

ENERGY FINDINGS

Carbon Shadow Pricing and Efficiency in Multimodal Freight Transport Networks: A Z-number DEA Analysis

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Findings

We integrate a \$50/ton CO₂ shadow price into a Z-number Data Envelopment Analysis (DEA) framework to evaluate carbon cost internalization across 59 logistics centers in Iran's freight transport network. Reflecting the transport sector's key role in emissions and energy use across multimodal freight corridors, rail-intensive sites show score increases up to +9.4% and rank improvements, while road-dependent hubs show score decreases down to -15.8% and rank declines. A strong negative correlation ($r = -0.94$) links rail share to rank improvement. Internalizing carbon externalities reshapes infrastructure priorities toward low-carbon modal configurations, offering a replicable tool for climate-responsive freight analysis under uncertainty

1. Questions

Strategic freight transport planning requires internalizing environmental externalities, yet few frameworks quantify how carbon costs reshape infrastructure efficiency under uncertainty. We address this gap by asking:

1. How does introducing a \$50/ton CO₂ shadow price affect the Z-number DEA efficiency scores and rankings of the 59 candidate Logistics Centers (LCs) in Iran's multimodal freight transport network?
2. To what extent do modal characteristics—particularly the rail-to-road freight share—explain variations in efficiency changes after carbon cost internalization?
3. How robust are the carbon-adjusted efficiency rankings under uncertainty in emissions estimation and transport demand, as represented through the α -cut and Z-number reliability structure?
4. How are carbon-induced efficiency gains and losses spatially distributed across Iran's national freight transport network?

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Table 1. Logistics Center Typology: LCI vs. LVI

Type	Count	Primary Functional Role	Geographic Distribution	Modal Requirements
LCI	29	core international gateways, customs clearance, connectivity to customer zones	Major corridors, borders, ports	Trimodal (road + rail + air/sea)
LVI	30	equitable domestic distribution, customs clearance, connectivity to customer zones	Provincial centers, borders, ports	Bimodal (road + rail)
Total	59	Complementary national network	All 31 provinces	-

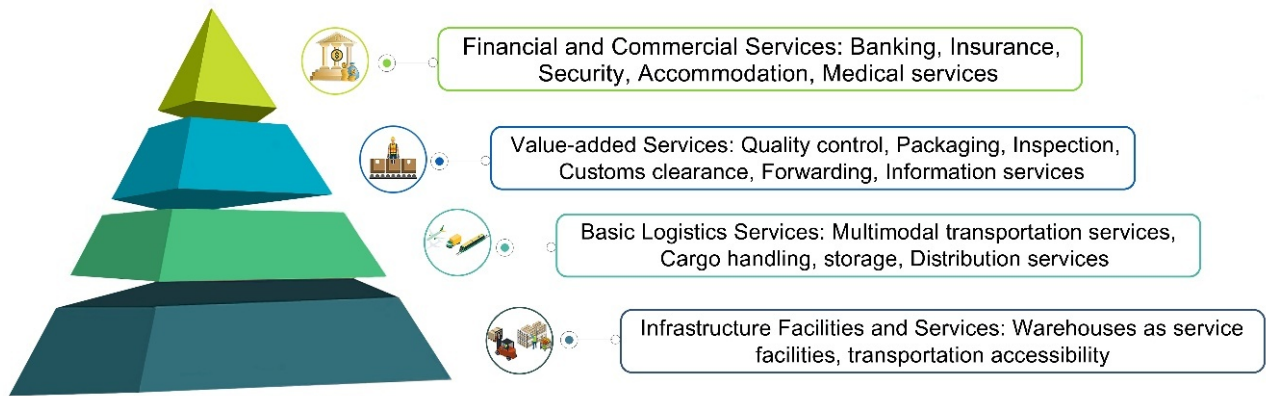


Figure 1. Hierarchical Service Structure of a Logistics Center. The hierarchical service structure progresses from infrastructure to logistics operations and value-added services, distinguishing LCs through integrated multimodal connectivity and freight handling capabilities.

These four questions are designed to progressively move from (1) direct empirical measurement of carbon pricing impacts on efficiency rankings, to (2) identification of the mechanism (modal split), to (3) testing the robustness of results under uncertainty, and finally to (4) maps the spatial distribution of efficiency gains and losses across the national network. This structure ensures that findings in Section 3 directly corresponds to research questions.

