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Science and Technology Input Efficiency Shortfalls and Industrial Organization Characteristics in Wenzhou

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Abstract: This study assesses Wenzhou's science and technology input efficiency relative to other cities in Zhejiang Province and examines the structure of its efficiency shortfall. Using innovation input and output data for 11 prefecture-level cities from 2019 to 2024, we apply data envelopment analysis, the Malmquist index, and an obstacle degree model. In 2024, Wenzhou's pure technical efficiency was 0.630, ranking ninth; the larger efficiency loss was associated with pure technical rather than scale efficiency. Its geometric mean annual total factor productivity index was 0.989, ranking tenth. Of eight diagnostic indicators, average operating revenue per enterprise had the highest obstacle degree, while the number of industrial enterprises above designated size had the lowest. Wenzhou has many firms of modest individual size despite relatively sound profitability. The evidence points to limited research and development resources available to individual firms as a plausible constraint. We therefore propose aggregating common technological needs through specialized platforms and linking fiscal disbursements to the application of research outcomes.

Keywords: Regional innovation; R&D input-output efficiency; Industrial organization; Firm-size distribution; Data envelopment analysis

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1. Introduction

The efficiency of science and technology inputs depends on how inputs are organized as well as on their scale. Wenzhou's R&D expenditure reached CNY 26.848 billion in 2024, ranking fifth among Zhejiang's 11 prefecture-level cities, while its R&D intensity was 2.76%. The value of technology transactions rose from CNY 21.032 billion in 2019 to CNY 70.914 billion in 2024, increasing from 3.50% to 7.30% of the city's GDP. Yet input growth has not yielded a commensurate improvement in conversion efficiency. Whether this shortfall reflects an unsuitable input scale or a limited ability to turn a given level of inputs into outputs has different

policy implications: the former points to scale adjustment, whereas the latter points to changes in organization.

Wenzhou provides a useful setting for examining this distinction. Its number of industrial enterprises above the designated size is among the highest in the province, but average operating revenue per enterprise ranks last. Even profitable firms willing to invest in R&D may struggle to assemble a full set of research resources when each firm is small. Aggregating common needs could turn dispersed demand into technological projects of sufficient scale. Using panel data for Zhejiang's 11 prefecture-level cities from 2019 to 2024, this study measures the static position and dynamic change of science and technology input efficiency, decomposes the efficiency shortfall, and relates city-level efficiency to firm size as a feature of industrial organization.

2. Literature review

2.1. Measuring regional innovation efficiency

Data envelopment analysis (DEA) is widely used to measure regional innovation efficiency in cities and industries, while the Malmquist index decomposes changes in total factor productivity [1,2]. Existing studies differ on whether efficiency gains or technological progress dominate observed improvements [3–5]. Three-stage DEA studies also find that low efficiency can reflect both pure technical and scale efficiency [6].

2.2. Firm size and access to R&D resources

Regional efficiency studies have paid less attention to how the distribution of firm size affects the conversion of inputs into outputs. Cohen and Klepper argued that larger firms can spread the fixed costs of R&D over more output [7], while related evidence finds that smaller firms depend more heavily on internal funds [8]. Because this evidence is mainly at the firm level, this study connects firm-size structure to city-level efficiency measurement.

3. Methods and data

3.1. Methods

We estimate input-oriented CCR and BCC models separately for each year. Overall technical efficiency (TE) measures aggregate input-output conversion. Pure technical efficiency (PTE) measures conversion at a given input level after accounting for scale effects. Scale efficiency (SE=TE/PTE) indicates whether the input scale is appropriate. All scores are relative to the sample frontier and are not absolute assessments.

To distinguish shifts in the frontier from catch-up by decision-making units, we use the Malmquist index [2]. We decompose the total factor productivity index (M) into efficiency change (EC) and technical change (TC), and EC into pure technical efficiency change (PECH) and scale efficiency change (SECH). Values above 1 indicate improvement; averages across periods are geometric means. PTE is the primary efficiency measure, with TE and SE reported for comparison. Because there are only 11 decision-making units, we assess ranking bias for the 2024 cross-section using 2,000 replications of the homogeneous Simar-Wilson bootstrap [9]. Robustness checks cover lagged inputs, winsorization, constant-price adjustment, alternative patent outputs, exclusion of small-sample cities, and a single-input specification. An obstacle degree model identifies the relative constraints associated with eight indicators.

3.2. Data sources and variables

The panel covers 11 prefecture-level cities in Zhejiang from 2019 to 2024, yielding 66 city-year observations.

