# Dividends of AI-Driven Logistics Reform in Vietnam: A Recursive Dynamic CGE Analysis

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**Abstract.** Vietnam's logistics costs are among the highest in Southeast Asia and a recognised bottleneck on export competitiveness. The government's *Logistics Development Strategy 2025–2035* mandates a reduction to 15% of GDP by 2030, but the technological adoption required to achieve this target has not been formally quantified. This paper employs a recursive dynamic Computable General Equilibrium (CGE) model with 40 sectors calibrated to Vietnam's 2019 Input-Output Table to simulate three scenarios: a Business-as-Usual trajectory (S1), an empirically grounded AI-ITS adoption path drawing on recent literature (S2), and a reverse-closure targeted scenario that solves for the minimum annual TFP growth rate required to achieve the government's price mandate (S3). Under the model and its calibration, the empirically plausible adoption trajectory raises projected real GDP by 0.75% and real wages by 0.62% above BAU by 2030 but yields only a ~10% logistics price reduction — about five percentage points short of the government target. Closing the gap to a full 15% price reduction in the simulation requires a uniform TFP growth rate of 2.75% per annum across road freight, rail freight, and warehousing, associated with a 1.20% GDP gain. The residual gap between S3 and the government's 15% cost-share target reflects inventory, administrative, and delay-related costs not captured by transport-sector TFP, suggesting complementary broader logistics ecosystem reforms.

## 1 Introduction

High logistics costs place a huge constraint on Vietnam's development. At approximately 20% of GDP — compared with 8–10% in advanced economies and 12–14% in regional peers — Vietnam's freight, storage, and handling costs suppress the price competitiveness of its exports and increase the cost of imported inputs for domestic industries [1]. Fuel expenditure alone accounts for 30–40% of road freight operating costs [1], and the rail network — dominated by the state-owned Vietnam Railways Corporation (VNR) — operates at low frequency and utilisation. The *Logistics Development Strategy 2025–2035* sets an explicit quantitative target: reduce the logistics cost share of GDP to 15% by 2030, a 5 percentage-point reduction to be achieved through infrastructure investment, regulatory reform, and technology adoption.

Artificial intelligence and Intelligent Transportation Systems (ITS) have emerged as a leading mechanism for achieving such reductions. AI-driven route optimisation, fleet telematics, predictive maintenance, and warehouse robotics have delivered measurable efficiency gains across logistics systems in advanced and emerging economies alike. McKinsey & Company [2] estimates that AI route optimisation reduces Fuel costs by up to 15%; Warehouse automation implementations document labor cost reductions ranging from 25–85% depending on the level of automation [3]; and AI-driven predictive maintenance deployments in marine logistics infrastructure have achieved a 21.4% reduction in unplanned downtime and a 13.8% reduction in overall maintenance costs [4]. At a macro level, the World Economic Forum [5] estimates that AI-driven operational efficiencies, including optimized asset management and routing, can reduce total freight emissions by 4–7%.

Computable General Equilibrium (CGE) modelling is a common method in economics to examine the economy-wide impacts of policy shocks. The World Bank points out that upgrading transport infrastructure not only expands market access but also strengthens Vietnam's input-output linkages [6]. However, existing Vietnam CGE studies rely on static frameworks and focus on infrastructure quantity rather than logistics-sector productivity.Therefore, it is difficult to quantify the inter-temporal effect of policy package in disaggregated logistics modes. The AI-ITS literature documents sectoral efficiency benchmarks but stops short of economy-wide quantification.

This paper aims to explore the impacts of AI-ITS on logistic, non-logistic sectors and the Vietnamese economy as a whole. We construct a 40-sector dynamic CGE model that surgically disaggregates road freight, rail freight, and warehousing from standard bundled concordances, enabling independent, mode-specific TFP shocks. Then, we design three scenarios including a reverse-closure ap-

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proach that endogenises the required TFP rate to achieve an exogenous price target. We show that by 2030, the government's 15% logistics cost reduction target should be not be solely attributable to transport-sector productivity improvements.

