital allocation, financial stability, and risk resilience, contribute positively to enhancing the efficiency of green innovation; and last, cash flow, inventory, and supply chain management constrain the enhancement of green innovation outcomes. Countermeasures are proposed, including improving internal management, increasing technology research and development, and strengthening risk management. The research is conducive to facilitating sustainable industrial transformation, advancing Ningbo's manufacturing sector into more sophisticated, intelligent, and eco-efficient operational models.

Contribution/Originality: This study (1) provides the green innovation performance of SRPI enterprises in Ningbo from 2017 to 2022, (2) examines the effect of internal variables on green innovation efficiency, and (3) explores measures to promote green innovation efficiency in SRPI enterprises.

1. INTRODUCTION

Since the 20th century, extracting non-renewable energy sources such as coal, petroleum, and gas has profoundly impacted human civilization, exacerbating climate change and resource depletion. Nations collaborate with global institutions to identify pathways for achieving the Sustainable Development Goals, having established greenhouse gas emission targets (Musah, Gyamfi, Kwakwa, & Agozie, 2023). In this context, the Chinese government has committed to reaching its peak carbon emissions before 2030, followed by achieving net-zero emissions within thirty years. Under strict carbon emission limits, small and medium-sized enterprises (SMEs), which primarily depend on labor-intensive and resource-intensive extensive development, face challenges in expanding production capacity

(Zhang, Yu, Zhao, & Lee, 2025). These enterprises urgently need to expedite the development of a green, low-carbon industrial system grounded in circular economy principles.

As vital contributors to green innovation, businesses have been the primary focus of past research, much of which has adopted a macro-level approach through sampling surveys (Kong & Deng, 2015; Wei, 2024). While these studies offer broadly applicable insights for enhancing corporate green innovation, specific strategies must be tailored to enterprises themselves and their specific regional contexts (Li & Wang, 2024). Current research shows that eastern China maintains a stable and leading position in green innovation efficiency, with Zhejiang Province excelling across all green innovation performance dimensions (Sun, Gao, & Fan, 2018). Ningbo, characterized as a city with low R&D intensity but high technology transfer efficiency, saw improvements in its green innovation performance between 2013 and 2017 (Lu, 2023) and experienced growth in the overall green manufacturing level (Wang, Jiang, & Liu, 2022). However, compared to other cities in Zhejiang Province, Ningbo's overall green innovation efficiency remains relatively low (Han, 2022), suggesting that Ningbo needs to further prioritize green innovation technologies. Recent scholarly attention has increasingly shifted toward optimizing green innovation performance in Ningbo. Much of this research concentrates on external factors such as financial innovation, green trade, and new industrialization efforts, providing recommendations for establishing green, low-carbon trade systems and developing platforms to support sustainable trade (Chen, 2024; Zhuang, Yang, & Cong, 2024). These studies primarily focus on the external environment of enterprises and rely on legal and theoretical analysis, while lacking specific methods for developing green innovation improvement strategies within companies.

To reduce the disparity in green innovation efficiency between Ningbo and other urban areas, efforts should focus on SMEs in Ningbo. Specialized, Refined, Peculiar, and Innovative (SRPI) enterprises are SMEs that possess advantages in specialization, refinement, distinctiveness, and innovation (Li, 2012). As representatives of SMEs, SRPI enterprises need to adhere to stricter standards for green development. While numerous studies have explored the growth mechanisms and performance of SRPI enterprises (Jia & Li, 2025; Li & Li, 2025), only a few have examined their green innovation efficiency concerning external factors such as government financial support and regulatory frameworks (Li & Ke, 2024; Xiao, 2024). The academic research on green innovation efficiency remains notably limited. Moreover, given the uncertainties in the green technology market and the current incomplete institutional support for SME development, SRPI enterprises need to strengthen their internal green innovation capabilities as a crucial strategy for resilience against external environmental shocks.

In Ningbo, SRPI enterprises constitute 26% of the total in Zhejiang Province, positioning them at the forefront of the development of SRPI enterprises. Therefore, focusing on SRPI enterprises in Ningbo to investigate eco-innovation performance and its determinants enables a comprehensive evaluation of their sustainable development capabilities, identifying both competitive advantages and areas for improvement. This approach could establish a replicable framework for enhancing green innovation performance among SMEs in Ningbo, thereby promoting sustainable economic development and green innovation in the region.

2. REVIEW OF LITERATURE

Compared to traditional innovation, green innovation typically refers to eco-innovation or environmental innovation (Xiao, Song, & Qian, 2019), spanning technological advancements in hardware and software that drive sustainable product development and environmentally conscious manufacturing methodologies (Chen, Lai, & Wen, 2006). To date, there is no widely accepted definition of green innovation in academia accessible to the general public (Charter & Clark, 2007). Although various ways exist to express green innovation within the academic literature, all existing definitions emphasize innovation and environmental benefits.

Scholarly investigations into green innovation efficiency have systematically addressed three key dimensions: performance benchmarking, determinant analysis, and regulatory framework optimization. Regarding methods for measuring green innovation efficiency, recent methodological refinements by Zou (2024) and Zhang et al. (2025)

demonstrate enhanced precision in corporate eco-innovation assessment through slack variable integration within triple-phase DEA frameworks. Meanwhile, Tian, Qiu, Jiang, Zhu, and Zhou (2021) and Han (2022) utilized network DEA models with dynamic Malmquist productivity metrics to assess green innovation performance. It is evident that academic investigations increasingly adopt non-parametric efficiency measurement frameworks for quantifying corporate green innovation performance, and many scholars employ DEA-based frontier estimation techniques (Liu, Li, & Wu, 2018; Qian, Liu, & Zhang, 2015). However, most of these studies are conducted at a macro level, with evaluation subjects often at the industry level (Huang, Li, & Sun, 2019; Ming, Zhang, & Liu, 2020; Ye, Zhang, & Zhang, 2022). Few studies focus on specific sectors or enterprises, particularly those in the SRPI category.

Based on current research findings, the efficiency of the transformation and commercialization phase generally surpasses that of the research and development phase across cities in Zhejiang Province, with significant inter-city developmental disparities (Han, 2022). Notably, the synergy between green technological innovation efficiency and ecological welfare performance in Ningbo has achieved an optimal equilibrium (Han, 2023). Its overall green innovation technology efficiency remains relatively low compared to other cities in Zhejiang.

Optimizing green innovation efficiency necessitates multidimensional analysis. Empirical findings reveal that organizational assets such as intangible resources, scale, and profitability positively affect construction firms' green innovation efficiency (Zhang et al., 2025). High-tech sectors demonstrate strong correlations between green innovation efficiency and industrial clustering dynamics, market competitiveness, and human capital quality, though foreign investment dependencies prove statistically insignificant (Zhang, Li, & Wang, 2020). Emerging evidence also highlights digital transformation's catalytic role in corporate green innovation (Wang & Fu, 2024). Scholarly consensus indicates persistent knowledge gaps regarding the systematic examination of endogenous enterprise variables in current green innovation efficiency research.

In conclusion, substantial scholarly investigations have been undertaken regarding SMEs' green innovation efficiency, yielding noteworthy findings that establish a robust empirical framework for current research. Nevertheless, existing academic discourse demonstrates limited focus on SRPI enterprises, indicating a critical gap in contemporary literature. Based on this gap, the study leverages 2017-2022 financial disclosures from Ningbo-based SRPI enterprises listed on Chinese stock exchanges. Methodologically, it employs input and output indicators to assess green innovation capabilities quantitatively. The analytical framework employs CCR-DEA frontier analysis for efficiency benchmarking, concurrently implementing system dynamics modeling via the Generalized Method of Moments (GMM) to identify endogenous determinants. This integrated approach yields actionable policy frameworks to optimize sustainable innovation pathways within Ningbo's specialized industrial clusters.