R&D expenditure, patent grants, the number of industrial enterprises above the designated size, operating revenue, total profits, resident population, and GDP come from the 2020–2025 editions of the Zhejiang Statistical Yearbook. Full-time-equivalent R&D personnel, industrial value added of enterprises above the designated size, and high-tech industry value added come from city-level data published by the Zhejiang Provincial Department of Science and Technology. Firm counts by size in Wenzhou come from the 2025 Wenzhou Statistical Yearbook. Inputs are R&D expenditure and full-time-equivalent R&D personnel. Output is an entropy-weighted composite index of invention patents granted and high-tech industry value added, with weights of 0.660 and 0.340, respectively; the 66 city-year observations are min-max normalized before aggregation. The obstacle degree analysis uses eight indicators: the number of industrial enterprises above the designated size; leading-industry scale, measured by the industrial value added of those enterprises; the share of high-tech industry value added in their total industrial value added; average operating revenue per enterprise; the level and intensity of R&D expenditure; the number of invention patents granted; and invention patents granted per 10,000 residents. Absolute scale and intensity each receive half of the total weight, with equal weighting within each group.

4. Results: Science and technology input efficiency

4.1. Static efficiency: Wenzhou in the lower provincial tier in 2024

In 2024, Wenzhou's PTE was 0.630, ranking ninth and below the provincial mean of 0.813. Its TE was 0.506, ranking eighth, and its SE was 0.803. **Table 1** shows the cross-city comparison. Zhoushan, Hangzhou, and Lishui were PTE-efficient. Because the CCR ranking is more sensitive to scale efficiency, we use PTE as the principal measure for comparison.

Table 1. Science and technology input efficiency in Zhejiang's 11 prefecture-level cities, 2024

City	PTE	PTE rank	TE	TE rank	SE	Returns to scale
Zhoushan	1.000	1	1.000	1	1.000	Constant
Hangzhou	1.000	1	0.733	2	0.733	Decreasing
Lishui	1.000	1	0.392	11	0.392	Increasing
Jiaxing	0.938	4	0.726	3	0.774	Decreasing
Quzhou	0.927	5	0.545	7	0.588	Increasing
Ningbo	0.853	6	0.637	4	0.747	Decreasing
Taizhou	0.725	7	0.601	6	0.830	Decreasing
Huzhou	0.702	8	0.603	5	0.859	Decreasing
Wenzhou	0.630	9	0.506	8	0.803	Decreasing
Shaoxing	0.611	10	0.492	9	0.804	Decreasing
Jinhua	0.562	11	0.487	10	0.866	Decreasing
Provincial mean	0.813	-	0.611	-	0.763	-

Wenzhou ranked ninth in PTE under the main model and six alternative specifications, with scores ranging from 0.630 to 0.857. Only a density-based specification with two outputs placed it eleventh; because that specification changes both the indicators and their units, its scores are not directly comparable with those of the other specifications. In the bootstrap results, Wenzhou ranked between ninth and eleventh in 0.9985

of replications and entered the top eight in only 0.0015. The bias-corrected score was 0.5976, with a 95% confidence interval of [0.5305, 0.6271]. Thus, the more defensible conclusion is that Wenzhou's PTE remained in the lower provincial tier, rather than that its exact rank was necessarily ninth.

4.2. Efficiency components: Conversion is weaker than scale allocation

In 2024, Wenzhou's PTE was 0.630 and its SE was 0.803, corresponding to pure technical and scale efficiency losses of 37.0% and 19.7%, respectively. The former was nearly twice the latter. Wenzhou exhibited decreasing returns to scale in all six years. More inputs could still raise output, but marginal efficiency would not necessarily improve without changes in how those inputs are organized.

Output composition affects the efficiency score but does not fully explain Wenzhou's relative ranking. In 2024, Wenzhou ranked third in total patent grants, but invention patents accounted for 10.2% of its grants, compared with 35.6% in Hangzhou. Replacing invention patents with all patent grants raised Wenzhou's PTE to 0.857, yet left its rank at ninth. Technology transaction data likewise show rapid growth in transaction value and contract numbers, while average contract value fell from CNY 6.720 million to CNY 4.839 million, a decline of 28.0%. These patterns suggest that further growth in innovation output cannot rely solely on increasing the number of participating firms.

4.3. Dynamic efficiency and frontier changes

Under the invention-patent output definition, Wenzhou's PTE rose from 0.816 in 2019 to 1.000 in 2020, then fell to 0.558 in 2022 and 0.542 in 2023. It recovered to 0.630 in 2024 but remained below its 2019 level. The city reached the sample frontier only in 2020, a pandemic year that should not be interpreted as an unqualified optimum. The detailed sequence is sensitive to the patent-output definition: using all patent grants yields PTE scores of 0.920, 0.923, 0.959, 0.886, 0.818, and 0.857 in 2019–2024, with ranks between seventh and ninth. Thus, the fall-and-recovery trajectory is specific to the invention-patent specification; the 2024 lower-tier position is more stable.