## 2 Methodology

### 2.1 Model Specification

We employ a single-country, recursive dynamic CGE model calibrated to Vietnam's 2019 Input-Output Table, following the approach of Thurlow [7] and Lofgren et al. [8]. This is an economic model that solves a sequence of static equilibria linked by laws of motion for capital, labour, and Total Factor Productivity (TFP).

**Production.** Each sector $j$ produces gross output $X_j$ by combining value-added $V_j$ and intermediate inputs $INT_{ij}$ through a Leontief top-level technology:

$$X_j = \min\left(\frac{V_j}{a_j^V}, \frac{INT_{ij}}{a_{ij}^Q}\right) \tag{1}$$

where $a_j^V$ is the unit value-added requirement and $a_{ij}^Q$ is the IO input coefficient for good $i$ in sector $j$. The value-added composite $V_j$ is formed by a CES aggregation of labour $L_j$ and capital $K_j$ [9]:

$$V_j = \alpha_j\left[\theta_L L_j^{-\rho_{VA}} + (1-\theta_L)K_j^{-\rho_{VA}}\right]^{-1/\rho_{VA}}, \quad \sigma_{VA} = \frac{1}{1+\rho_{VA}} \tag{2}$$

where $\alpha_j$ is a sector-specific scale parameter, $\theta_L \in (0, 1)$ is the labour share, and $\sigma_{VA} = 0.5$ follows GTAP estimates for developing economies.

**Trade.** Vietnam is treated as a small open economy. Exports are determined via CET transformation ($\sigma_E = 2.0$) and imports via Armington CES aggregation ($\sigma_M = 2.0$), generating imperfect substitution between domestic and foreign varieties [10].

**Closure.** Labour is perfectly mobile across sectors; an economy-wide wage $w$ clears the aggregate market. Capital is sector-specific within each period, with rental rates $r_j$ equilibrating at full utilisation. The current account balance is fixed in foreign currency; the real exchange rate adjusts to maintain external balance. The CPI serves as the numéraire.

**Capital accumulation** follows the perpetual inventory method [11]:

$$K_j(t+1) = (1-\delta)\,K_j(t) + I_j(t) \tag{3}$$

where $K_j(t)$ is the capital stock in sector $j$ at period $t$, $\delta$ is the economy-wide depreciation rate, and $I_j(t)$ is real investment allocated to sector $j$. Investment is distributed across sectors proportionally to relative rental rates [12]. Labour and population grow exogenously from GSO projections and the SSP2 scenario.

**TFP shocks.** Productivity enters as a standard Hicks-neutral efficiency shifter on the value-added coefficient. A permanent annual shock rate $g_{j,s}^{TFP}$ in year $s$ accumulates multiplicatively:

$$a_j^V(t) = \frac{a_j^{V,0}}{\prod_{s=t_0}^{t}(1+g_{j,s}^{TFP})} \tag{4}$$

where $a_j^{V,0}$ is the base-year coefficient, $t_0 = 2019$, and $s$ indexes each intervening period. As $a_j^V(t)$ falls, fewer factor inputs are required per unit of output, driving down domestic prices. The baseline TFP path is endogenously calibrated to GSO GDP targets via a bisection closure swap [13].

### 2.2 Sector Aggregation

The 171-sector Vietnam IO table is aggregated to 40 sectors using a purpose-built concordance. We isolate RDF (Road Freight), RAF (Rail Freight), and WHS (Warehousing), the three primary policy-shock sectors. Passenger and mixed-mode transport is consolidated into a residual OTP (Other Transport, covering road and rail passengers). Remaining logistics sectors are retained as separate codes for full cost-share accounting: WTP (Water Transport), ATP (Air Transport), and PST (Postal and Delivery Services). This disaggregation enables separate identification of cost pass-through for each AI-ITS channel and supports the Laspeyres logistics cost index across all seven transport codes.