3. MEASUREMENT OF GREEN INNOVATION EFFICIENCY OF SRPI ENTERPRISES IN NINGBO

3.1. Green Innovation Efficiency Measurement and CCR-DEA Model

An efficiency evaluation framework based on DEA methodology was developed to quantify sustainable innovation outcomes in SRPI enterprises. By considering SRPI enterprises as Decision-Making Units (DMUs), the potential frontier for green innovation efficiency was established. Let the production system contain n DMUs. Each DMU consumes m input vectors ($i \in [1, \mathrm{m}]$) and generates s-dimensional desirable output vectors, mathematically represented as $x \in R^m$ and $y \in R^s$ respectively. The input-output matrices are formalized as:

$$X = (x_1, x_2, \Lambda, x_n) \in R^{m*n} \qquad (1)$$

$$Y = (y_1, y_2, \Lambda, y_n) \in R^{s*n} \qquad (2)$$

Compared to the BCC model, the CCR model emphasizes the overall efficiency of DMUs rather than specifically highlighting scale effects. Using a ratio-based approach as the evaluation metric, the CCR model is more suitable for measuring the overall efficiency of an entire organization or system. It provides critical insights into whether resources are being utilized effectively and outputs are maximized. Given its methodological advantages in holistic efficiency assessment, this study adopts the CCR framework to quantify cross-sectional eco-innovation performance across SRPI enterprise clusters. The formalized optimization model is structured as:

$$\min\ [\theta - \varepsilon(\textstyle\sum_{j=1}^{m} s^- + \sum_{j=1}^{s} s^+)]$$

$$s.t.\begin{cases} \sum_{j=1}^{n} x_j\lambda_j + s^+ = \theta x_0 \\ \sum_{j}^{n} x_i\lambda_i - s^- = y_0 \\ \lambda_j \geq 0, s^+ \geq 0, s^- \geq 0 \end{cases} \qquad (3)$$

In this model, θ represents the efficiency score of the DMU, with values ranging between 0 and 1. x denotes the input vectors, and y represents the output vectors. s^- and s^+ serve as the slack variables corresponding to inputs and outputs, respectively, and λ is a non-negative weight variable. When $\theta = 1$, it indicates that the enterprise is on the frontier of green innovation efficiency for that year, meaning its green innovation activities achieve optimal overall efficiency relative to the inputs.

3.2. Selection of Green Innovation Efficiency Index and Data Sources

3.2.1. Selection of Green Innovation Efficiency Index

The input dimension for assessing eco-innovation efficiency in SRPI clusters consists of two main components: human capital allocation and R&D capital stock. Human capital is operationalized using research personnel's full-time equivalent (FTE), a standardized measure for innovation workforce quantification validated in contemporary studies (Yan & Zhang, 2021). Financially, the capital stock composition integrates internal R&D expenditure with net productive assets, reflecting both flow and stock dimensions of innovation investment, a methodological alignment with Guan, Yam, and Pun's (2010) framework on sustainable innovation drivers.

To operationalize the measurement of corporate R&D capital accumulation, this study adopts the capital depreciation-adjusted perpetual inventory framework. The knowledge stock evolution process is formalized as:

$$RD_{it} = K_{i(t-1)} + (1-\delta)RD_{i(t-1)} \qquad (4)$$

In this formula, RD_{it} indicates the accumulated R&D capital for the company i during year t, while $RD_{i(t-1)}$ denotes its value from the previous year. $K_{i(t-1)}$ denotes the discounted R&D investment of the company i in year $t-1$ (with a discount rate of 8%). The parameter δ denotes the depreciation rate applied to R&D capital. Under the premise that R&D capital (RD) growth aligns proportionally with R&D investment expansion (K), the baseline R&D capital stock is formulated as:

$$RD_{i0} = K_{i0}/(\delta + g) \qquad (5)$$

g denotes the mean annual expansion rate of R&D investment (K). According to existing literature, where 15% serves as the standard depreciation coefficient for R&D expenditures, this study maintains consistency by retaining this rate.

SRPI enterprises primarily function in manufacturing sectors, measuring productivity through economic returns and technological advancements. Economic output reflects the company's ability to convert inputs into capital factors. It is measured by new product sales revenue as the economic output indicator (Wang, Li, & Zhang, 2016). However, since companies do not disclose this specific indicator, this study uses the primary business revenue of listed companies as a substitute. Additionally, innovation potential is quantified through R&D intensity, adjusting for organizational scale variations.

This study uses the World Intellectual Property Organization (WIPO) Green List to measure technological outputs and identify environmentally focused patents. Given the 1 to 2 years authorization cycle for patents, this study emphasizes granted green patents over applications as innovation indicators due to their greater reliability in measuring the maturity of sustainable innovation. The detailed construction of the indicator system is shown in Table 1.

Table 1. Green innovation efficiency indicator system of SRPI enterprises in Ningbo.

Target layer	Primary dimension	Secondary dimension	Tertiary element	Unit
Green innovation efficiency	Input index	Financial input	Net fixed assets of enterprises	Ten thousand yuan
			Internal expenditure on R&D funds	Ten thousand yuan
		Labor input	The total number of R&D personnel of enterprises	Person
	Output index	Technological output	R&D intensity	Piece
		Economic output	Ratio of enterprise R&D expenses to operating income	%
			Revenue from the central business	Yuan

3.2.2. Data Sources

Since the ratification of the Paris Agreement in 2015, environmental governance has been prioritized significantly in both the global public and private sectors. This study examines corporate data from 2017 to 2022, accounting for temporal decoupling in policy-corporate dynamics. The analytical cohort derives from the 2022 SRPI registry published by the Ningbo Municipal Bureau of Economy and Information Technology.

By September 2022, Ningbo boasted a considerable number of SRPI-listed companies, predominantly in manufacturing. The sample companies span various fields, including materials, biotechnology, healthcare, information technology, and more, providing a representative sample. The final analytical cohort comprised 33 qualified entities after implementing three exclusion criteria: (1) delisted organizations, (2) enterprises with initial public offerings (IPOs) during the observation window, and (3) firms exhibiting critical data deficiencies. Table 2 presents the final list of firms obtained for the analysis, as follows:

Table 2. List of SRPI enterprises.

Securities code	Securities abbreviation	Region
870139.NQ	Zhejiang Mailang Electric Co., Ltd	Haishu District
300969.SZ	Ningbo Hengshuai Co., Ltd	Jiangbei District
832186.NQ	Ningbo Welldon Infant and Child Safety Technology Co., Ltd	Jiangbei District
300566.SZ	Ningbo Exciton Technology Co., Ltd	Jiangbei District
603088.SH	JDM Jingdamachine (Ningbo) Co., Ltd.	Jiangbei District
836409.NQ	Ningbo Ming Feng Inspection & Testing Research Institute Co., Ltd	Zhenhai District
836961.NQ	Ningbo Southwest Magnetech Development Co., Ltd	Zhenhai District
300328.SZ	Hailun Piano Co., Ltd	Beilun District
832525.NQ	Ningbo Deye Technology Co., Ltd	Beilun District
872165.NQ	Ningbo Cate Maker Intelligent Kitchenware Co., Ltd.	Beilun District
002322.SZ	Ningbo Ligong environment and energy technology Co., Ltd	Beilun District
834682.BJ	Ningbo Qrunning Cable Co., Ltd	Beilun District
A23195.SH	Ningbo Spey Technology Co., Ltd	Beilun District
002119.SZ	Ningbo Kangqiang Electronics Co., Ltd.	Yinzhou District
870727.NQ	Ningbo Liyang New Material Company Limited	Yinzhou District
A21038.SH	Ningbo Zhongchun High Tech Co., Ltd	Yinzhou District
831693.NQ	Ningbo Yamao Optoelectronics Co	Fenghua District
870220.NQ	Zhejiang Hengji Yongxin New Materials Co., Ltd	Fenghua District
605555.SH	Ningbo Dechang Electrical Machinery made Co., Ltd	Yuyao City
831734.NQ	Ningbo Zhantong Telecom Equipment Co., Ltd	Yuyao City
603215.SH	Zhejiang Biyi Electric Appliance Co., Ltd	Yuyao City
831893.NQ	Zhejiang Wugu Copper Industry Co., Ltd.	Yuyao City
300539.SZ	Ningbo Henghe Precision Industry Co., Ltd.	Cixi City
300880.SZ	Ningbo Jianan Electronics Co., Ltd	Cixi City

Securities code	Securities abbreviation	Region
835027.NQ	Ningbo Jiangchen Automation Equipment Co., Ltd.	Cixi City
301198.SZ	Ningbo Joy Intelligent Logistics Technology Co., Ltd	Cixi City
001278.SZ	Ningbo Yibin Electronic Technology Co., Ltd	Cixi City
871740.NQ	Jenscare Scientific Co., Ltd	Cixi City
300863.SZ	Ningbo Kbe electrical technology Co., Ltd	Ninghai County
300727.SZ	Ningbo Runhe High-Tech Materials Co., Ltd	Ninghai County
300100.SZ	Ningbo Shuanglin Auto Parts Co., Ltd	Ninghai County
300314.SZ	Ningbo David Medical Device Co., Ltd	Xiangshan County
688306.SH	Ningbo Pia Automation Holding Corp.	Hi-Tech Zone

3.3. Results and Analysis of Green Innovation Efficiency Measurement in Ningbo

3.3.1. Overall Score of Green Innovation Efficiency in Ningbo

The study utilizes MaxDEA software to assess efficiency quantification and component decomposition for green innovation performance among Ningbo's 33 SRPI enterprises. Table 3 systematically displays their overall comprehensive, technical, and scale efficiency scores and Figure 1 illustrates the evolution of these three indicators.