2. Methods

Data and Scope. We analyze 59 Logistics Centers (LCs) across Iran, including 29 Logistics Cities (LCIs) and 30 Logistics Villages (LVIs). Each LC is characterized by location, throughput, and modal split. Demand allocation derives from 124 customer zones within a national freight distribution network (Ministry of Roads and Urban Development of the Islamic Republic of Iran 2019). The two LC types perform complementary roles in hub-and-spoke freight transport structures and corridor-based logistics flows ((Roso 2008); [Table 1](#) and [Figure 1](#)).

Carbon Intensity Calculation. For each LC, CO₂ intensity (g CO₂/ton·km) was computed using the Global Logistics Emissions Council (GLEC) Framework v3.0 factors: road = 62 g/ton·km, rail = 24 g/ton·km, weighted by each site's modal mix. Annual CO₂ emissions (ktons) = intensity (g/ton·km) × throughput (tons) × haul distance (km) / 10⁶.

Carbon Cost Integration. A shadow price of \$50/ton CO₂—aligned with the World Bank’s 2024 Guidance Note on Shadow Price of Carbon in Economic Analysis and Iran’s climate policy benchmarks—was applied to annual emissions to derive an annual carbon cost (M), introduced as an additional undesirable fuzzy input (A-component) in the Z-number DEA model, capturing environmental externalities in freight transport decision-making. The reliability component (B = 0.85) reflects uncertainty in emission estimation and transport demand variability.

Z-number DEA Specification. We employ a Z-number DEA framework (Azadeh and Kokabi 2016) that incorporates both data imprecision and estimate reliability. Following Zadeh (2011), each variable is represented as a Z-number pair (A, B), where A is the fuzzy value and B is the reliability score. For computational efficiency, we convert each Z-number to a weighted fuzzy number (Wang and Chin 2011) by multiplying A by B. The reliability component B = 0.85 is applied to carbon cost estimates.

Output-Oriented BCC-DEA with α – cut

The efficiency score θ_j for each DMU_j at a given α – cut level is obtained by solving:

$$\begin{aligned}
 & \text{Min } \theta_j(\alpha) \\
 & \text{s. t.} \\
 & \sum_k \lambda_k X_{ik}(\alpha) \leq \theta_j(\alpha) \cdot X_{ij}(\alpha) \quad \forall i \text{ (inputs)} \\
 & \sum_k \lambda_k Y_{rk}(\alpha) \geq Y_{rj}(\alpha) \quad \forall r \text{ (outputs)} \\
 & \sum_k \lambda_k = 1, \quad \lambda_k \geq 0
 \end{aligned}$$

where $X_{ik}(\alpha) = \alpha \cdot X_{ik}^m + (1 - \alpha) \cdot X_{ik}^u$ for inputs, and $Y_{rk}(\alpha) = \alpha \cdot Y_{rk}^m + (1 - \alpha) \cdot Y_{rk}^l$ for outputs. The original inputs cover economic, financial, and climatic dimensions (see [Table 2](#)). The outputs capture demand potential, service requirement, and social benefit. The intensity variables λ_k represent the contribution of peer DMU_k to the efficiency frontier. Carbon cost enters as an undesirable fuzzy input in the carbon-adjusted scenario, allowing the model to evaluate trade-offs between economic efficiency and transport-related emissions. Uncertainty is handled via α -cut at $\alpha = 0.01$; the lower bound reflects conservative transport assessment under uncertainty. Following output-oriented BCC-DEA

Table 2. DEA Input and Output Indicators

Category	Indicator	Description	Role in DEA
Inputs	Economic Participation Rate	Percentage of economically active population	Labor availability
	Land Cost	Relative cost of land acquisition	Financial constraint
	Labor Cost	Average regional wage levels	Operational expense
	Construction Cost	Facility development cost	Capital investment
	Relative Humidity	Climatic factor affecting storage	Environmental constraint
	Number of Frost Days	Climatic factor affecting operations	Environmental constraint
Outputs	Population Size	Regional population served	Demand potential
	Demand Level	Freight demand (primarily staple goods)	Service requirement
	Unemployment Rate	Inverse indicator (higher is better)	Social benefit

convention (Charnes et al. 1978), scores greater than 1 indicate inefficiency (proportional output expansion needed). For the carbon-adjusted scenario, carbon cost enters as an additional undesirable input.