### 2.3 Scenarios

**S1 — Business-as-Usual.** No AI-ITS shocks are applied to RDF, RAF, or WHS. Economy-wide TFP is calibrated to official GDP targets using the SSP2 forecast of Fontagné et al. [18]. S1 defines the counterfactual against which all dividends are measured.

**S2 — Empirical AI-ITS Adoption.** Sector-specific annual TFP shocks are applied over 2023–2030, phased to mirror a standard S-curve adoption trajectory. Because no econometric estimate of AI-ITS TFP elasticity is available for Vietnam, the shock magnitudes in this scenario are *calibration assumptions*, not estimated parameters, and S2 results should accordingly be read as conditional projections under these assumptions rather than forecasts.

Magnitudes are translated from literature cost-reduction benchmarks to annual Hicks-neutral TFP rates via a transparent three-step procedure: (i) identify the gross efficiency ceiling reported in firm- or project-level studies in advanced economies; (ii) apply a *developing-economy adoption discount* of approximately one-third to reflect the well-documented technology diffusion lag between frontier and follower economies, drawing on the cross-country evidence of Comin and Hobijn [16] on adoption lags and the World Bank's assessment of Vietnam's digital readiness gap [17]; (iii) further discount for the fact that CGE TFP shocks capture only the value-added component of cost savings (fuel savings, for instance, enter via the petroleum intermediate-input channel and are excluded from the value-added bundle to avoid double counting). Table 1 documents the resulting mapping for each shock channel; the sensitivity of results to alternative calibration choices is acknowledged in Section 3.6.

**Table 1.** TFP calibration mapping: ceiling to applied rate

| Channel | Ceiling | Discount | Peak |
|---|---|---|---|
| RDF | 15% [14] | ∼1/3 | 2.0% |
| RAF | 13.8% [4] | ∼1/2 | 1.5% |
| WHS | 30–45% [14] | VA 0.55 | 2.5% |

Annual schedules are S-curve phased. For RDF, we apply 1.5% (2023–24), 2.0% (2025–28), and 1.5% (2029–30), supported by McKinsey [14] and WEF [5] benchmarks and enabled by Decree 10/2020/NĐ-CP mandating GPS tracking on commercial vehicles; compound ≈ 14.9%. For RAF, we apply 1.0% (2025–26), 1.5% (2027–29), and 1.0% (2030), reflecting VNR's later AI rollout under the Railway Development Strategy 2021–2030. Digital Twin supports predictive maintenance in rail [15], with downtime and cost benchmarks of 21.4% and 13.8% extrapolated from comparable AI-driven predictive-maintenance deployments in marine logistics infrastructure [4]; compound ≈ 7.7%. For WHS, the schedule is 1.5%/2.0%/2.5%/2.5%/2.0%/1.5%/1.0%/1.0% from 2023 to 2030, motivated by AMR/AS-RS and MARL deployments delivering 30–45% labour savings [14] against a 55% labour share in WHS value-added; compound ≈ 14.9%.

**S3 — Targeted Policy (Reverse Closure).** S3 inverts the standard closure to answer the policy question directly: *what minimum uniform annual TFP rate $\tau$, applied simultaneously to RDF, RAF, and WHS from 2023–2030, achieves a 15% reduction in the composite logistics price index by 2030?*

In the standard forward closure, $\tau$ is exogenous and prices are endogenous. S3 makes the 2030 output-weighted composite price the exogenous target and $\tau$ the unknown, solved via Brent bisection:

$$\tau^* = \underset{\tau}{\operatorname{argmin}} \left| \frac{\bar{P}_L(\tau) - \bar{P}_L^{BL}}{\bar{P}_L^{BL}} + 0.15 \right| \tag{5}$$
$$\bar{P}_L = \textstyle\sum_{j \in \{\text{RDF,RAF,WHS}\}} w_j P_j^D$$

where $\bar{P}_L^{BL}$ is the output-weighted composite logistics price in 2030 under BAU, $P_j^D$ is the domestic price of sector $j$, $w_j$ are base-year gross-output shares, and 0.15 is the government's mandated 15% price reduction target — the objective is met when $\bar{P}_L(\tau^*) = 0.85\,\bar{P}_L^{BL}$, making the bracketed expression exactly zero. The bisection converged in 8 evaluations, yielding $\tau^* = 2.7503\%$ p.a., a required cumulative TFP gain of $1.0275^8 - 1 \approx 24.2\%$ across all three sectors by 2030 (Table 2).