Table 3. Green innovation efficiency of SRPI enterprises in Ningbo.

Year	SRPI enterprises in Ningbo		
	CRS	VRS	Scale
2017	0.612	0.649	0.953
2018	0.612	0.656	0.934
2019	0.605	0.673	0.883
2020	0.612	0.734	0.852
2021	0.614	0.695	0.872
2022	0.560	0.632	0.900
Average	0.603	0.673	0.899

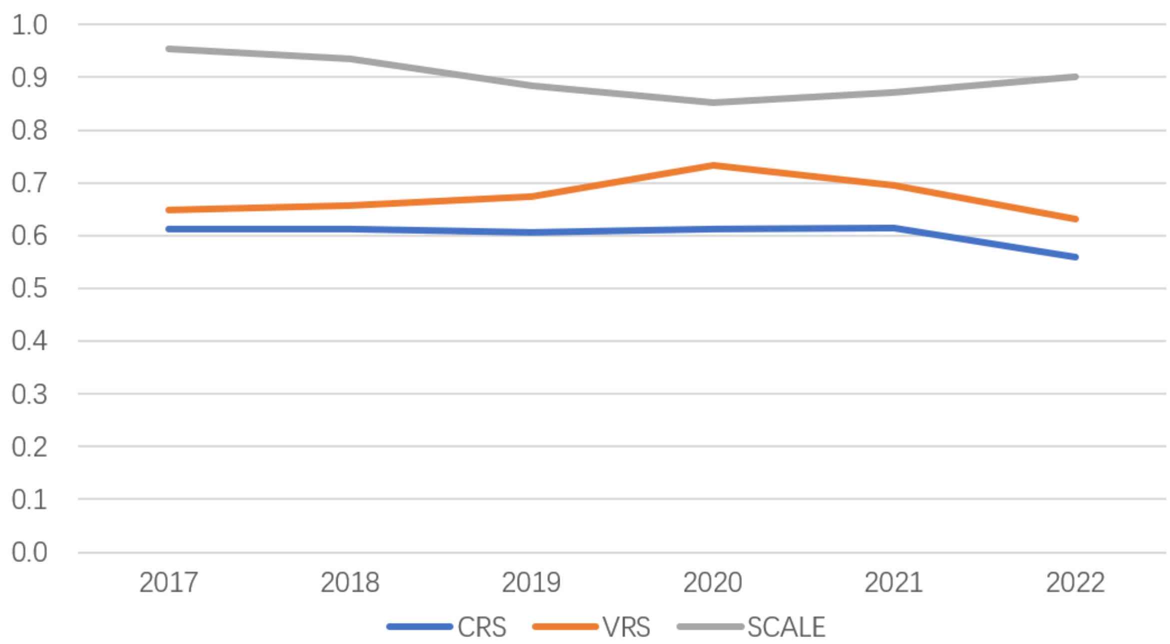

Figure 1. Green innovation efficiency of SRPI enterprises in Ningbo based on the DEA model.

First, comprehensive technical efficiency (CRS) is an aggregate indicator that reflects the optimal use of production factors, assuming the most productive scale size. In DEA analysis, when comprehensive technical efficiency equals 1, it signifies optimal efficiency in corporate financial shared service operations. Empirical computations reveal that the mean CRS trajectory for the SRPI cohort from 2017 to 2022 was 0.612, 0.612, 0.605, 0.612, 0.614, and 0.560, respectively. These values remained relatively stable, though a decline was observed in 2022. This indicates that from 2017 to 2021, the allocation and utilization capabilities of innovation resources among SRPI companies were relatively low and require improvement.

Second, pure technical efficiency (VRS) reflects the portion influenced by corporate management and technology. When pure technical efficiency reaches 1, the sample companies have maximized their management and technological resources, attaining a practical level in the analysis. The average pure technical efficiency from 2017 to 2022 was 0.649, 0.656, 0.673, 0.734, 0.695, and 0.632, respectively. While yearly averages of pure technical efficiency consistently surpass those of comprehensive technical efficiency, both metrics remain suboptimal across the evaluation period. This persistent gap between theoretical potential and actual performance has depressed green innovation efficiency indices.

Third, scale efficiency (Scale) refers to changes in production efficiency that are influenced by scale factors. An efficiency scale value of 1 suggests that the sample companies have appropriate operational inputs and are optimally configured. The average scale efficiencies from 2017 to 2022 were 0.953, 0.934, 0.883, 0.852, 0.872, and 0.899, respectively. Although scale efficiency is the highest among the three efficiency values, it has consistently been less than 1 across all years.

3.3.2. Comparative Analysis of Green Innovation Efficiency in Ningbo

Table 4 illustrates the regional differences in green innovation efficiency metrics for SRPI enterprises from 2017 to 2022.

Table 4. Green innovation efficiency of SRPI enterprises in Ningbo based on the DEA model.

Region/year	Efficiency decomposition	2017	2018	2019	2020	2021	2022	Average
Haishu District	CRS	-	1.000	1.000	1.000	0.952	0.798	0.950
	VRS	-	1.000	1.000	1.000	1.000	0.806	0.961
	SCALE	-	1.000	1.000	1.000	0.952	0.990	0.988
Jiangbei District	CRS	0.527	0.414	0.366	0.543	0.469	0.472	0.465
	VRS	0.529	0.437	0.444	0.616	0.512	0.581	0.520
	SCALE	0.996	0.942	0.838	0.865	0.911	0.836	0.898
Zhenhai District	CRS	-	0.819	0.782	0.610	0.686	0.646	0.709
	VRS	-	0.828	0.794	0.816	0.807	0.669	0.783
	SCALE	-	0.987	0.980	0.789	0.851	0.961	0.914
Beilun District	CRS	0.789	0.524	0.508	0.569	0.597	0.608	0.599
	VRS	0.795	0.578	0.591	0.630	0.719	0.786	0.683
	SCALE	0.991	0.894	0.840	0.881	0.838	0.814	0.876
Yinzhou District	CRS	0.799	0.715	0.730	0.706	0.823	0.649	0.737
	VRS	0.800	0.721	0.732	0.714	0.829	0.674	0.745
	SCALE	0.999	0.989	0.996	0.988	0.986	0.966	0.987
Fenghua District	CRS	0.709	0.545	0.552	0.521	0.492	0.474	0.549
	VRS	0.785	0.598	0.576	0.562	0.532	0.484	0.589
	SCALE	0.906	0.922	0.962	0.925	0.923	0.980	0.936
Yuyao City	CRS	0.681	0.752	0.743	0.720	0.750	0.644	0.715
	VRS	0.713	0.795	0.777	0.792	0.836	0.773	0.781
	SCALE	0.959	0.943	0.952	0.904	0.906	0.858	0.920
Cixi City	CRS	0.667	0.627	0.515	0.619	0.573	0.499	0.583
	VRS	0.673	0.634	0.540	0.656	0.608	0.548	0.610
	SCALE	0.990	0.988	0.958	0.951	0.948	0.927	0.960
Ninghai County	CRS	0.549	0.629	0.565	0.566	0.564	0.515	0.565
	VRS	0.735	0.820	0.704	0.668	0.683	0.667	0.713
	SCALE	0.796	0.808	0.812	0.837	0.818	0.805	0.813
Xiangshan County	CRS	0.288	0.210	0.217	0.291	0.247	0.274	0.254
	VRS	0.295	0.223	0.354	1.000	0.438	0.329	0.440
	SCALE	0.976	0.944	0.612	0.291	0.563	0.833	0.703
High-Tech Zone	CRS	0.497	0.499	0.679	0.585	0.605	0.583	0.575
	VRS	0.513	0.583	0.892	0.621	0.677	0.631	0.653
	SCALE	0.969	0.855	0.761	0.942	0.894	0.924	0.891