DEA Indicators

Within DEA framework, criteria that contribute positively to regional logistics suitability are classified as outputs, whereas variables imposing operational or environmental constraints are considered as input variables. Relative humidity is included as an environmental constraint in the model due to its recognized impact on warehouse durability, climate-control energy demand, and packaging integrity. This approach aligns with broader IPCC assessments on the vulnerability of infrastructure systems to climatic stressors (IPCC 2022). The selected indicators were limited to variables with nationally consistent spatial coverage across all candidate logistics centers. Future studies may incorporate additional climate-related indicators such as temperature variability, flood exposure, or extreme heat risk. The specific input and output indicators are detailed in [Table 2](#). The choice of indicators may be adapted based on data availability in different country contexts, enhancing the framework's transferability across emerging economies.

Replication. All Python code, Z-number DEA specifications, and synthetic logistics dataset are provided in Supplemental Information. Raw data are restricted due to confidentiality agreements with national transport authorities; researchers can apply provided code to their own regional transport data.

Model Parameters. Key parameters and data sources are summarized in [Table 3](#).

3. Findings

Rank Shifts and Score Changes. After carbon adjustment, 45% of LCs (27/59) changed rank by ≥ 5 positions. Rail-dominant sites improved their rankings: Gorgan (rank change +5, score +8.9%), Sari (rank change +4, score +8.1%), Rudbar (rank change +3, score +7.8%). Conversely, road-dependent

Table 3. Model Parameters and Data Sources for Carbon-Adjusted Z-number DEA Analysis

Parameter	Value	Source
Carbon shadow price	\$50/ton CO ₂	World Bank (2024)
Road emission factor	62 g CO ₂ /ton·km	GLEC Framework v3.0
Rail emission factor	24 g CO ₂ /ton·km	GLEC Framework v3.0
Risk-aversion parameter (β)	0.35	Calibrated from LCA
Uncertainty level (α)	0.01	Conservative scenario
Reliability component (B)	0.85	Expert judgment

hubs lost rank positions: Ahvaz (rank change -28, score -15.8%), Bandar Abbas (rank change -24, score -14.0%), Zahedan (rank change -22, score -14.7%). This confirms that modal structure critically determines freight transport efficiency rankings under carbon pricing ([Figure 2](#)).

Modal Share Correlation. Rail share strongly correlates with rank change (Pearson $r = -0.94$, $p < 0.001$). Freight systems with higher rail share are more carbon-efficient and economically resilient under carbon pricing. Sites with rail share $\geq 80\%$ ($n=14$) gained an average of +4.2 ranks; those with rail share $\leq 40\%$ ($n=11$) lost an average of -16.3 ranks. This pattern confirms that modal composition governs environmental and economic performance in freight transport systems ([Figure 2](#)).

Top Performer Stability. Karaj (LCI-12), baseline #1 (85% rail, score 1.120), retained its #1 position after carbon adjustment, with its score increasing to 1.198 (+7.0%). The top-five post-adjustment ranks are all held by LCs with rail share $\geq 75\%$, indicating that high-efficiency hubs with strong rail connectivity remain robust under environmental cost internalization.

Sensitivity and Robustness. Varying the uncertainty parameter α from 0.01 to 0.10 altered absolute scores by $\leq 3.2\%$ but preserved the rank order of the top-10 rail-intensive LCs. The correlation between rail share and rank change remained strong ($r \in [-0.91, -0.96]$) across all α values, with $r = -0.94$ at $\alpha = 0.01$, indicating that the core finding is robust to plausible variations in uncertainty modeling.