## 3 Results

### 3.1 Logistics Sector Prices and Output

Figure 2 plots simulated domestic price deviations from the BAU baseline. Under S2, the model projects road

**Table 2.** Required vs. empirical cumulative TFP gains by 2030

| Sector | S2 Empirical | S3 Required | Gap (pp) |
|---|---|---|---|
| Road Freight (RDF) | 14.9% | 24.2% | +9.3 |
| Rail Freight (RAF) | 7.7% | 24.2% | +16.5 |
| Warehousing (WHS) | 14.9% | 24.2% | +9.3 |

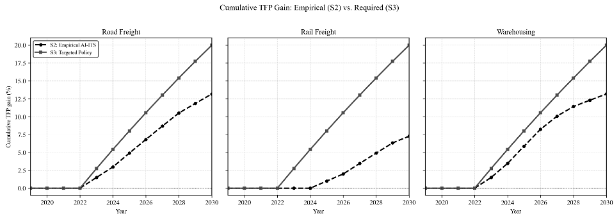


**Figure 1.** Cumulative TFP gain paths — S2 (empirical) vs. S3 (required) — for each target sector.

freight prices to fall progressively: −3.8% by 2025, −6.1% by 2027, and −8.4% by 2030. Simulated warehousing prices decline more steeply (−4.9%, −8.4%, −11.6%), reflecting the larger, front-loaded TFP schedule. Rail freight lags (−0.8%, −2.3%, −4.0%) under its delayed onset and smaller cumulative shock. Under S3, the uniform $\tau^*$ implies convergent, deeper cuts in the simulation: −12.8% (RDF), −17.3% (WHS), and −10.3% (RAF) by 2030.

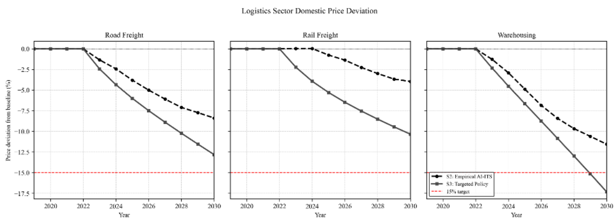


**Figure 2.** Domestic price deviations from BAU — road freight, rail freight, and warehousing (2019–2030).

Table 3 summarises logistics sector outcomes at 2030. A notable simulated feature is the sharp asymmetry between WHS price reduction and output expansion. Under S3, a 17.3% modelled price cut co-occurs with a 37.9% output surge — driven in the model primarily by export demand. As simulated Vietnamese warehousing becomes cheaper relative to world prices, foreign users substitute toward Vietnamese logistics services through the Armington mechanism, generating a large export volume response (+73.1%) within the model. This distinction between price competitiveness and total logistics value is central to interpreting the cost share result in Section 3.5.

The composite price index $\bar{P}_L$ in Equation (5) uses 2019 IO gross-output shares $(w_{\text{RDF}}, w_{\text{RAF}}, w_{\text{WHS}}) \approx (0.424, 0.004, 0.572)$ (sectors 125, 123, 130; totals 262.3, 2.7, 354.2 tril. VND). Applying these to Table 3 prices gives

$$\Delta\bar{P}_L^{S2} = 0.424(-8.4) + 0.004(-4.0) + 0.572(-11.6) \approx -10.2\%, \tag{6}$$

**Table 3.** Logistics sector outcomes at 2030 (% deviation from BAU)

| | Price | | Output | | Exports | |
|---|---|---|---|---|---|---|
| Sector | S2 | S3 | S2 | S3 | S2 | S3 |
| RDF | −8.4 | −12.8 | +3.9 | +6.4 | +19.2 | +31.5 |
| RAF | −4.0 | −10.3 | +0.4 | +0.9 | +8.3 | +24.2 |
| WHS | −11.6 | −17.3 | +21.8 | +37.9 | +42.0 | +73.1 |

the ∼10% headline used in abstract and conclusion. The same weights yield $\Delta\bar{P}_L^{S3} \approx -15.4\%$, within rounding of the 15% S3 bisection target.