Owing to the absence of data about the Qianwan Area, coupled with the circumstance that Haishu District, Xiangshan County, and the High-Tech Zone each contain only a single company as the subject of research, which does not provide adequate regional representativeness, these four areas are hereby excluded from the comparative analysis. Consequently, a comparison was made among the remaining eight districts. The initial analysis focuses on a comprehensive technical efficiency evaluation across Ningbo's administrative divisions. Figure 2 depicts the mean comprehensive technical efficiency measurements for different urban districts, demonstrating temporal variations throughout the 2017-2022 observation period. Yinzhou District, Yuyao City, and Zhenhai District all demonstrate efficiency scores that exceed Ningbo's overall average, suggesting that the SRPI companies in these three districts possess a relatively greater capacity for allocating and utilizing innovation resources. In contrast, Jiangbei District has a lower average comprehensive technical efficiency value than other districts.

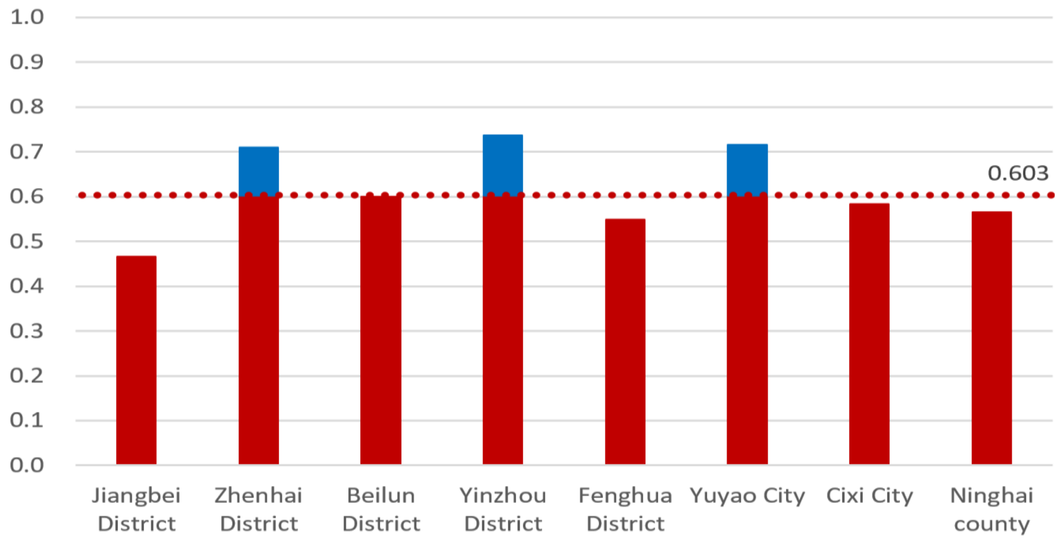

Figure 2. Comparison of average comprehensive technical efficiency of SRPI enterprises across regions of Ningbo.

The comprehensive technical efficiency values for various districts in 2022 are shown in Figure 3. In 2022, Yuyao City, Yinzhou District, Zhenhai District, and Beilun District had relatively high values. However, a comparative analysis reveals that the Jiangbei and Fenghua districts underperform compared to regional benchmarks, indicating significant optimization potential and room for improvement.

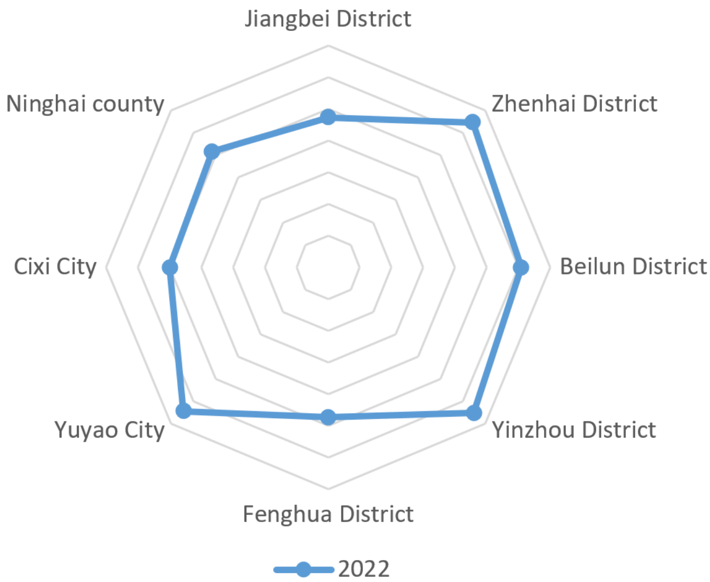

Figure 3. Comparison of comprehensive technical efficiency of SRPI enterprises across regions of Ningbo, 2022.

The analytical focus shifts to pure technical efficiency evaluation. Figure 4 presents horizontal comparisons in mean pure technical efficiency scores across various regions from 2017 to 2022. Zhenhai District, Yuyao City, Yinzhou District, Ninghai County, and Beilun District all impress with their efficiency scores surpassing Ningbo's average pure technical efficiency. By comparison, Jiangbei District has a lower average pure technical efficiency value than other districts.

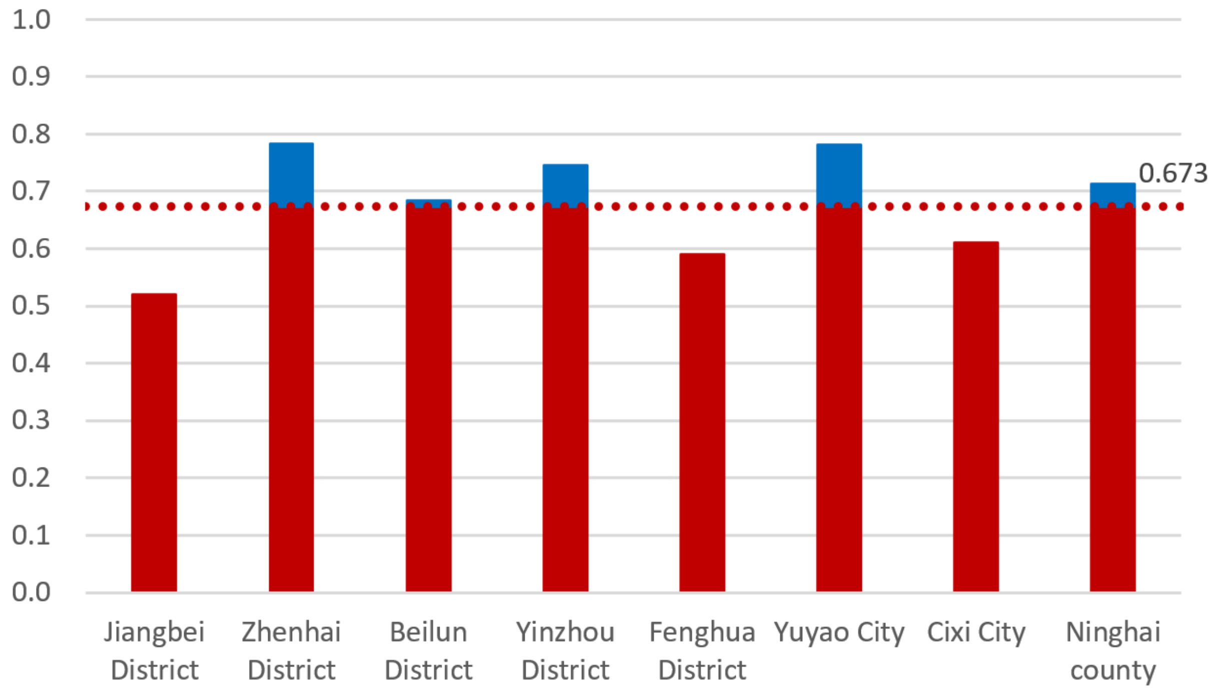

Figure 4. Comparison of average pure technical efficiency of SRPI enterprises in various regions of Ningbo.

