

Multidimensional Assessment and Strategic Optimization of U.S. Tariff Policy Evidence from Key Sectors

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Abstract: The reciprocal tariff regime announced by the United States in April 2025 raised the average tariff level sharply and exposed firms and policy makers to a poorly mapped space of economic, security, and fiscal outcomes. This study develops an integrated decision-analytics framework that traces tariff effects through three strategic sectors — soybeans, automobiles, and semiconductors — and links them to fiscal revenue and macroeconomic restructuring. Using HTS-coded trade data for 2020–2024, we combine isolation-forest screening and t-SNE visualization with ridge regression and VARX scenario forecasting, a dynamic-panel System GMM design with value-at-risk (VaR/CVaR) measures, a nested CES demand system embedded in a bi-objective optimization solved by L-BFGS-B and Bayesian surrogate search, a Laffer-curve model augmented by a Stackelberg retaliation game and SVAR analysis, and a fixed-effects/VAR/Probit/DID battery for policy evaluation. Tariff exposures are strongly heterogeneous: a 1% tariff rise reduces soybean import shares by up to 26.2% (Brazil) but Japanese auto imports by only 2.4% and chip market shares by 2.2%. Chip tariffs trace an efficiency–security frontier in which high-end rates dominate security risk ($r = 0.72$). The estimated revenue-maximizing tariff falls from 3.86% to 2.78% once foreign retaliation is anticipated, far below the current burden. Counter-tariff policy triggers significant capital reshoring (fixed-asset investment +90.7%) without short-run output gains, implying that capacity revitalization lags capital relocation.

Keywords: CES demand model, difference-in-differences, Laffer curve, manufacturing reshoring, multi-objective optimization, Stackelberg game, System GMM, tariff policy, trade risk, value at risk.

1. Introduction

In April 2025 the United States introduced a reciprocal tariff policy that set a unified benchmark rate for all trading partners and imposed surcharges on deficit countries, abandoning the most-favored-nation principle and pushing the average tariff level to new heights. The policy may raise fiscal revenue and relieve trade deficits in the short run, but it also restricts exports, feeds inflation, and invites retaliation on critical inputs such as rare earths and lithium batteries. The stakes reach beyond trade accounts: tariff adjustments propagate through agriculture, manufacturing, and services, reshape supply chains, and condition where multinational firms locate capacity. Both policy makers and firms therefore need a quantitative map connecting tariff rates to sectoral outcomes, revenue, and re-industrialization.

Existing evidence remains fragmented. Indicator-style analyses describe exposure but do not quantify behavioral responses; single-equation regressions rarely survive the endogeneity of tariff policy; and optimization studies of tariff design seldom close the loop with retaliation, fiscal sustainability, and causal policy evaluation [9]–[11]. This paper addresses these gaps with a five-module framework calibrated on 2020–2024 U.S. trade data, covering: (i) soybean trade among China, the United States, Brazil, and Argentina; (ii) Japanese automobiles in the U.S. market with firm-level non-tariff responses; (iii) differentiated chip tariffs under efficiency and security objectives; (iv) tariff revenue on a Laffer curve under a Stackelberg retaliation game; and (v) macroeconomic transmission and manufacturing reshoring. It offers three contributions: sector-specific elasticity estimates that support differentiated tariff design; an efficiency–security Pareto analysis for chip tariffs; and a game-consistent optimal tariff together with causal evidence on reshoring.

2. Theoretical Framework

The analysis rests on the theory of strategic trade policy. A large importer can exploit terms-of-trade power: an import tariff improves welfare up to an optimal rate beyond which trade contraction dominates [10], and when exporters can retaliate strategically, the rates that survive equilibrium interaction are lower still [11]. Sectoral incidence is governed by substitution possibilities, formalized in the CES/Armington tradition: the more differentiated the good, the less quantity responds to tariff-induced price changes [9]. Fiscal implications follow the Laffer logic — revenue is the product of a rate and a shrinking base, generating an inverted-U relation — while the risk view treats tariff shocks as loss distributions to be

summarized by value-at-risk (VaR) and expected shortfall (CVaR), instruments imported from financial risk management. Finally, causal evaluation of policy responses draws on panel fixed effects, dynamic feedback systems, and difference-in-differences designs that compare treated and untreated sectors before and after intervention. Three propositions organize the empirics: P1, tariff pass-through is heterogeneous across sectors in proportion to substitutability; P2, anticipated retaliation lowers the revenue-maximizing tariff; P3, protection induces capital reshoring before output responds.