### 3.2 Economy-Wide Dividends

Figure 3 and Table 4 report the macro dividends. Under S2, projected GDP rises 0.26% above BAU by 2025 and 0.75% by 2030 as lower input costs compound through IO linkages and capital deepening; S3 yields ≈60% larger gains at each checkpoint, reaching +1.20% by 2030. Two model channels operate: direct cost reduction across freight-using industries, and capital deepening as higher profitability attracts investment (capital above BAU by 0.23/0.33 pp under S2/S3 in 2030). Simulated real wages track GDP closely (+0.62% under S2 and +0.94% under S3 by 2030), combining direct labour demand under the full-employment closure with an indirect purchasing-power effect from lower simulated logistics prices.

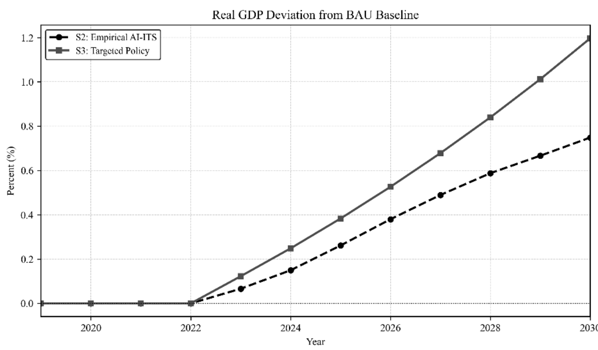


**Figure 3.** Real GDP deviation from BAU baseline (%) for S2 and S3, 2019–2030.

**Table 4.** Macro checkpoints: % deviation from BAU

| Scenario | Year | GDP | Wage | Capital | Invest. |
|---|---|---|---|---|---|
| S2 | 2025 | +0.26 | +0.23 | +0.01 | +0.15 |
| S2 | 2027 | +0.49 | +0.42 | +0.07 | +0.38 |
| S2 | 2030 | +0.75 | +0.62 | +0.23 | +0.67 |
| S3 | 2025 | +0.38 | +0.34 | +0.02 | +0.25 |
| S3 | 2027 | +0.68 | +0.58 | +0.10 | +0.53 |
| S3 | 2030 | +1.20 | +0.94 | +0.33 | +1.01 |

### 3.3 Upstream Spillovers

Lower simulated logistics prices act through two opposing channels for non-logistics sectors: direct cost pass-through favouring freight-intensive industries, and factor reallocation drawing labour and capital toward the expanding logistics complex under the full-employment closure. Net sectoral responses are heterogeneous (see Section 3.4 and Figure 4). The real exchange rate depreciates by −0.20/−0.37 pp under S2/S3 by 2030, providing a modest Armington offset for tradeables.

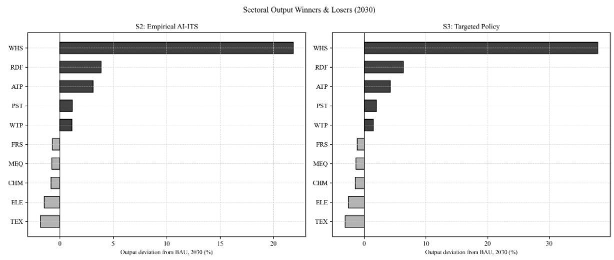


**Figure 4.** Sectoral output deviation from BAU at 2030 — top and bottom performers under S2 and S3. Winners (dark bars): WHS = Warehousing, RDF = Road Freight, ATP = Air Transport, PST = Postal Services, WTP = Water Transport. Losers (grey bars): TEX = Textiles & Apparel, ELE = Electronics & ICT, CHM = Chemicals & Pharmaceuticals, MEQ = Electrical Equipment & Machinery, FRS = Forestry.