Figure 5 presents the pure technical efficiency values for various districts in Ningbo for 2022. Yuyao City, Yinzhou District, Beilun District, and Ninghai County exhibited relatively high values in 2022, while Cixi City and Fenghua District show potential for improvement in pure technical efficiency.

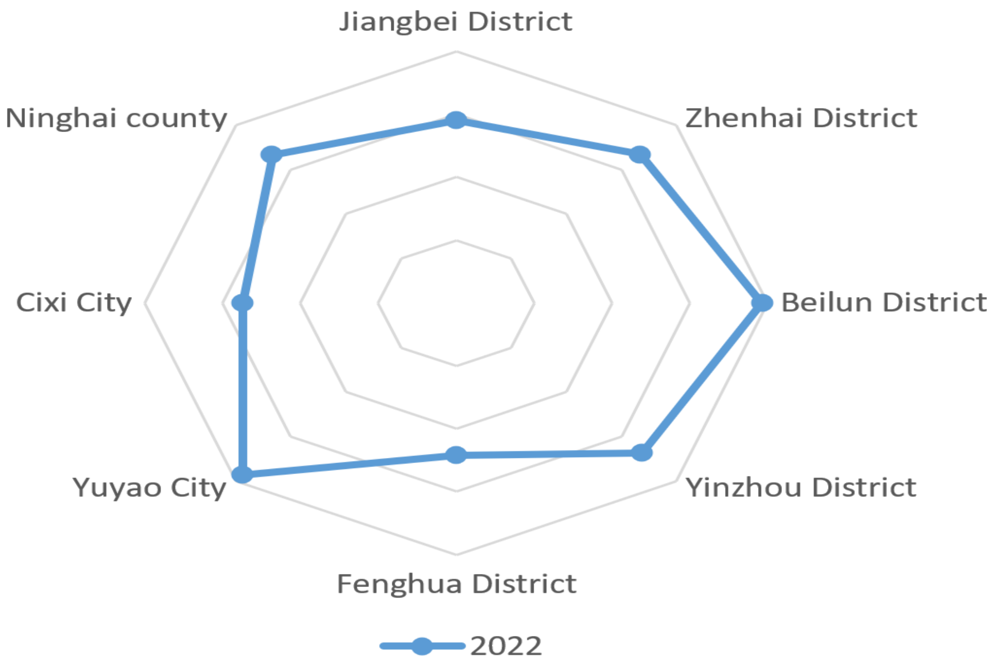

Figure 5. Comparison of pure technical efficiency of SRPI enterprises in various regions of Ningbo, 2022.

Third, scale efficiency. Figure 6 shows the average scale efficiency values for various districts in Ningbo from 2017 to 2022. Yinzhou District, Cixi City, Fenghua District, Zhenhai District, and Yuyao City all exhibit efficiency scores surpassing Ningbo's average scale efficiency. In comparison, Ninghai County has a lower average scale efficiency value than other districts.

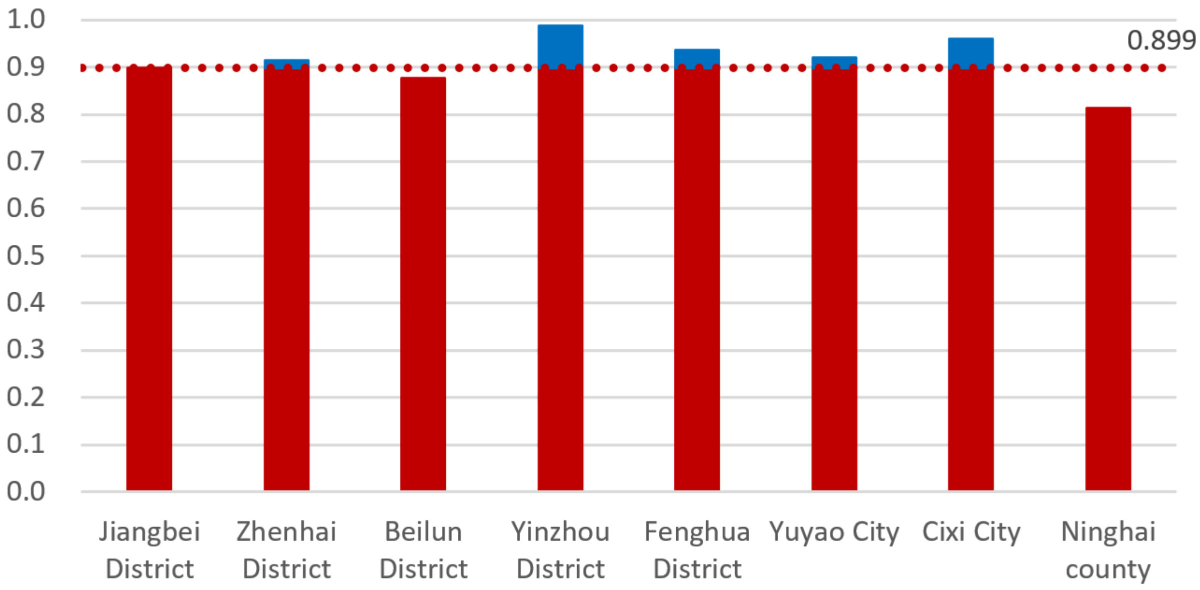

Figure 6. Comparison of average scale efficiency of SRPI enterprises in various regions of Ningbo.

Figure 7 illustrates the scale efficiency values for different districts in Ningbo in 2022. The scale efficiency values for Fenghua District, Zhenhai District, Yinzhou District, and Cixi City were relatively high in 2022. In contrast, Beilun District and Ninghai County have the potential to optimize scale efficiency performance relative to regional operational standards.

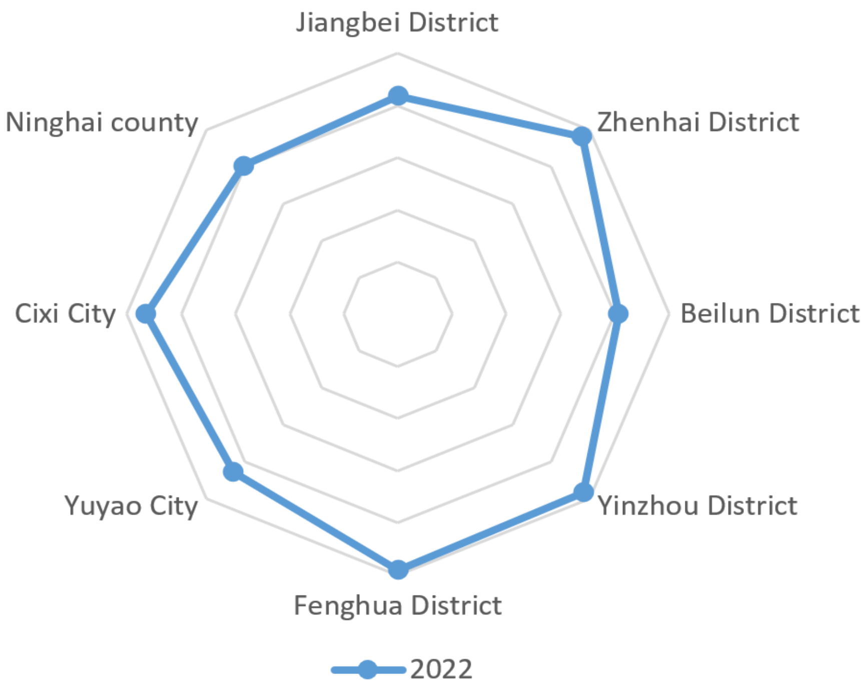

Figure 7. Comparison of scale efficiency of SRPI enterprises in various regions of Ningbo, 2022.

