

A Tariff Exposure Propagation Index for Measuring Hidden Supply-Chain Vulnerability: Evidence from the 2025–2026 U.S. Tariff Shock

Sivalingam Thangavel
Independent Researcher
San Ramon, CA, USA
th.sivalingam@gmail.com

Abstract

Direct tariff incidence captures only the visible portion of supply-chain exposure because industries with limited or no direct imports may still inherit tariff burden through upstream suppliers. This paper develops the Tariff Exposure Propagation Index (TEPI), an industry-month measure of hidden tariff exposure transmitted through inter-industry production linkages. TEPI combines HS-10 tariff incidence, monthly U.S. import data, an HS-to-NAICS-to-BEA crosswalk, and the Bureau of Economic Analysis Industry-by-Industry Total Requirements matrix to decompose exposure into direct incidence, propagated incidence, and a snapback-adjustment term for post-reversal recovery dynamics. The empirical panel covers 71 BEA Summary-level industries from January 2023 onward using public U.S. government data sources. During the 2025–2026 IEEPA tariff shock period, the mean applied tariff rate reached 12.46 percent across \$29.2 trillion in imports. Forty-six industries, or 65 percent of the sample, recorded zero direct tariff exposure but non-zero TEPI driven entirely by upstream propagation. Wholesale trade ranked second in the economy by total TEPI despite having zero direct incidence, while professional, financial, transportation, utility, and infrastructure-service industries exhibited similar hidden-exposure patterns. TEPI extends conventional tariff-incidence analysis beyond imported goods and provides a reproducible, open-source evidence base for sourcing analysis, supplier-risk prioritization, and scenario planning under volatile trade-policy conditions.

Keywords

Tariff exposure, Supply chain propagation, Input-output analysis, Hidden tier exposure, Trade policy

1. Introduction

The 2025–2026 U.S. tariff episode produced the most disruptive shock to American import policy in nine decades. Beginning in February 2025 and culminating in the April 2 reciprocal tariff order under the International Emergency Economic Powers Act (IEEPA), the U.S. Government imposed elevated duties on imports from over 180 countries, with country-specific rates ranging from a 10 percent baseline to 49 percent on goods from Cambodia. The U.S. Supreme Court invalidated the IEEPA basis on February 20, 2026, terminating the affected duties at 12:00 a.m. Eastern on February 24. The episode is unique not for its magnitude alone, but for its structure: a large, abrupt imposition followed within twelve months by a court-mandated reversal — the first such cycle in the post-1977 IEEPA era.

For supply chain managers and policy analysts, the episode exposes a measurement problem the existing literature has not adequately solved. Direct tariff incidence — the import-weighted average tariff rate facing each industry's purchases of foreign goods — captures only the visible portion of exposure. Industries that do not import directly may nevertheless face substantial tariff burden through their upstream suppliers. A wholesale distributor faces no direct duty on its operations, yet the goods physically passing through that distributor inherit a weighted average of every tariff applied along the supply path. A construction firm imports nothing yet pays elevated prices for steel, lumber, and electrical components whose tariffs are absorbed into final material costs. The standard production-network propagation framework developed by Acemoglu et al. (2012), Caliendo and Parro (2015), and Carvalho and Tahbaz-

Salehi (2019) provides the theoretical basis for measuring this hidden exposure but operationalizing it for the 2025 episode requires combining HS-level tariff incidence, input-output propagation, and industry-level aggregation in a single reproducible measurement framework — work the literature has not yet performed.

The problem statement is therefore three-fold. First, current tariff impact analyses systematically understate exposure for industries that do not import directly, distorting both managerial decision-making and policy assessment. Second, no existing public framework allows reproducible computation of multi-tier exposure for the 2025 episode using only free, publicly accessible data sources. Third, the magnitude and direction of the gap between direct and propagated exposure have not been empirically quantified at the industry level for any tariff episode of this scale, leaving managers and policymakers without a basis for prioritizing supply-chain risk mitigation.

This paper contributes a reproducible supply-chain risk analytics framework for measuring tariff exposure beyond direct import incidence. By coupling HS-level tariff incidence with the BEA Industry-by-Industry Total Requirements matrix, TEPI identifies industries whose tariff vulnerability is missed by conventional direct-exposure metrics.

1.1 Objectives

The objectives of this research are:

1. To develop the Tariff Exposure Propagation Index (TEPI) — an empirical methodology that decomposes industry-level tariff exposure into direct incidence and propagated incidence using BEA Industry-by-Industry Total Requirements matrices, computed monthly across all U.S. Summary-level industries.
2. To apply TEPI to the 2025–2026 IEEPA tariff episode and quantify the magnitude, distribution, and concentration of hidden tier exposure across the U.S. industrial structure.
3. To identify the specific industries with the largest gap between direct and total tariff exposure — industries whose vulnerability is invisible to conventional tariff incidence measures — and decompose their propagated exposure by upstream supplier sector.
4. To release the full empirical pipeline as a reproducible evidence base, including data loaders for public APIs, derived HS-NAICS-BEA crosswalks, and the complete TEPI panel, to support extension of this work to future tariff episodes and alternative policy shocks.