Table 2 reports the Malmquist results. Wenzhou's geometric mean annual total factor productivity index over 2019–2024 was 0.989, ranking tenth. The corresponding technical change and efficiency change indices were 1.084 and 0.913. Within this sample, the estimated frontier moved outward while Wenzhou's catch-up weakened. The annual PECH and SECH indices were 0.949 and 0.961, respectively, indicating a larger decline in pure technical efficiency. These are model-based changes in a small-city panel, not direct measures of province-wide technological progress.

Table 2. Malmquist total factor productivity index and its components for Wenzhou, 2019–2024

Period	M	EC	TC	PECH	SECH
2019-2020	1.375	1.110	1.239	1.226	0.905
2020-2021	0.786	0.821	0.957	0.752	1.092
2021-2022	0.812	0.587	1.384	0.742	0.791
2022-2023	0.962	0.946	1.017	0.971	0.974
2023-2024	1.123	1.253	0.896	1.162	1.078
Geometric mean	0.989	0.913	1.084	0.949	0.961

5. Discussion: Industrial organization and the efficiency shortfall

5.1. Sources of constraint: Many firms, small individual scale

Table 3 places Wenzhou's indicators and obstacle degrees in provincial context. Its GDP ranked third, R&D expenditure fifth, and share of high-tech industry value added fourth; R&D personnel density and GDP per capita both ranked eighth. Invention patents per enterprise were 0.56, ranking ninth.

Table 3. Wenzhou's provincial rankings and obstacle degrees for eight indicators, 2024

Indicator	Wenzhou, 2024	Provincial rank	Obstacle degree (%)
Average operating revenue per enterprise (CNY 100 million)	0.841	11	20.8
Invention patents granted (count)	5,523	4	18.0
Invention patents granted per 10,000 residents (count)	5.61	6	17.7
Leading-industry scale (CNY 100 million)	1,736.9	5	14.9
R&D expenditure (CNY 100 million)	268.48	5	14.6
R&D intensity (%)	2.76	6	8.5
Share of high-tech industry value added (%)	73.0	4	3.8
Industrial enterprises above designated size (count)	9,796	2	1.8

Although Wenzhou ranked second in the number of industrial enterprises above designated size and fourth in the profit-to-revenue ratio, its average operating revenue per enterprise was only 49% of the provincial median. This pattern suggests that limited R&D resources available to each firm are a more plausible constraint than a shortage of firms. The obstacle degrees of the total number of invention patents and patents per 10,000 residents sum to 35.7%, consistent with a weaker density of higher-quality outputs.

5.2. A possible mechanism: Indivisible fixed costs

R&D teams, specialized equipment, pilot-scale facilities, and long-term technological projects entail substantial fixed costs that cannot be reduced in proportion to firm size. A firm with average operating revenue of CNY 84.1 million may be profitable and willing to invest in R&D, yet still be unable to finance a complete set of research resources on its own. Smaller firms also depend more heavily on internal funds [8]. City-level scale efficiency measures whether total inputs are appropriately scaled, whereas the size of individual firms affects whether those inputs can support viable projects. Wenzhou's larger pure technical than scale efficiency loss suggests that the constraint may arise after inputs have been dispersed across firms.

Among Zhejiang's industrial enterprises above the designated size in 2024, large firms averaged 296.1 person-years of R&D personnel and CNY 71.25 million in original-cost R&D instruments and equipment. The corresponding figures were 63.0 person-years and CNY 16.78 million for medium-sized firms; 18.2 person-years and CNY 6.03 million for small firms; and 8.9 person-years and CNY 3.85 million for micro firms. Of Wenzhou's 9,796 industrial enterprises above the designated size, 49 were large, 396 medium-sized, and 9,351 small. Small firms accounted for 95.5%, leaving only 4.5% classified as medium-sized or large.

Table 4 reports supplementary city-level regressions of PTE on the natural logarithm of average operating revenue per enterprise. Coefficients in the first 12 of 13 specifications are positive, ranging from 0.1428 to 0.2855; 11 meet the 1% threshold when two-sided *t*-tests use city-cluster degrees of freedom. With both city and year fixed effects, the coefficient is 0.0737 and is not statistically significant. The baseline coefficient of 0.1578 corresponds to a model-predicted PTE difference of approximately 0.109, or 10.9 percentage points, for

a doubling of average operating revenue per enterprise. This cross-city association is not a causal effect.