4. ANALYSIS OF INTERNAL INFLUENCING FACTORS ON GREEN INNOVATION EFFICIENCY OF SRPI ENTERPRISES IN NINGBO

4.1. Selection of Influencing Factors on Green Innovation Efficiency and Construction of the GMM Model

4.1.1. Analysis of Influencing Factors and GMM Model

Employing computational results from green innovation efficiency assessments, this study establishes a multivariate framework using comprehensive technical efficiency (CRS), pure technical efficiency (VRS), and scale efficiency (Scale) as the dependent variables, as shown in Table 5. This study applies the generalized method of moments (GMM) econometric approach to longitudinal data from 33 SRPI enterprises in Ningbo, utilizing Stata 17 to systematically analyze the determinants affecting this environmental performance metric over the 2017-2022 timeframe.

Table 5. Dependent variables table.

No.	Variable name
Y1	Scale efficiency
Y2	Pure technical efficiency
Y3	Comprehensive technical efficiency

4.1.2. Selection of Internal Influencing Factors

The endogenous influences affecting the operational efficiency of green technology development, as selected within the enterprise, include: Resource Input (X1) represented by monetary funds; Market Credit (X2) measured by notes receivable and accounts receivable; Supply Chain Management (X3) indicated by prepayments; Internal Fund Allocation (X4) represented by total other receivables; Inventory Management (X5) indicated by inventory levels; Cash Flow Management (X6) represented by current assets; Technical Foundation (X7) measured by fixed assets; Financial Stability (X8) indicated by deferred income tax assets; Risk Resilience (X9) represented by total assets; Financing Capabilities (X10) measured by total liabilities; Capital Strength (X11) indicated by the sum of total liabilities and shareholders' equity; and Governance Structure (X12) represented by the total shareholders' equity attributable to the parent company.

Table 6. Corresponding indicators for explanatory variables.

No.	Variable name	Indicator
X1	Resource input	Cash
X2	Market credit	Notes receivable and accounts receivable
X3	Supply chain management	Prepayments
X4	Internal fund allocation	Total other receivables
X5	Inventory management	Inventory
X6	Cash flow management	Current assets
X7	Technical foundation	Fixed assets
X8	Financial stability	Deferred income tax assets
X9	Risk resilience	Total assets
X10	Financing capabilities	Total liabilities
X11	Capital strength	Total liabilities and shareholders' equity
X12	Governance structure	Total shareholders' equity attributable to the parent company

4.1.3. GMM Model Construction

The Generalized Method of Moments (GMM) generalizes the traditional method of moments. Provided that the model parameters fulfill specific moment conditions, this methodology applies to regression analysis. The green innovation indicators and financial report data relevant to this study's research topic exhibit non-linear correlation characteristics. Therefore, in contrast to the conventional Ordinary Least Squares (OLS) estimation approach, the

GMM model is better suited for research fields that involve multi-factor interactions, like green innovation, as it offers a more accurate empirical basis for the study.

Therefore, the dependent variables are operationalized through three efficiency dimensions: comprehensive technical efficiency, pure technical efficiency, and scale efficiency. Concurrently, twelve independent variables are specified: X1 (Resource Input) through X12 (Governance Structure), systematically capturing organizational operational characteristics. To enhance the model's dynamic explanatory power and address potential issues such as endogeneity, heteroscedasticity, and multicollinearity, lagged values of the dependent variables are introduced as independent variables into the regression model. The model is specified as follows:

$$GIE_{it} = a_0 + a_1 GIE_{it-1} + \sum_2^n a_i factor_{it} + a_{n+1} + \varepsilon_{it} \quad (6)$$

Regarding the aforementioned equation, GIE_{it} indicates the efficiency level of green innovation among firms in the region i during period t, while GIE_{it-1} denotes the lagged value of these efficiency measures from the previous period. α_{n+1} represents the constant term, and $\mathcal{E}_{it}$ denotes the random error term.

Three regression models corresponding to green innovation efficiency components were developed to assess the 12 predetermined influencing factors: Model (1) with scale efficiency as the dependent variable; Model (2) employing pure technical efficiency; Model (3) utilizing comprehensive technical efficiency.

The model specifications are as follows:

$$Model(1): Scale_{it} = a_0 + a_1 Scale_{it-1} + \sum_2^n a_i factor_{it} + a_{n+1} + \varepsilon_{it} \quad (7)$$

$$Model(2): VRS_{it} = a_0 + a_1 VRS_{it-1} + \sum_2^n a_i factor_{it} + a_{n+1} + \varepsilon_{it} \quad (8)$$

$$Model(3): CRS_{it} = a_0 + a_1 CRS_{it-1} + \sum_2^n a_i factor_{it} + a_{n+1} + \varepsilon_{it} \quad (9)$$

4.2. Correlation Analysis and ADF Test

Before constructing the GMM model, correlation analysis and the Augmented Dickey-Fuller (ADF) test were conducted. Correlation analysis is used to verify whether severe multicollinearity issues exist among the independent variables, as high correlations may affect the accuracy and stability of the regression model. The ADF test evaluates time series stationarity as a unit root detection mechanism. Given that the data in this study exhibit time series characteristics, this test is necessary to rule out spurious regression problems that might arise from non-stationary time series.

4.2.1. Correlation Analysis

Considering the variations of variables across time and entities, partial correlation analyses controlling for year and individual effects were conducted on both dependent and independent variables. The preliminary results of the partial correlation coefficients in Table 7 indicate that three influencing factors, Supply Chain Management (X3), Technical Foundation (X7), and Financing Capabilities (X10), show significant correlations with green innovation efficiency, making them valuable for further analysis. The specific findings are as follows:

Supply Chain Management (X3) exhibits a significant negative correlation with pure technical efficiency (Y2) and comprehensive technical efficiency (Y3). This suggests that current issues or challenges may exist in management, technological innovation, and resource input among SRPI enterprises.

Technical Foundation (X7) maintains a robust positive linkage to scale efficiency (Y1). This indicates that a strong technical foundation contributes to business scale expansion and resource allocation management. Enhancing technological innovation is crucial for SRPI enterprises to improve green innovation efficiency.

Financing capabilities (X10) significantly correlate with scale efficiency (Y1). This suggests that better financing capabilities enable SRPI enterprises to obtain necessary funds more efficiently. This aids in expanding production scales, introducing advanced equipment and technologies, optimizing production processes, and effectively enhancing their scale efficiency.

Table 7. Partial correlation analysis results.

No.	Y1	Y2	Y3
X1	0.0187	0.1488	0.1667
X2	0.1550	0.0267	0.1090
X3	-0.1256	-0.2638*	-0.3016*
X4	-0.0022	-0.1198	0.1736
X5	-0.0513	-0.1650	-0.1198
X6	-0.1219	0.1203	0.0378
X7	0.2587*	0.1345	0.2306
X8	0.0395	0.0627	-0.0192
X9	0.0412	0.1004	0.1308
X10	0.3573**	-0.0201	0.0995
X11	-0.1087	-0.1535	-0.2397
X12	0.0412	0.1004	0.1308

Note: * $p < 0.05$, ** $p < 0.01$.

The intervariable correlation matrix (Table 8) reveals coefficients predominantly below a 0.4 threshold, suggesting acceptable multicollinearity levels that satisfy GMM estimation requirements.

Table 8. Correlation analysis of variables.

No.	Y1	Y2	Y3	X1	X2	X3	X4
Y1	1						
Y2	0.864*	1					
Y3	0.555*	0.189	1				
X1	0.0992	0.123	-0.0545	1			
X2	0.110	0.0310	0.167	0.0281	1		
X3	-0.325	-0.252	-0.151	-0.0706	-0.183	1	
X4	0.143	0.126	0.0268	0.0218	-0.200	0.182	1
X5	-0.118	-0.121	-0.0130	0.136	0.340	-0.0803	-0.147
X6	0.0358	0.124	-0.0776	-0.122	-0.207	0.214	0.171
X7	0.232	0.128	0.221	-0.0292	0.322	-0.252	-0.231
X8	0.00330	0.0738	0.0916	0.0312	-0.207	0.0403	-0.191
X9	0.170	0.121	0.168	0.0260	0.0685	-0.122	0.00330
X10	0.107	-0.0199	0.331	-0.137	0.198	-0.0640	0.0775
X11	-0.240	-0.161	-0.171	-0.299	-0.354	0.0479	-0.0207
X12	0.170	0.121	0.168	0.0260	0.0685	-0.122	0.00330
	X5	**X6**	**X7**	**X8**	**X9**	**X10**	**X11**
X5	1						
X6	-0.278	1					
X7	0.0792	-0.298	1				
X8	0.00420	0.203	-0.103	1			
X9	0.169	-0.0797	0.00720	-0.0647	1		
X10	0.198	-0.0636	0.273	0.00540	-0.0869	1	
X11	-0.0933	0.264	-0.228	0.224	-0.307	0.0769	1
X12	0.169	-0.0797	0.00720	-0.0647	1	-0.0869	-0.307
	X12						
X12	1						

Note: * $p < 0.05$.