3. Data and Methodology

3.1 Data and Preprocessing

We assemble HTS-coded trade panels for 2020–2024: soybeans (HTS 1201) for China, the United States, Brazil, and Argentina; automobiles by source country; and integrated circuits (HTS 8542) disaggregated into processors, memory, amplifiers, other ICs, and parts, grouped into high-, mid-, and low-end classes. Missing values were absent, but high-dimensional noise required screening: an Isolation Forest isolates anomalous observations through random partitioning, with samples whose average isolation path falls below a threshold removed [3], [6], and t-SNE embeds the cleaned feature space in two dimensions to visualize country-level structure [1].

3.2 Sectoral Response Models

For soybeans, ridge regression quantifies the effect of six drivers (tariffs, prices, exchange rates, demand, competition intensity, and time) while controlling collinearity:

$$\min_{\beta} \sum_i (y_i - \sum_j \beta_j x_{ij})^2 + \lambda \sum_j \beta_j^2 \quad (1)$$

with λ tuned by five-fold cross-validation, followed by a VARX(p, s) system in which tariffs enter as exogenous inputs to forecast three-year export paths under alternative scenarios [4], [5]. For automobiles, market structure is summarized by the Herfindahl–Hirschman Index, and a dynamic panel model with lagged imports and firm response variables (capacity relocation, cost optimization) is estimated by System GMM to handle the endogeneity induced by lag terms. Tariff risk is quantified with VaR and expected shortfall at 90–99% confidence levels.

3.3 Chip Tariffs as Bi-Objective Optimization

Chip varieties are first classified by a Gaussian mixture model (silhouette = 0.68). A two-layer nested CES demand system then links tariffs to market shares through effective prices [9]:

$$s_j = w_j p_j^{1-\sigma} / \sum_k w_k p_k^{1-\sigma}, p_j = p_j (1 + \tau_j) \quad (2)$$

where w_j is the preference weight and σ the elasticity of substitution. Policy design maximizes a weighted objective combining economic efficiency (trade scale net of tariff costs) and structural security (diversification of key-chip dependence); the parameterized weighted-sum method traces the Pareto frontier with L-BFGS-B, and a Bayesian surrogate — Gaussian-process regression with expected-improvement acquisition — accelerates the global search:

$$EI(x) = (\mu(x) - f^*) \Phi(z) + \varphi(z) \sigma(x), z = (\mu(x) - f^*) / \sigma(x) \quad (3)$$

3.4 Fiscal Channel: Laffer Curve and Retaliation

Tariff revenue is modeled on a log-linear Laffer curve estimated over 2020–2024,

$$\ln T_t = a + b \ln \tau_t + \varepsilon_t, R(\tau) = \tau \cdot Q(\tau) \quad (4)$$

and embedded in a Stackelberg game in which the United States anticipates partners' optimal retaliation path when choosing its tariff [8]:

$$\tau^* = \operatorname{argmax}_{\tau} \tau \cdot Q(\tau, \tau_B^*(\tau)), dR / d\tau = 0 \quad (5)$$

A structural VAR ($y_t = [\text{revenue, trade volume, tariff rate}]'$) then traces the dynamic response to policy shocks.

3.5 Macroeconomic Transmission and Policy Evaluation

Thirteen macro indicators feed three complementary designs: industry fixed-effects regressions of value-added growth on sectoral tariffs; a five-variable VAR(2) with impulse responses and variance decomposition; and a Probit model of manufacturing reshoring. Causal identification of the 2023 counter-tariff policy uses a difference-in-differences design with

rare-earth and lithium-battery sub-sectors as the treated group:

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 P_i + \beta_3 (T_i \times P_i) + \gamma_k X_{kit} + \varepsilon_{it} \tag{6}$$

where β_3 identifies the net policy effect under the parallel-trends assumption.

4. Empirical Results

4.1 Soybean Trade: Substitution and Reallocation

Rank correlations reveal substitution-based competition between the United States and Brazil (Kendall $\tau = -0.521$) and complementary adjustment between the United States and Argentina ($\tau = +0.324$). Import tariff elasticities are extreme for the South American exporters — -26.2 for Brazil and -4.1 for Argentina — against a negligible $+0.05$ for the United States (Table I). VARX scenarios show U.S. soybean exports falling from a \$302.2 bn baseline (2026) to \$271.9 bn, \$241.7 bn, and \$211.5 bn under $+10\%$, $+20\%$, and $+30\%$ tariffs, while Argentina’s share rises from 7.1% toward 32.2% under high-tariff paths. Figure 1 shows the realized 2020–2024 import structure: Brazil sustains the dominant share, the United States erodes around the 2023 dip, and Argentina spikes transiently — evidence that tariff shocks restructure rather than merely reprice the soybean landscape.