Table 4. Regressions of pure technical efficiency on average operating revenue per enterprise

Specification	*N*	Log avg. revenue per firm	Clustered SE	*t*-statistic	R^2
(1) Baseline (full sample)	66	0.1578***	0.0316	4.990	0.2579
(2) Exclude Zhoushan	60	0.1986***	0.0350	5.666	0.2166
(3) Exclude Zhoushan and Lishui	54	0.2205***	0.0386	5.707	0.2930
(4) Exclude all frontier DMUs	43	0.2432***	0.0437	5.568	0.3239
(5) Exclude 2020	55	0.1833***	0.0435	4.210	0.3468
(6) Add year fixed effects	66	0.1777***	0.0386	4.600	0.4085
(7) Control for GDP per capita	66	0.2577***	0.0581	4.438	0.3366
(8) Control for R&D intensity	66	0.1663***	0.0447	3.717	0.2828
(9) Control for high-tech share	66	0.1934***	0.0328	5.891	0.3310
(10) Control for profit margin	66	0.1569***	0.0277	5.674	0.2816
(11) Control for firm count	66	0.1428***	0.0475	3.006	0.2668
(12) All controls	66	0.2855***	0.0637	4.482	0.3928
(13) City and year fixed effects	66	0.0737	0.1437	0.513	0.6920

Notes: The dependent variable is PTE. Standard errors are clustered by city. Stars use two-sided *t* reference distributions with G-1 degrees of freedom, where G is the number of city clusters in each specification: ***$P < 0.01$. Sample exclusions apply only to these regressions; DEA efficiency scores were not re-estimated. R-squared is specification-specific.

A variance decomposition shows that 91.45% of the total variation in the logarithm of average operating revenue per enterprise lies between cities. Correspondingly, its coefficient becomes statistically insignificant after including city and year fixed effects, so the sample does not identify a significant within-city association. This is consistent with cross-city differences driving the overall correlation, but does not establish why those differences arise. With only 11 city clusters, inference from clustered standard errors should also be treated cautiously. PTE is a bounded efficiency score estimated by DEA; these regressions provide supplementary associational evidence only and do not support causal inference.

The frontier analysis also has limited discrimination: 23 of the 66 city-year observations lie on the BCC frontier. The precise efficiency levels and year-to-year movements are therefore less secure than the broad cross-city pattern. Inferences from 11 clustered cities and a bounded, estimated dependent variable should be read as descriptive and supplementary.

6. Conclusion and policy recommendations

Wenzhou's aggregate science and technology inputs are substantial, but its 2024 pure technical efficiency remains in the lower tier of Zhejiang's 11-city comparison. The relative weakness is more closely associated with input-output conversion than with scale efficiency. Its industrial structure combines many firms of modest individual size with relatively sound profitability, and average operating revenue per enterprise has the highest obstacle degree. The city-level regressions are consistent with a firm-size constraint, although they do not establish a causal mechanism. Because the annual efficiency path is sensitive to the patent-output definition and R&D personnel data have a coverage break, the policy interpretation rests mainly on the cross-sectional pattern and the distinction between pure technical and scale efficiency.

Policy should therefore focus on aggregating dispersed technological needs into projects of viable scale and linking more fiscal disbursements to demonstrated application outcomes. Existing awards for high-tech enterprises and ex-post R&D subsidies can remain, but their relative shares should be adjusted.

6.1. Aggregating common technological needs through specialized platforms

For each industry segment, authorities could compile a list of common technological needs. Industrial innovation service centers, pilot-scale facilities, or specialized operators could then turn recurring problems in materials, processes, testing, and digitalization into projects that can be commissioned, tendered, and evaluated. Such platforms would screen needs, select delivery partners, arrange intellectual property rights, and disseminate results. The costs of collecting needs and defining projects should be budgeted separately. Initial pilots could focus on smart electrical equipment, industrial pumps and valves, and automotive components, where firms are concentrated, and common problems are relatively clear.

6.2. Extending disbursement criteria from eligibility and inputs to application outcomes

Outcome measures should match the activity. Key-technology projects can be assessed against technical targets and pilot-scale validation; shared platforms against the number of firms served, equipment utilization, and reuse of results; and process upgrades against overall equipment effectiveness, defect rates, and output per worker. Longer projects could receive staged payments at project initiation, pilot validation, and application, with application outcomes recorded in subsequent funding assessments of firms and platforms.

6.3. Improving catch-up by diffusing mature technologies

As the frontier advances and Wenzhou's catch-up remains weak, policy resources need not all be devoted to frontier research. Platforms or industry associations could organize the adoption of established processes, testing methods, and digital modules across multiple firms. Firms could receive ex-post support for acquiring mature technologies from universities and research institutes once production-line results are verified. Leading firms and industry associations could demonstrate their use, reducing the cost of matching each firm to a provider.

6.4. Adding density measures to aggregate performance indicators

Alongside aggregate measures such as R&D expenditure, technology transaction value, and patent grants, the performance framework should include R&D spending per firm, R&D personnel density, and average technology contract value. Invention patents per enterprise can serve as a monitoring indicator. For high-tech enterprises and technology-based small and medium-sized enterprises, reports should track both the net increase in firm numbers and changes in average operating revenue per firm, so that growth in firm counts does not conceal limited individual scale.

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