Spatial and Structural Synthesis. Building on the observed rank shifts (45% of LCs changing by ≥ 5 positions), gaining sites cluster in northern and northwestern Iran, where historical rail connectivity to agricultural production zones corresponds with lower carbon intensity. Losing sites concentrate in southern and southeastern corridors, where road dominance persists despite strategic port access ([Figure 3](#)). This spatial divergence corresponds directly to modal composition: sites with $\geq 75\%$ rail share consistently retain or improve rankings, while road-dependent nodes ($< 40\%$ rail) exhibit compounded efficiency penalties. The consistency of these patterns across all α -cut specifications ($\alpha \in [0.01, 0.10]$) confirms that the observed rank shifts are structurally determined by modal mix rather

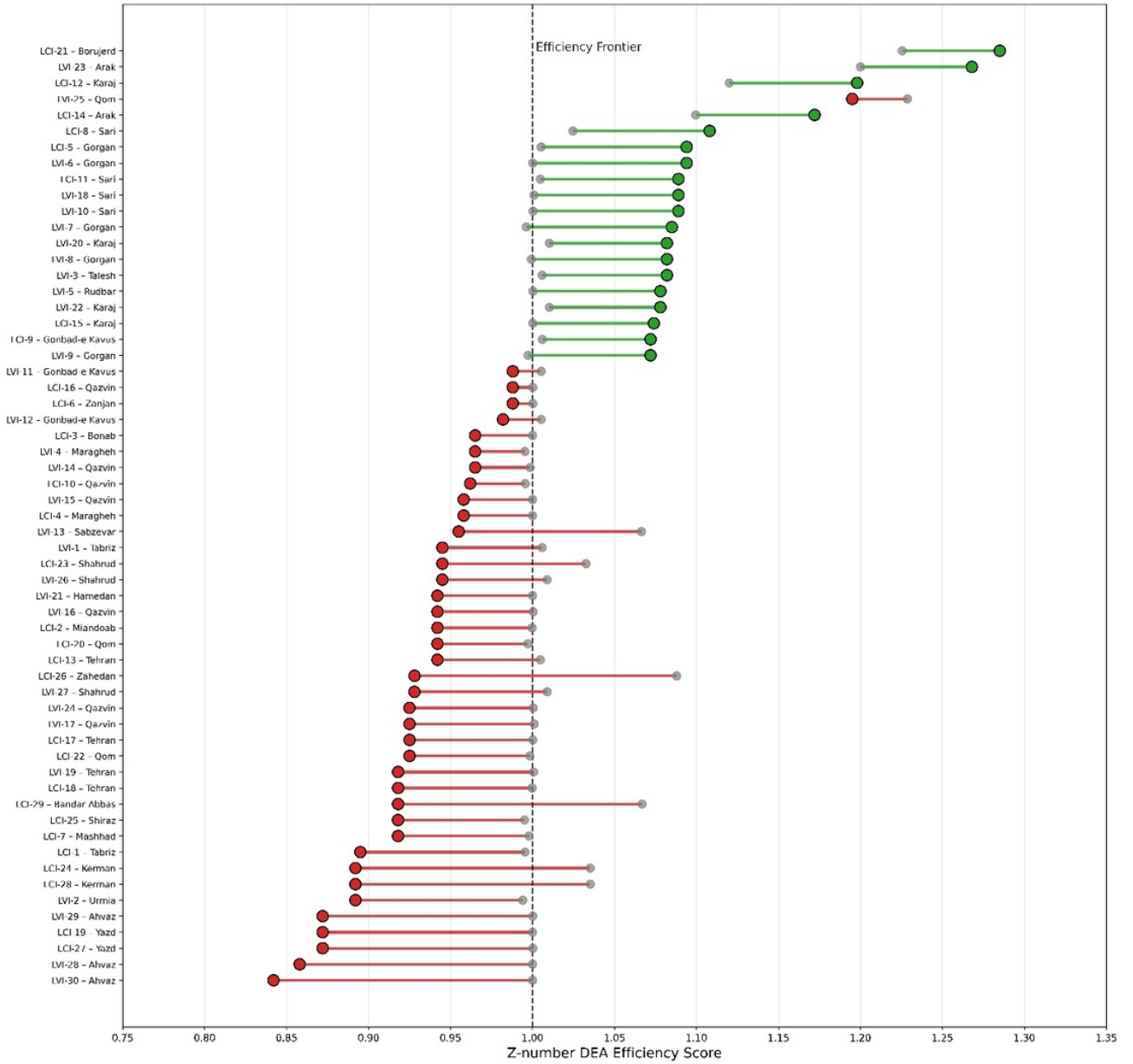


Figure 2. Dumbbell plot comparing baseline and carbon-adjusted Z-number DEA scores for 59 logistics centers. Following output-oriented BCC-DEA convention, scores greater than 1 indicate inefficiency (proportional output expansion needed). Rail-intensive sites show score increases and rank improvements (green), while road-dependent sites show score decreases and rank declines (red). The dashed line indicates the efficiency frontier (score = 1.0).

than transient cost fluctuations. These findings quantify how carbon cost internalization systematically differentiates infrastructure performance across Iran's multimodal freight network, providing a transparent baseline for resilience-aware assessment under uncertainty.

