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Innovation Efficiency and Spatiotemporal Differentiation of Logistics Enterprises: A Three-Stage DEA Analysis

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Abstract:

Innovation efficiency is examined for 23 Chinese A-share logistics-related listed firms over 2019-2024. The balanced panel contains 138 firm-year observations. A three-stage DEA model is used to separate the effect of the operating environment and statistical noise from firm-level inefficiency; the results are then read together with a Malmquist productivity decomposition and annual global Moran's I tests. After adjustment, mean TE, PTE, and SE are 0.346, 0.518, and 0.705. The environmental correction is extremely small and leaves the ranking of firms almost unchanged. For the full period, the Malmquist index is 0.964: efficiency catch-up is positive, but technological change remains below one and offsets that gain. No year shows significant global spatial autocorrelation under either inverse-distance or four-nearest-neighbor weights. The evidence therefore points less to a shortage of R&D inputs than to differences in how firms organize, absorb, and convert those inputs into innovation outcomes.

Keywords:

Logistics Enterprises, Innovation Efficiency, Three-stage DEA, Malmquist Index, Spatial Differentiation

1. Introduction

Digital platforms, intelligent equipment, green transport, and data-based coordination are now common in logistics operations. Larger R&D budgets, however, do not automatically produce more patents, stronger services, or better operating results. The more relevant question is how effectively R&D labor and capital are converted into technological and commercial outcomes, especially when listed logistics firms differ widely in network scale and R&D organization.

Recent studies approach logistics and innovation efficiency from complementary perspectives. Three-stage DEA combined with the Malmquist index has been used to evaluate Chinese listed logistics firms and has revealed marked differences in innovation efficiency [1]. Regional research has also examined the spatial and temporal pattern of logistics efficiency [2]. Low-carbon cold-chain logistics studies have used DEA-based efficiency measurement to identify efficiency differences and their determinants [3]. More recently, three-stage DEA has been applied to low-carbon logistics efficiency in China's eastern coastal areas [4]. Taken together, these

studies suggest that static efficiency, productivity change, and spatial variation should be interpreted separately, especially when environmental adjustment is small or spatial clustering is statistically weak.

The analysis therefore asks three questions. Does environmental and noise adjustment materially change measured firm efficiency? Is productivity change driven mainly by catch-up or by movement of the frontier? And do adjusted efficiency scores show spatial dependence across registered firm locations? Additional regressions are used only as robustness checks for associations with provincial environmental variables.

2. Methodology and Data

2.1. Three-stage DEA framework

The first stage uses input-oriented CCR and BCC DEA models. Recent reviews of DEA development show that these formulations remain standard tools for separating overall technical efficiency from pure technical and scale effects in multi-input, multi-output settings [5]. The input orientation is appropriate here because logistics enterprises can more directly control R&D personnel and R&D expenditure than innovation outputs. Technical efficiency (TE) is obtained from the CCR specification, pure technical efficiency (PTE) from the BCC specification, and scale efficiency is defined as SE = TE/PTE.

In the second stage, the input slacks obtained from the first-stage BCC model are treated as dependent variables in stochastic frontier analysis (SFA). Recent firm-level innovation-efficiency research has used the same three-stage logic to separate environmental effects and statistical noise from managerial inefficiency [6]. For each input, the slack is decomposed into an environmental component, symmetric statistical noise, and non-negative managerial inefficiency. Provincial per-capita GDP, science and technology expenditure, and technology-market turnover are used as environmental variables. After estimating the environmental and noise components, the original inputs are adjusted so that all observations face a comparable operating environment and random state, while managerial inefficiency is retained. The third stage reruns the CCR and BCC models using adjusted inputs and unchanged outputs.

To judge whether the second-stage adjustment has practical consequences, the first- and third-stage efficiency scores are compared in three ways: their mean differences, their Spearman rank correlations, and paired Wilcoxon tests. The last test is not interpreted on its own. A very small but consistently signed change may be statistically detectable in 138 paired observations while remaining negligible from an economic point of view.