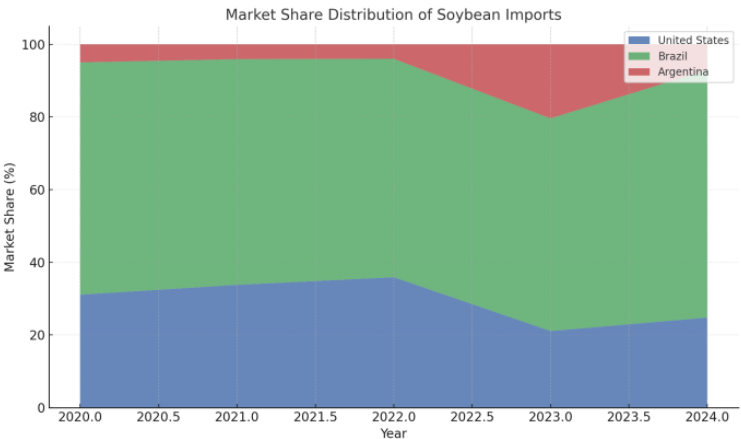


Figure 1. Market share distribution of soybean imports by origin, 2020–2024 (stacked shares). Brazil dominates throughout; the U.S. share dips in 2023 and Argentina spikes transiently.

4.2 Japanese Automobiles: Persistence and Risk

U.S. auto-import concentration fell (HHI $0.248 \rightarrow 0.222$) as Japan’s share declined from 32.4% to 27.1% despite a 2022 export peak of \$14.65 bn. The System GMM estimates imply that a 1% tariff increase cuts Japanese auto imports by 2.4%, while a 30% capacity relocation buffers the decline to about 3.5% in the affected scenarios — direct evidence that non-tariff firm strategies materially offset tariff shocks. Risk measures compound the picture: at a 50% tariff the 95% VaR reaches \$193 mn (CVaR \$88 mn), and modeled loss rates climb from 2.5% to 17.3% as tariffs rise from 5% to 50% (Figure 2), with VaR and CVaR moving nearly in parallel — tail risk is intense but not fat-tailed.

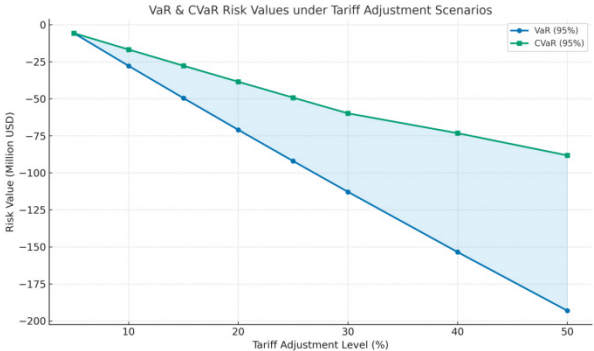


Figure 2. VaR and CVaR (95%) of Japanese automobile imports under tariff adjustments of 5–50%. Both risk measures grow monotonically; the shaded band is the VaR–CVaR gap.

4.3 Chip Tariffs: The Efficiency–Security Frontier

CES estimates (substitution elasticity $\sigma = 2.6$; preference parameters significant at the 1% level) yield a tariff elasticity of -2.22% for chip market shares, similar across grades — chips respond mildly because high-end varieties are hard to substitute. Optimizing the dual objective traces the frontier in Figure 3: economic efficiency plateaus near 0.912 while national-security risk climbs from below 100 to above 300 along the frontier, a steeply asymmetric trade-off. Sensitivity analysis attributes a security-sensitivity coefficient of 0.85 to high-end tariffs (correlation with risk $r = 0.72$) versus 0.62 for mid-end tariffs on efficiency; perturbing high-end rates by $\pm 30\%$ moves efficiency by only $\pm 0.32\%$ but risk by $\pm 0.78\%$. K-means partitioning of frontier solutions (silhouette = 0.32) separates efficiency-first from security-first policy families, supporting differentiated rather than uniform chip tariffs.