### 3.4 Export Competitiveness

Figure 5 disaggregates export volume deviations at 2030 under S2 for key goods-producing industries. The result is counterintuitive: only MVH (Motor Vehicles and Transport Equipment) records a positive export deviation (+1.2% above BAU), while every other tracked sector loses export volume — TEX (−1.8%), OCR (Other Crops, −1.6%), ELE (−1.5%), MEQ (−1.1%), PDR (Paddy Rice, −1.0%), FSH (Fisheries and Aquaculture, −0.6%), and OFD (Processed Foods, −0.5%).

This pattern reflects a factor reallocation mechanism embedded in the model. As simulated AI-ITS productivity gains accrue in WHS, RDF, and directly linked transport sectors, those sectors expand and attract capital and labour from the rest of the economy. In the model's full-employment closure, this reallocation crowds out other tradeable industries competing for the same fixed factor pool — a mechanical consequence of the closure that should not be read as a causal prediction (see Section 3.6). MVH is the exception: as a heavy, high-value good with high freight cost intensity, the direct cost-pass-through outweighs factor crowding. For lighter or less logistics-intensive manufactures (textiles, electronics, agriculture),

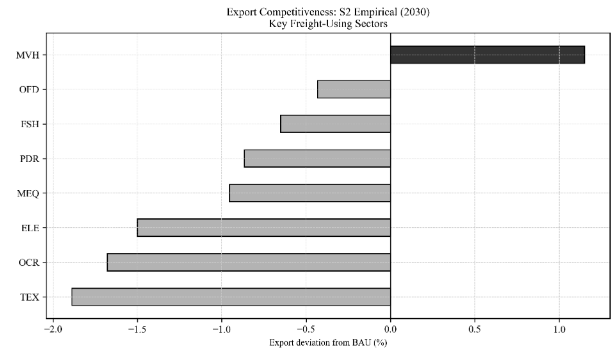


**Figure 5.** Export volume deviation from BAU at 2030 under S2 Empirical AI-ITS, key freight-using sectors. Sector codes: MVH = Motor Vehicles & Transport Equipment, OFD = Processed Foods, FSH = Fisheries & Aquaculture, PDR = Paddy Rice, MEQ = Electrical Equipment & Machinery, ELE = Electronics & ICT, OCR = Other Crops, TEX = Textiles & Apparel.

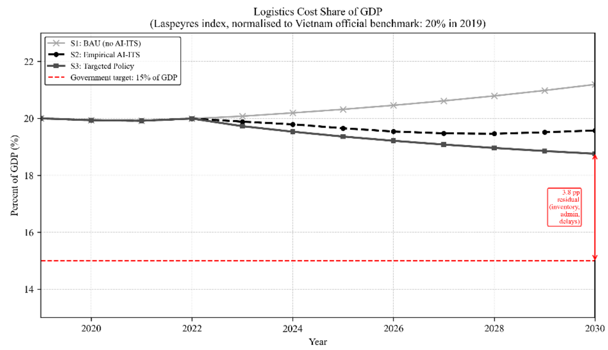


**Figure 6.** Logistics cost share of GDP — Laspeyres price index normalised to the Vietnam official 20% benchmark (2019).

the factor channel dominates — suggesting that complementary measures (automation support, trade facilitation for exporters) are useful alongside AI-ITS investment.