2.2. Dynamic and spatial analysis

Intertemporal productivity is evaluated with the Malmquist productivity index and its efficiency-change and technological-change decomposition. Recent logistics applications use this framework to distinguish catch-up from frontier movement. The index is expressed as MI = EC x TC, where MI is total factor productivity change, EC is efficiency change, and TC is technological change. EC is further separated into pure efficiency change (PEC) and scale efficiency change (SEC). Values above one indicate improvement and values below one indicate deterioration. Because very

small base-period efficiency values can generate extreme ratios, the overall results are summarized by geometric means for the 115 adjacent-period firm observations.

Spatial analysis uses registered firm locations and third-stage PTE. Global Moran's I is calculated annually with inverse-distance weights and checked using four-nearest-neighbor weights; significance is based on 9,999 permutations. Recent logistics-efficiency research similarly distinguishes descriptive spatial variation from formal dependence testing. Because global dependence is insignificant, the efficiency-weighted center and standard deviational ellipse are used only for descriptive spatial analysis.

2.3. Sample and variables

The panel covers 23 A-share logistics-related listed enterprises that are observed in every year from 2019 through 2024, giving 138 firm-year observations. R&D personnel and R&D expenditure serve as inputs, while patent applications and operating revenue are treated as outputs. Patent applications combine invention and utility-model applications. Five firm-year observations with verified zero patent applications are kept as genuine zeros rather than replaced. The three environmental variables are matched by the province in which each firm is registered. R&D, revenue, and registered-location information come from annual reports and public disclosures; patent records are cross-checked with public patent information, and provincial variables are compiled from national and provincial statistical sources. The variables and measurement units used in the efficiency analysis are summarized in Table 1.

Table 1. *Variables used in the efficiency analysis.*

Type	Variable	Symbol	Measurement
Input	R&D personnel	RDPerson	Number of employees
Input	R&D expenditure	RDSpend	CNY million
Output	Patent applications	PatentTotal	Number of applications
Output	Operating revenue	Revenue	CNY 100 million
Environment	Per-capita GDP	ln_pcgdp	Natural logarithm
Environment	Science and technology expenditure	ln_sci_tech	Natural logarithm
Environment	Technology-market turnover	ln_tech_market	Natural logarithm

3. Results and Discussion

3.1. Environmental adjustment and static efficiency

The second-stage SFA results show a boundary pattern. The likelihood-ratio statistics are 158.428 for the R&D-personnel slack equation and 178.097 for the R&D-expenditure equation (both $p < 0.001$). Yet gamma approaches one and the variance attributed to symmetric noise is close to zero. None of the three provincial variables is significant in either equation. In this sample, the selected macro variables explain little of firm-level input slack, while random noise contributes very little under the adopted SFA specification.

The size of the adjustment confirms this interpretation. Average R&D personnel changes by only $7.75 \times 10{-}4$ persons and R&D expenditure by $3.74 \times 10{-}4$ million yuan. Relative adjustment rates are about $1.20 \times 10{-}4\%$ and $1.27 \times 10{-}4\%$. Mean TE, PTE, and SE change by only $1.3 \times 10{-}5$, $5.0 \times 10{-}6$, and $1.3 \times 10{-}5$, while Spearman correlations remain 1.000, 0.987, and 1.000. The second stage is statistically identifiable but does not materially reshape the efficiency profile.

After adjustment, the sample-wide means of TE, PTE, and SE are 0.346, 0.518, and 0.705. PTE is clearly lower than SE. Within the DEA decomposition, this pattern points more strongly to weaknesses in R&D organization, technology absorption, and the conversion of research inputs into outputs than to a simple mismatch in operating scale. The annual third-stage efficiency results are reported in Table 2.

Table 2. *Annual third-stage efficiency.*

Year	TE	PTE	SE
2019	0.317	0.543	0.588
2020	0.363	0.599	0.635
2021	0.305	0.501	0.671
2022	0.358	0.521	0.755
2023	0.364	0.445	0.812
2024	0.371	0.499	0.771

The yearly figures also show that the source of improvement changes over time. TE rises from 0.317 in 2019 to 0.363 in 2020, drops to 0.305 in 2021, and then recovers gradually to 0.371 in 2024. PTE follows a different path: it reaches 0.599 in 2020, falls to 0.445 in 2023, and recovers only partly in 2024. SE, by contrast, increases from 0.588 in 2019 to 0.812 in 2023 before easing to 0.771. The recent rise in TE is therefore associated mainly with better scale efficiency rather than with a parallel improvement in pure technical efficiency. This distinction matters because the same TE movement can reflect very different managerial problems. Figure 1 plots the annual movements of TE, PTE, and SE over the sample period.