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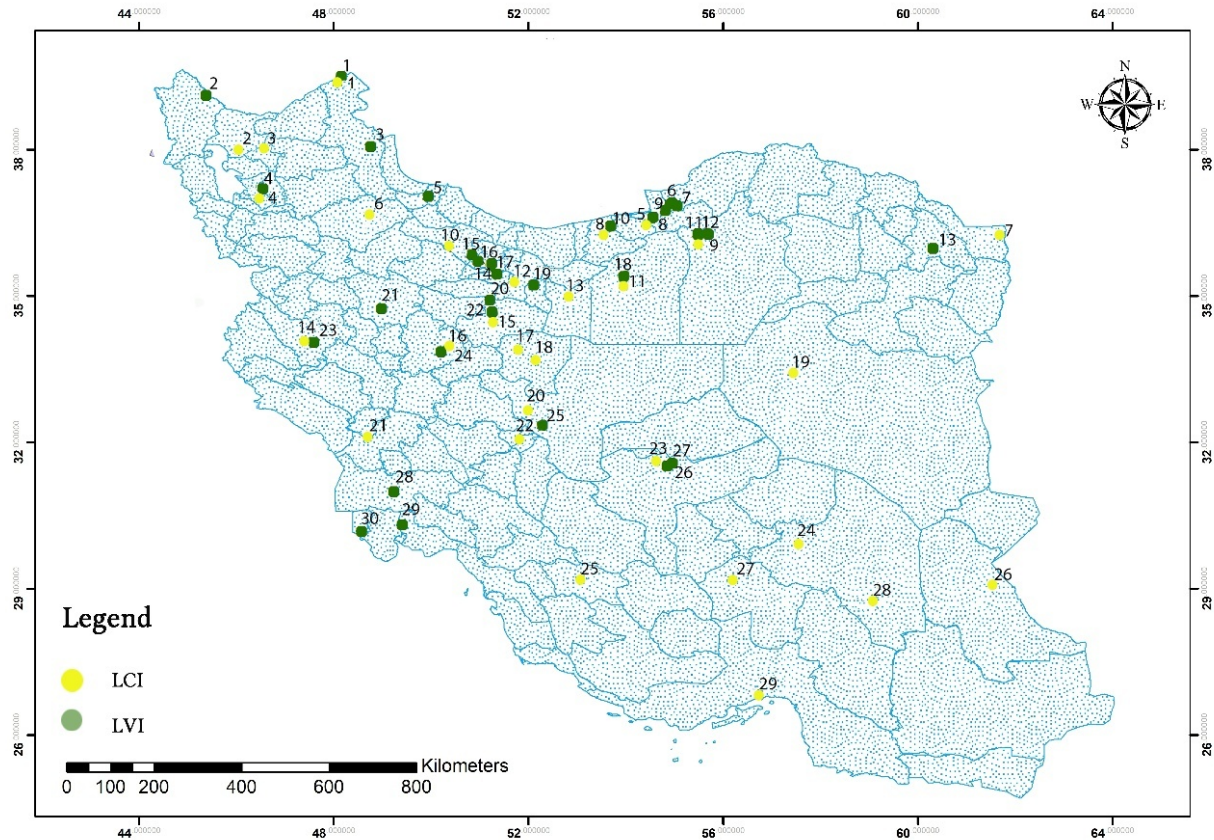


Figure 3. Geographic Distribution of 59 Candidate Logistics Centers Across Iran. LCIs are positioned along major corridors, borders, and ports, while LVIs provide provincial coverage with presence at borders and ports, supporting national freight distribution and connectivity.

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SUPPLEMENTARY MATERIALS

Supplementary files: Python codes, synthetic datasets, and README instructions.

Download: <https://findingspress.org/article/163951-carbon-shadow-pricing-and-efficiency-in-multimodal-freight-transport-networks-a-z-number-dea-analysis/attachment/351088.zip>