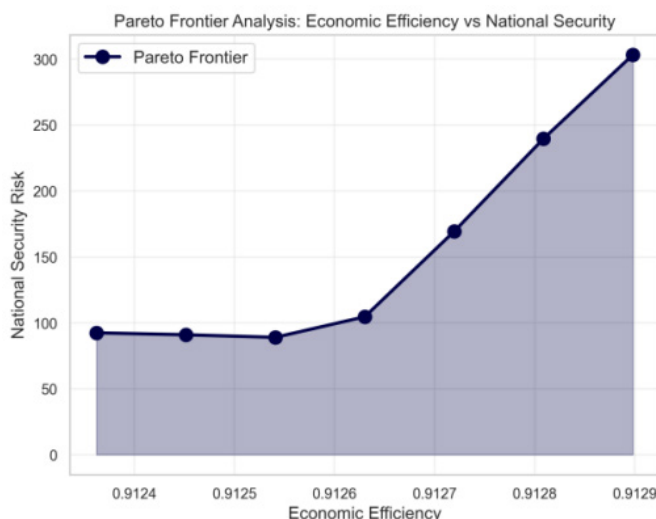


Figure 3. Pareto frontier of the chip-tariff bi-objective program: national-security risk rises nonlinearly as economic efficiency improves beyond ≈ 0.9126 .

4.4 Tariff Revenue: Over-Taxation on the Laffer Curve

U.S. tariff revenue climbed from \$70.9 bn (2020) to a \$129.3 bn peak (2022), fell to \$88.0 bn in 2023, and rebounded to \$91.8 bn in 2024. The fitted Laffer curve ($R^2 = 0.517$; demand elasticity 26.9, significant at 1%) places the revenue-maximizing rate at 3.86% under the basic specification; anticipating partners' optimal retaliation in the Stackelberg game lowers it to 2.78% (Figure 4). The current average tariff burden stands far above both values — on the declining branch of the curve, where moderate tariff cuts would raise revenue. SVAR impulse responses reinforce the fiscal warning: under an unchanged policy path, revenue growth turns negative within the 2025–2027 horizon after a short-lived initial gain, confirming the medium-run cost of over-taxation.

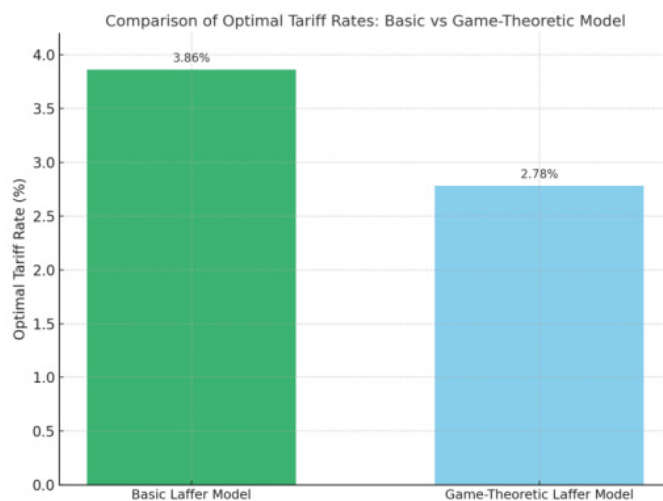


Figure 4. Revenue-maximizing tariff rates from the basic Laffer model (3.86%) and the Stackelberg game model with anticipated retaliation (2.78%).

4.5 Macro Transmission and Manufacturing Reshoring

Sectoral fixed effects identify agriculture as the most tariff-sensitive sector ($R^2 = 0.926$): each 1 pp tariff increase lowers value-added growth by 0.33 pp, amplified to 0.50 pp under counter-tariff shocks (Table II). The VAR(2) system shows manufacturing investment responding within the first period while GDP and household income react with a two- to three-period lag — investment leads, aggregates follow. The Probit model links reshoring probability to the U.S.–overseas tariff gap (coefficient 1.10, marginal effect +0.214) and the counter-tariff index (+0.893, ME +0.177). Exploiting the 2023 counter-tariff event, the DID estimate is $\beta_3 = +2.42$ ($p < 0.05$): treated sectors' fixed-asset investment jumped 90.65% (\$72.7 bn → \$138.6 bn) while value added was flat (−1.35%). Rolling forecasts extend the pattern to 2029 (Figure 5): investment continues to scale toward ≈\$240 bn, but output converges only gradually — capital reshores faster than capacity revitalizes.