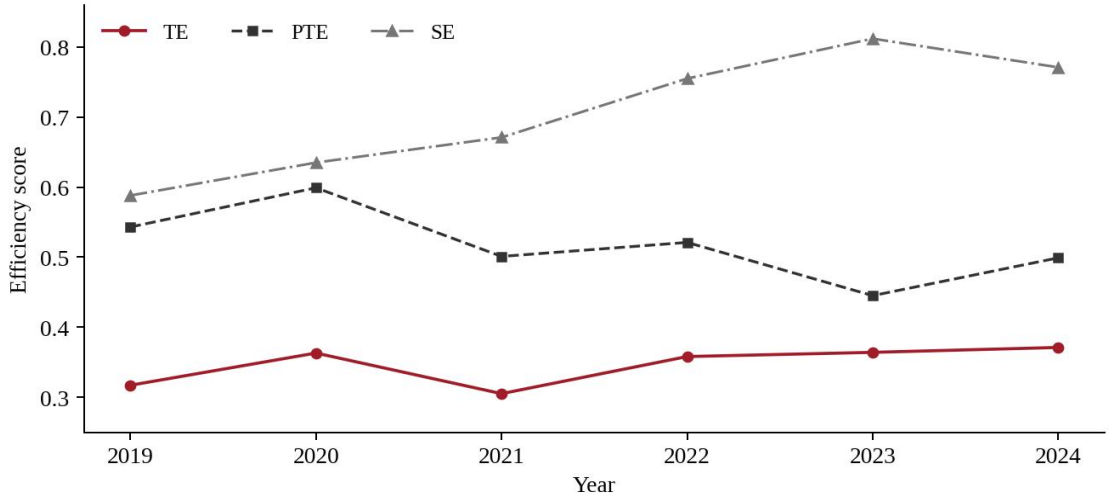

Figure 1. *Annual Changes in Third-Stage Innovation Efficiency.*

3.2. Malmquist productivity change

The Malmquist results add a different view of the annual DEA scores. For 2019-2024, the geometric mean of MI is 0.964, compared with 1.069 for EC and 0.903 for TC. Firms move closer to the frontier on average, but the frontier shifts in an unfavorable direction. Thus, higher static TE in later years can coexist with lower overall productivity. Annual DEA describes relative position within a period; the Malmquist decomposition separates catch-up from frontier movement.

The period-by-period values make this contrast easier to see. MI exceeds one in both 2019-2020 and 2020-2021, when TC is 1.107 and 1.185, respectively. In 2021-2022, EC jumps to 1.305, but TC falls to 0.728, leaving MI at 0.949. Thus, a strong

catch-up effect in that interval is not enough to offset the deterioration in the technology component. The full period-by-period decomposition is reported in Table 3.

Table 3. *Malmquist index decomposition.*

Period	MI	EC	TC	PEC	SEC
2019-2020	1.104	0.997	1.107	1.107	0.900
2020-2021	1.085	0.915	1.185	0.747	1.225
2021-2022	0.949	1.305	0.728	1.139	1.145
2022-2023	1.062	1.014	1.047	0.923	1.099
2023-2024	0.692	1.154	0.599	1.201	0.962

The same contrast is evident at the end of the sample. In 2022-2023, both EC and TC are above one and MI reaches 1.062. In 2023-2024, EC remains favorable at 1.154, but TC falls to 0.599 and MI drops to 0.692. The late decline is therefore associated mainly with frontier movement rather than a broad failure of firms to improve their relative efficiency. This decomposition does not, by itself, identify the cause of the technological shift. Figure 2 visualizes the corresponding movements in MI, EC, and TC across adjacent periods.