4.2.2. ADF Test

The ADF procedure assesses time series stationarity through unit root detection. Stationary series (p<0.05, rejecting the null hypothesis) exhibit no unit roots. Before testing, a logarithmic transformation ensured variance stabilization. Table 9 summarizes the stationarity test outcomes.

Table 9. ADF unit root test results.

Variable	Inverse chi-squared	Modified inv. chi-squared	(Adjusted) P-value	Conclusion
LnX1	224.5707	30.5387	0.0000	Stationary
LnX2	58.5923	5.5165	0.0000	Stationary
LnX3	35.7775	2.0770	0.0189	Stationary
LnX4	230.3656	31.4123	0.0000	Stationary
LnX5	139.3566	17.6922	0.0000	Stationary
LnX6	242.0836	33.1788	0.0000	Stationary
LnX7	120.0523	14.7819	0.0000	Stationary
LnX8	119.0278	14.6275	0.0000	Stationary
LnX9	308.2972	43.1609	0.0000	Stationary
LnX10	171.0259	22.4665	0.0000	Stationary
LnX11	240.8588	32.9942	0.0000	Stationary
LnX12	308.2972	43.1609	0.0000	Stationary
LnY1	95.4055	11.0663	0.0000	Stationary
LnY2	188.3361	25.0761	0.0000	Stationary
LnY3	176.5239	23.2953	0.0000	Stationary

According to Table 9, all variables have p-values below 5%, with the logarithmic transformations of all variables except LnX3 producing p-values below 1%. This indicates that the null hypothesis is rejected for these variables, confirming that they are stationary. Therefore, the data are suitable for constructing a GMM model.

4.3. Analysis of the Impact Degree of Influencing Factors on Green Innovation Efficiency

4.3.1. Two-way Fixed Effects Model

Before implementing a two-way fixed effects specification, a Hausman test was conducted to guide model selection between fixed and random effects approaches. The test yielded a statistically significant result ($p=0.0003$), compelling rejection of the null hypothesis (which posits that random effects are appropriate) at the 0.1% significance level, thereby justifying the adoption of the two-way fixed effects framework.

Employing the LSDV methodology, the two-way fixed effects specification demonstrates statistical significance across all three models ($p<0.001$).

The regression coefficient of -0.338 for Inventory Management (X5) in Table 10 indicates statistically significant adverse effects on pure technical efficiency (Y2) at the 1% level. This suggests that inefficient inventory management practices may lead to resource wastage, increased costs, or reduced operational efficiency, affecting the firm's technical efficiency. Hence, excessive inventory accumulation can result in poor performance regarding pure technical efficiency.

Table 10. Two-way fixed effects specification regression results.

Variable	Model (1)	Model (2)	Model (3)
lnX1	-0.157 (0.0873)	0.141 (0.0949)	0.0364 (0.0546)
lnX2	0.132 (0.118)	0.0130 (0.0844)	0.0680 (0.0782)
lnX3	0.127 (0.101)	-0.0604 (0.0891)	0.0368 (0.0792)
lnX4	0.0587 (0.131)	-0.0980 (0.131)	0.0105 (0.0712)
lnX5	0.261 (0.138)	-0.338** (0.123)	-0.107 (0.0703)
lnX6	-0.0256 (0.0763)	0.0575 (0.0701)	0.0386 (0.0527)
lnX7	-0.0959 (0.104)	-0.00951 (0.0829)	-0.0237 (0.0625)
lnX8	-0.00114	0.00915	-0.0439

Variable	Model (1)	Model (2)	Model (3)
	(0.102)	(0.0931)	(0.0885)
lnX9	0.00768 (0.116)	-0.0000779 (0.0906)	0.0249 (0.0781)
lnX10	0.0335 (0.0916)	-0.0629 (0.0746)	-0.0749 (0.0676)
lnX11	0.0311 (0.116)	-0.115 (0.101)	-0.0976 (0.0826)
lnX12	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
_cons	3.032* (1.327)	5.648*** (1.188)	4.650*** (0.882)
R2	0.684	0.816	0.896
adj. R2	0.474	0.693	0.826

Note: Numbers in parentheses are t-values; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Static panel estimations may fail to capture dynamic interdependencies in green innovation efficiency determinants. The model was refined using the GMM to account for endogeneity issues in dynamic data and mitigate potential biases arising from these issues.

4.3.2. GMM Model Estimation Analysis

Table 11 was generated by creating a system GMM model using the three indicators of green innovation efficiency as dependent variables for SRPI enterprises. All three models show 1% statistical significance and pass the Sargan test, with p-values greater than 0.1.

Table 11. GMM model regression results.

Variable	lnY1	lnY2	lnY3
$L.lnY_{1/2/3}$	0.635*** (0.119)	0.720*** (0.0958)	0.931*** (0.0864)
lnX1	-0.0114 (0.0931)	0.0309 (0.0890)	0.0174 (0.0759)
lnX2	0.00824 (0.0981)	-0.000656 (0.0922)	-0.0533 (0.0789)
lnX3	-0.0813 (0.0989)	-0.00981 (0.0960)	0.0227 (0.0832)
lnX4	0.166 (0.0983)	-0.198* (0.0991)	-0.116 (0.0851)
lnX5	0.0963 (0.108)	-0.230* (0.101)	-0.132 (0.0867)
lnX6	-0.0777 (0.0962)	-0.0146 (0.0924)	-0.0168 (0.0790)
lnX7	-0.109 (0.103)	-0.0478 (0.0898)	-0.114 (0.0787)
lnX8	-0.00110 (0.102)	0.0608 (0.0920)	-0.0286 (0.0799)
lnX9	-0.123 (0.109)	0.152 (0.101)	0.0729 (0.0864)
lnX10	0.0834 (0.0981)	0.0849 (0.0931)	0.0515 (0.0801)
lnX11	-0.146 (0.105)	0.0402 (0.101)	-0.0128 (0.0859)
_cons	1.691 (1.096)	1.298 (1.064)	1.131 (0.895)
AR(1)	0.003	0.000	0.001
Sargan	0.177	0.119	0.313

Note: Numbers in parentheses are t-values; *** $p < 0.001$.

The empirical regression results show that Internal Fund Allocation (X4) and Inventory Management (X5) have statistically significant impacts on pure technical efficiency (Y2), both with negative regression coefficients. This indicates that higher levels of internal fund allocation and increased inventory accumulation can reduce the pure technical efficiency of SRPI enterprises. Possible reasons include increased internal fund allocation, which may lead to more resource crowding and rising management costs; growing inventories, which may result in capital tie-up; increased management complexity; lower market responsiveness; and other issues. Consequently, these two factors negatively affect the enterprise's pure technical efficiency.

The GMM estimation results were compared with the OLS estimation results. The OLS regression results showed that Internal Fund Allocation (X4) has a significant positive correlation with scale efficiency (Y1), indicating that an increase in internal fund allocation can benefit the efficiency of expanding production scale. Although other statistics are not significant, they still provide some reference value.

Table 12. OLS regression results.