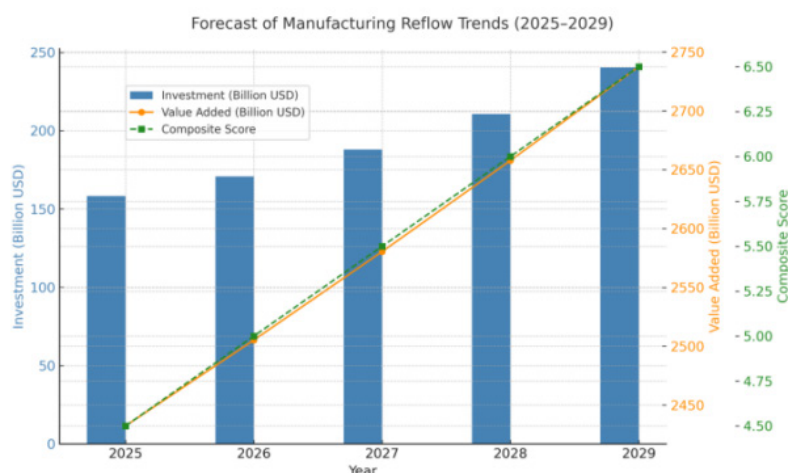


Figure 5. Forecast of manufacturing reshoring trends, 2025–2029: investment (bars) rises steadily; value added and the composite score (lines, right axis) improve more slowly.

Table 1. Estimated Tariff Sensitivities by Sector

Sector / flow	Estimate	Method	Reading
Soybean imports — Brazil	−26.24	Elasticity (OLS)	Extreme response
Soybean imports — Argentina	−4.14	Elasticity (OLS)	High response
Soybean imports — USA	+0.05	Elasticity (OLS)	Insignificant
Japanese auto imports	−2.40	System GMM	Per 1% tariff rise
Chip market shares	−2.22	Nested CES	Per 1% tariff rise

Elasticities: % change in the flow per 1% tariff increase.

Table 2. Policy-Evaluation Estimates for the Counter-Tariff Shock

Model	Indicator	Estimate	Effect
Fixed effects (agri.)	Tariff rate → VA growth	−0.332 pp	$R^2 = 0.926$
Probit	Tariff gap	+1.103 ($p=0.017$)	ME +0.214
Probit	Counter-tariff index	+0.893 ($p=0.029$)	ME +0.177
DID (β_3)	Investment / value added	+2.42 ($p<0.05$)	+90.65% / −1.35%

ME: marginal effect on reshoring probability. DID compares rare-earth and lithium-battery sub-sectors (treated) with other manufacturing before vs. after 2023.

5. Discussion and Implications

The evidence supports all three propositions. Pass-through is heterogeneous exactly where substitution differs (P1): soybeans, a homogeneous commodity traded on thin margins, adjust drastically, while chips and differentiated autos adjust modestly — so uniform tariff escalation buys little revenue or security at disproportionate agricultural cost. Anticipated retaliation compresses the revenue-maximizing rate from 3.86% to 2.78% and shifts the SVAR revenue path into negative territory by 2027 (P2), matching the strategic-trade prediction that unilateral optimal rates do not survive equilibrium

interaction. And protection relocates capital before output (P3): a 90.65% investment surge with flat value added shows reshoring is real but incomplete. For policy, the results argue for differentiated chip tariffs that exploit the flat region of the efficiency–security frontier, moderation of aggregate rates toward the game-consistent optimum, and complementary industrial-policy instruments that convert capital inflow into productive capacity. For multinational firms, the elasticities quantify the payoff of capacity relocation and cost optimization as non-tariff responses, and the VaR/CVaR term structure offers a template for pricing tariff exposure in supply-chain design — auto-sector losses of up to \$193 mn at the 95% level are material at prevailing margins.

6. Conclusion

Framing the 2025 U.S. reciprocal tariff policy as a multi-objective decision problem, this study integrated data screening, sectoral econometrics, nested-CES bi-objective optimization, Laffer–Stackelberg fiscal analysis, and causal policy evaluation into one evidence base. Tariff exposure ranges from extreme (soybeans) to modest (autos, chips); the chip-tariff frontier prices security in efficiency terms; the revenue-optimal rate lies far below the prevailing burden once retaliation is anticipated; and reshoring, while statistically robust, is so far a capital phenomenon. The lasting managerial lesson is that tariff design — and corporate response — is an exercise in managing heterogeneity: instruments calibrated to sectoral substitutability dominate uniform escalation on every objective the policy purports to serve. Limitations include the 2020–2024 estimation window, which predates the full reciprocal regime, and surrogate-model assumptions in the Bayesian search; extending the framework to general-equilibrium price feedbacks is a natural next step.

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