### 3.5 Logistics Cost Share of GDP

Figure 6 presents the Laspeyres logistics cost share, which is the cost of purchasing the BAU volume of transport and warehousing services at scenario-specific prices, expressed as a percentage of real GDP. The 2019 model-derived baseline share of ≈12% is normalised to the official Vietnamese government benchmark of 20%, preserving the relative trajectories under each scenario while anchoring the level to the observed statistic:

$$\text{Share}_t^{Las} = \frac{\sum_{j\in\mathcal{L}} P_{j,t}^{D} \cdot X_{j,t_0}}{GDP_t^{real}} \times \text{scale}, \quad \text{scale} = \frac{20.0\%}{\text{model share}_{2019}} \tag{7}$$

where $\mathcal{L} = \{\text{RDF, RAF, OTP, WTP, ATP, WHS, PST}\}$, $P_{j,t}^{D}$ is the domestic price in year $t$, $X_{j,t_0}$ is the BAU output in the base year held fixed as the volume weight, and $GDP_t^{real}$ is real GDP.

A Paasche-type alternative using observed quantities $X_{j,t}^{PO}$ would yield a *rising* apparent share, since induced volume expansion (notably the +73% WHS export surge under S3) overwhelms the price effect. The Laspeyres index strips out induced demand and isolates the price channel that the government target measures.

Three patterns emerge. First, the simulated BAU is not flat: without AI-ITS, the share rises from 20% to ≈21.2% by 2030 as logistics outgrows the wider economy. Second, both scenarios reverse this trend — S2 brings the share to ≈19.4% and S3 to ≈18.8% (a 1.2 pp cumulative fall from 2019). Third, a residual ∼3.8 pp gap separates S3 from the 15% target, attributable to non-transport-VA components (customs delays, inventory, cold-chain, port handling) on which AI route optimisation and warehouse robotics alone cannot influence.

### 3.6 Limitations

Several caveats apply. (i) S2 TFP shocks are calibration assumptions from advanced-economy benchmarks with a judgement-based developing-economy discount; results scale roughly linearly with these rates, and formal sensitivity analysis is left to future work. (ii) The full-employment, sector-mobile labour closure mechanically amplifies the factor-crowding pattern in Section 3.4; unemployment or imperfect mobility would dampen losses to textiles and electronics. (iii) Armington/CET elasticities are fixed at standard values ($\sigma_M = \sigma_E = 2.0$); the WHS export response is particularly sensitive to this choice. (iv) The model abstracts from imported-equipment and adoption costs of AI-ITS, which would attenuate gains. (v) Inventory, customs, and delay costs — part of the official 20% cost share but outside transport-sector value-added — are not directly addressable by TFP shocks in this framework. All numerical findings should accordingly be read as conditional projections under the model, not as causal estimates.

## 4 Conclusion

This paper used a recursive dynamic CGE model to explore the economy-wide effects of AI-ITS adoption in Vietnam under an empirical-adoption scenario (S2) and a reverse-closure targeting scenario (S3). Four model-based findings stand out. First, AI-ITS is positive-sum across the macro aggregates examined: S2 projects a 0.75% GDP gain and 0.62% real-wage gain above BAU by 2030, with broad-based spillovers. Second, the empirical path falls about five percentage points short of the government's price mandate — assumed cumulative TFP gains (≈14.9% RDF/WHS, 7.7% RAF; Table 2) translate to only a ∼10% composite price decline (Equation 6). Third, hitting the 15% target in the model requires ≈2.75% annual TFP across all three sectors (≈24.2% cumulative); the largest empirical-vs-required gap is rail (∼+16.5 pp), pointing to VNR digitalisation as a priority. Fourth, even under S3 the simulated cost share remains ≈18.8% of GDP — 3.8 pp above target — consistent with the share embedding inventory, administrative, and delay components outside the transport-sector value-added bundle.

Three policy implications follow, subject to the caveats in Section 3.6. (i) The size of the rail TFP gap suggests weighing the marginal return of Railway Development Strategy resources on Digital Twin and predictive maintenance against further track investment. (ii) Warehousing's steep price-per-TFP response and large output multiplier (+37.9% under S3) suggest gains from front-loading WHS automation. (iii) Because the model projects crowding-out losses for textiles and electronics under full employment, complementary instruments (automation grants, bonded-warehouse access) merit consideration — noting that the crowding magnitude is closure-dependent.

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