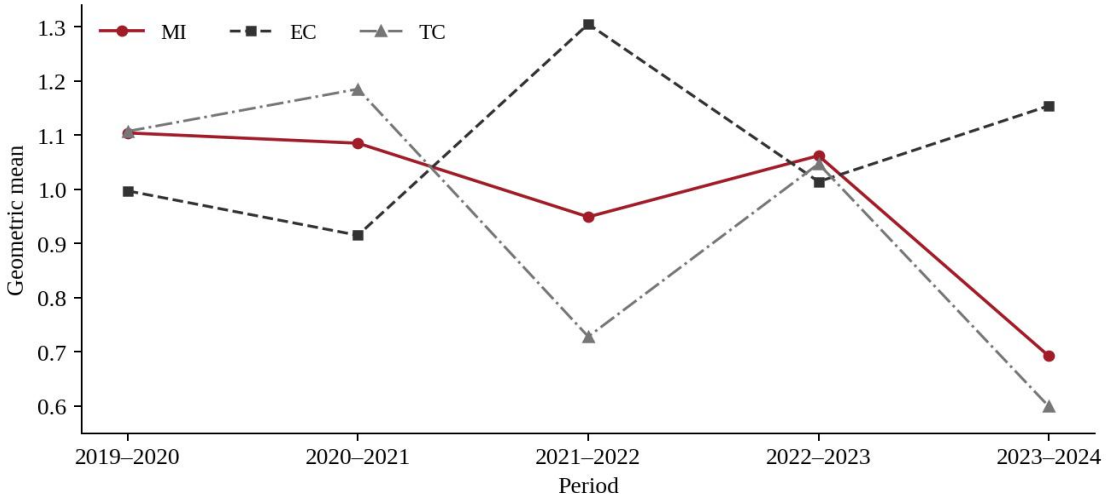

Figure 2. *Decomposition of the Malmquist Productivity Index.*

3.3. Spatial differentiation

The 23 firms are registered in ten provincial-level regions, but the distribution is far from even. Zhejiang and Guangdong each contain five sample firms, whereas several regions are represented by only one. A provincial mean can consequently move because of a single company. For this reason, the geographic results below describe the listed-firm sample and should not be interpreted as estimates of the efficiency of an entire provincial logistics industry.

The formal spatial test does not indicate stable global clustering. With inverse-distance weights, Moran's I takes values of -0.013, -0.146, -0.196, -0.205, -0.168, and -0.089 from 2019 to 2024, and every permutation p-value is above 0.20. Replacing the weight matrix with four nearest neighbors leads to the same substantive result. The sign is negative in most years, but the estimates are too imprecise to reject spatial randomness. The annual Moran's I statistics and permutation p-values are reported in Table 4.

Table 4. *Global Moran's I Tests.*

Year	Inverse-distance I	p-value	4-NN I	p-value
2019	-0.013	0.783	0.036	0.472
2020	-0.146	0.438	-0.077	0.790
2021	-0.196	0.237	-0.135	0.438
2022	-0.205	0.212	-0.077	0.808
2023	-0.168	0.322	-0.079	0.782
2024	-0.089	0.731	-0.063	0.872

Several of the Moran statistics are negative, which is consistent with a sample in which relatively high- and low-efficiency firms are geographically interspersed. The pattern is descriptive, however, not statistically established. Since neither weighting scheme produces significant global dependence, estimating a spatial lag, spatial error, or spatial Durbin model would add complexity without a supported spatial signal in the present data. Figure 3 compares the annual Moran's I values under the two spatial-weight specifications.