Variable	lnY1	lnY2	lnY3
lnX1	-0.103 (0.118)	0.105 (0.135)	0.0389 (0.135)
lnX2	0.0814 (0.122)	0.0290 (0.140)	0.0122 (0.140)
lnX3	-0.0453 (0.118)	-0.261 (0.135)	-0.251 (0.135)
lnX4	0.266* (0.122)	0.0768 (0.139)	0.234 (0.139)
lnX5	0.123 (0.122)	-0.221 (0.140)	-0.0780 (0.140)
lnX6	-0.131 (0.121)	-0.0375 (0.139)	-0.0901 (0.138)
lnX7	0.190 (0.119)	0.0454 (0.136)	0.145 (0.136)
lnX8	0.195 (0.120)	0.130 (0.137)	0.146 (0.137)
lnX9	0.00140 (0.118)	0.00386 (0.135)	0.0128 (0.135)
lnX10	0.129 (0.119)	0.0376 (0.136)	0.0804 (0.136)
lnX11	-0.0980 (0.126)	-0.0235 (0.144)	-0.0750 (0.144)
_cons	1.171 (1.298)	3.596* (1.482)	2.571 (1.481)
R^2	0.250	0.113	0.160

Note: Numbers in parentheses are t-values; * $p < 0.05$.

Based on the estimation results from the GMM and OLS models, the following conclusions were drawn:

Concerning enablers in green innovation systems: First, the coefficients for Resource Input (X1), Risk Resilience (X9), and Financing Capabilities (X10) for comprehensive technical efficiency (Y3) were found to be positive. Second, the coefficients for Resource Input (X1), Financial Stability (X8), Risk Resilience (X9), and Financing Capabilities (X10) concerning pure technical efficiency (Y2) were also positive. Third, the coefficients for Market Credit (X2), Internal Fund Allocation (X4), Inventory Management (X5), and Financing Capabilities (X10) concerning scale efficiency (Y1) were positive.

Regarding barriers in green innovation systems: First, the coefficients for Inventory Management (X5), Cash Flow Management (X6), and Financing Capabilities (X10) concerning comprehensive technical efficiency (Y3) were negative. Second, the coefficients for Supply Chain Management (X3), Inventory Management (X5), and Cash Flow Management (X6) concerning pure technical efficiency (Y2) were also negative. Third, the coefficients for Resource

Input (X1), Supply Chain Management (X3), and Cash Flow Management (X6) with scale efficiency (Y1) were adverse.

The parametric consistency between GMM and OLS estimates, both in coefficient magnitudes and directional effects, attests to the modeling framework's empirical robustness.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

This study employs 2017-2022 panel data from Ningbo's SRPI-listed firms, analyzing green innovation efficiency through tripartite metrics: comprehensive technical efficiency, pure technical efficiency, and scale efficiency. Further analysis was conducted using the Dynamic GMM estimation to address endogenous regressor concerns. Principal findings indicate.

(1) Conclusion One: Empirical analysis reveals suboptimal performance in Ningbo's SRPI enterprises across three-dimensional efficiency metrics, with geospatial disparities in eco-innovation efficiency emerging among distinct administrative districts. An in-depth examination of comprehensive technical efficiency metrics reveals that Zhenhai District, Yinzhou District, and Yuyao City performed well, while Jiangbei District had relatively lower comprehensive technical efficiency. In terms of pure technical efficiency, Zhenhai District, Yinzhou District, Yuyao City, and Ninghai County performed well, while Jiangbei District had relatively lower pure technical efficiency. For scale efficiency, Yinzhou District, Fenghua District, and Cixi City performed well, while Ninghai County had relatively lower scale efficiency. Overall, Yinzhou District demonstrates superior performance across three-dimensional efficiency metrics.

(2) Conclusion Two: Regarding the influencing factors of green innovation efficiency for SRPI enterprises in Ningbo, based on the composition of green innovation efficiency measurement, 12 influencing factors, including resource input, market credit, and supply chain management, were selected for regression analysis. Based on correlation analysis, three factors—supply chain management, technical foundation, and financing capabilities—showed significant correlations with green innovation efficiency. Specifically, supply chain management exhibited a significant negative correlation with comprehensive and pure technical efficiency, while technical foundation and financing capabilities showed a significant positive correlation with scale efficiency.

Based on GMM and OLS model estimations, for comprehensive technical efficiency, resource input, risk resilience, and financing capabilities have positive impacts. In contrast, inventory management and cash flow management have negative impacts. For pure technical efficiency, resource input, financial stability, risk resilience, and financing capabilities have positive impacts, whereas supply chain management, inventory management, and cash flow management have negative impacts. For scale efficiency, market credit, internal fund allocation, inventory management, and financing capabilities have positive impacts, while resource input, supply chain management, and cash flow management have negative impacts.

Enterprises should prioritize resource input, risk resilience, and financing capabilities to optimize comprehensive and pure technical efficiencies. Additionally, enhancing financial stability can further improve pure technical efficiency. To enhance scale efficiency, enterprises can work on market credit, internal fund allocation, inventory management, and financing capabilities.

(3) Connections between two conclusions: The influencing factors of green innovation efficiency proposed in Conclusion Two provide theoretical support for improving regional enterprise efficiency as outlined in Conclusion One. By optimizing internal management, resource input, and technology investment, targeted improvements can be made to address efficiency shortcomings and reduce regional disparities.

Taking Jiangbei District as an example, where comprehensive and pure technical efficiency are relatively low, local enterprises need to make corresponding adjustments to improve overall regional green innovation efficiency. For instance, Hengpu Co., Ltd. (300969.SZ) and Huierdun (832186.NQ) experienced a decline in inventory turnover rates from 2017 to 2022. Given that inventory management (X5) harms pure technical efficiency (Y2), they should strengthen dynamic inventory monitoring and establish JIT inventory management systems to reduce inventory accumulation. Additionally, according to the positive impact of resource input (X1) on comprehensive technical efficiency (Y3), Hengpu Co., Ltd. should leverage its monetary advantages to increase investments in green technology research and development. Ningbo Jingda (603088.SH) should optimize payment cycles to improve supply chain management and enhance pure technical efficiency (Y2). Furthermore, Jiangbei District can implement regional policy support measures, such as establishing special funds for green innovation to support technological upgrades and supply chain optimization, setting up regional accounts receivable trading platforms to accelerate capital recovery, and establishing collaborative mechanisms among enterprises to share warehousing and logistics resources, thereby reducing inventory management costs.

Conclusion Two offers a scientific approach to fostering regional green innovation synergy through specific measures. Other regions, such as Ninghai County (low scale efficiency), Cixi City (pure technical efficiency needs improvement), and Xiangshan District (lowest comprehensive technical efficiency), should adjust their strategies based on their specific green innovation efficiency shortcomings and circumstances to achieve regional green innovation synergy.

5.2. Recommendations

5.2.1. Improve Internal Management

Enhancing internal management systems is a pivotal driver for optimizing green innovation efficiency, with demonstrable impacts across scale, pure technical, and comprehensive technical efficiency metrics. To achieve this, enterprises should strategically implement rigorous capital governance frameworks that allocate dedicated green innovation budgets while preventing fund misallocation. Building on financial controls, dynamic inventory systems that integrate JIT strategies and demand forecasting prove essential to elevate turnover rates and reduce warehousing costs. Concurrently, streamlining supply chains through green procurement standards accelerates response cycles while lowering administrative costs.

5.2.2. Strengthen Technical Infrastructure

Technical infrastructure demonstrates a robust positive correlation with scale efficiency, underscoring that enterprises should adopt a synergistic innovation strategy. First, prioritizing R&D investment is critical to accelerate technological iteration cycles and sustain competitive advantage. Concurrently, implementing dynamic resource allocation mechanisms encompassing human capital deployment and material logistics ensures optimal utilization efficiency. Additionally, adapting imported technologies via localized innovation processes allows companies to internalize outside knowledge, optimizing efficiency in scale according to their specific operational contexts. Fostering high-quality talent improves the company's intelligent management and technological innovation capabilities, supporting the transformation and application of green innovation results.

5.2.3. Strengthen Risk Management

Risk resilience significantly impacts both pure and comprehensive technical efficiency, requiring a systematic resilience-building framework. First, optimizing the capital structure through careful debt-equity management and strategic earnings retention strengthens financial robustness. Second, forging equity partnerships with technologically complementary investors amplifies resource synergies, particularly in circular production systems. Third, proactive risk surveillance protocols should be institutionalized to systematically map endogenous and exogenous risk vectors impacting green innovation performance.

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