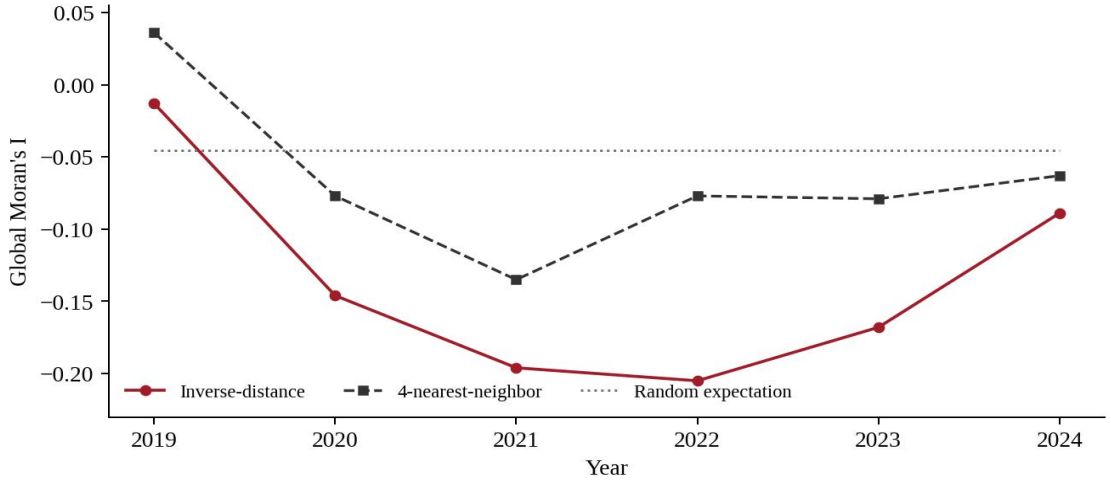

Figure 3. *Annual Global Moran's I under Alternative Spatial Weights.*

The efficiency-weighted center provides a more descriptive view of the spatial change. It moves from 116.504 degrees E and 30.959 degrees N in 2019 to 116.720 degrees E and 30.122 degrees N in 2024, a net displacement of about 95.39 km toward the south-southeast. The annual path is not one-way: the center shifts in different directions over the six years. The standard deviational ellipse also keeps a broadly northeast-southwest orientation. These measures are useful for showing where the sample's efficiency weight is located, but they should not be read as evidence of spillovers between firms or provinces.

3.4. Robustness and interpretation

A final set of regressions checks whether the environmental variables are stably associated with third-stage TE or PTE. Tobit models use firm-cluster bootstrap inference, while a fractional-response logit provides an alternative specification. In recent three-stage DEA applications, such regressions are treated as supplementary evidence rather than as another DEA stage. Science and technology expenditure and technology-market turnover are not stable across specifications; per-capita GDP is negatively associated with PTE, but the clustered evidence remains marginal.

This limited regression evidence is consistent with the very small second-stage adjustment. Firms in the same province share the same macro indicators in the model, yet they can still differ substantially in R&D governance, technology adoption, project selection, and commercialization. In the present setting, the value of the three-stage procedure lies partly in showing that the environmental correction is small; it would be misleading to assume in advance that provincial conditions must explain a large share of firm-level inefficiency.

4. Conclusions

Static efficiency remains relatively low in the sample: mean TE, PTE, and SE are 0.346, 0.518, and 0.705. The gap between PTE and SE matters because the recent improvement in TE comes mainly from scale efficiency, while PTE does not show the same sustained rise. The SFA correction also changes neither efficiency levels nor firm rankings to an economically meaningful extent, indicating only a small net role for the selected provincial conditions and statistical noise in measured input slacks.

The dynamic results tell a less favorable story than the later-year TE figures alone might suggest. The overall MI is 0.964: EC is above one at 1.069, but TC is only 0.903. The contrast is particularly clear in 2023-2024, when firms continue to catch up relative to the frontier while TC drops to 0.599. Spatially, neither the inverse-distance nor the four-nearest-neighbor specification produces significant global autocorrelation in PTE. The roughly 95.39 km south-southeast movement of the efficiency-weighted center is therefore best viewed as a descriptive change in the sample's geographic balance rather than as evidence of spatial spillover.

Managerial priorities depend on the source of inefficiency. Firms with low PTE should focus on project selection, R&D coordination, knowledge absorption, and conversion into patents or commercial results. Firms with stronger PTE but weak SE should instead examine whether the scale of innovation resources matches their output structure. The Malmquist results also show that catch-up is not enough; sustained productivity growth requires advances that move the frontier outward, including intelligent warehousing, transport optimization, low-carbon equipment, and data-intensive logistics services.

Several limitations remain. The sample contains only listed firms with continuous data and is geographically concentrated, so the efficiency scores are relative to this group. Provincial indicators are coarse and cannot capture firm-specific innovation ecosystems. The SFA equations also reach a boundary solution with very small noise variance, which limits strong interpretation of the environmental decomposition. Longer panels, finer firm-level environmental measures, and more direct commercialization outputs would provide a useful test of these findings.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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