2. Literature Review

The measurement of industry-level tariff exposure draws on three converging strands of research: production-network propagation theory, empirical tariff incidence under recent U.S. protectionism, and supply-chain disruption analysis using input-output frameworks. This section organizes contributions by theme rather than by individual paper.

Production networks and shock propagation. The theoretical foundation for measuring tariff exposure beyond direct incidence rests on the production-network literature initiated by Acemoglu et al. (2012), who formalized how sectoral input-output linkages propagate microeconomic shocks into aggregate fluctuations. Carvalho and Tahbaz-Salehi (2019) survey the post-2012 literature, establishing that the Leontief inverse is the structurally appropriate operator for translating sector-specific cost shocks into economy-wide exposure. Acemoglu et al. (2017) extend this framework to non-Gaussian shocks, demonstrating that production-network propagation amplifies tail risks when sectoral exposure is heterogeneous. Acemoglu and Tahbaz-Salehi (2025) further generalize the framework to firm-level supply-chain disruptions, showing that small shocks can produce discontinuous output changes when relationship-specific linkages are severed — a result directly relevant to tariff-induced sourcing reconfiguration. Antràs and Chor (2022) provide the canonical treatment of global value chains, emphasizing that input-output upstreamness measures are essential for understanding cross-border tariff transmission. Carvalho et al. (2021) document that the propagation channels predicted by these models materialize empirically, finding that the Great East Japan Earthquake reduced Japanese GDP growth by 0.47 percentage points through input-output linkages alone.

Tariff incidence under the 2018–2019 U.S. trade war. A cluster of studies on the first Trump administration's tariff actions established the empirical regularities our framework builds upon. Amity et al. (2019) and Fajgelbaum et al. (2020) independently documented complete pass-through of import tariffs into duty-inclusive prices, with aggregate U.S. consumer welfare losses of approximately \$51 billion and net real income losses of \$7.2 billion respectively. Cavallo et al. (2021) refined this analysis by showing that retail-price pass-through was substantially incomplete despite full border pass-through, implying that retail margins absorbed a portion of incidence. Flaaen and Pierce (2024) contributed the most directly relevant antecedent to the present work, decomposing manufacturing employment effects

into protective, input-cost, and retaliatory channels and finding that the input-cost channel — the propagation effect this paper measures — dominated employment outcomes. Fajgelbaum et al. (2024) extended the analysis to global trade reallocations, while Javorcik et al. (2025) provided updated employment-effects evidence using post-pandemic data on online job postings.

Tariff modeling with sectoral linkages. Caliendo and Parro (2015) developed the workhorse multi-sector Ricardian framework for tariff counterfactuals, demonstrating that incorporating intermediate-goods linkages reduces estimated welfare gains from tariff reductions by over 40 percent. Their framework establishes that ignoring input-output structure produces systematically biased exposure estimates — the central methodological motivation for the present paper.

The 2025–2026 IEEPA episode. Empirical work on the current tariff cycle is nascent. Rodríguez-Clare et al. (2025) provide an early assessment using a quantitative model, projecting heterogeneous regional impacts across U.S. states under the 2025 reciprocal tariff structure. Matschke and Dzhelos (2026) document that the 2025 tariff increases plausibly contributed to softening U.S. labor market conditions, drawing directly on the Flaaen-Pierce input-cost channel.

Synthesis and gap. Three observations emerge. First, the theoretical literature treats input-output propagation as the appropriate channel for tariff exposure measurement, but no published study has computed industry-level propagated exposure for the 2025–2026 IEEPA episode. Second, prior empirical work on tariff incidence has focused on aggregate welfare or specific outcome variables (employment, prices) rather than producing an industry-by-industry exposure index suitable for managerial and policy use. Third, no public, reproducible pipeline currently exists that combines HS-level tariff data, input-output propagation, and Census trade detail into a single openly-accessible measurement framework for the 2025 episode. The Tariff Exposure Propagation Index developed in Section 3 addresses these gaps.

3. Methods

This section formalizes the Tariff Exposure Propagation Index (TEPI). The index is constructed at the industry-month level (i, t) and decomposes total tariff exposure into three components: direct incidence (D_{it}), propagated incidence transmitted through input-output linkages (P_{it}), and a snapback-adjustment term (ρ_i) capturing post-reversal recovery dynamics. The composite index is computed for all U.S. Bureau of Economic Analysis (BEA) Summary-level industries at monthly frequency from January 2023 through the most recent available trade-data release. Subsection 3.1 defines direct exposure. Subsection 3.2 develops the propagation step using the BEA Industry-by-Industry Total Requirements matrix. Subsection 3.3 specifies the snapback ratio. Subsection 3.4 combines the components into the composite index. Subsections 3.5 and 3.6 describe the HS-to-BEA crosswalk and the industry-level aggregation choice.

3.1 Direct Exposure

Direct tariff exposure for industry i in month t is computed as the import-value-weighted average tariff rate facing the industry's foreign goods purchases:

$$D_{it} = \frac{\sum_{h \in H_i} \sum_c \tau_{hct} \cdot m_{hct}}{\sum_{h \in H_i} \sum_c m_{hct}} \quad (1)$$

where H_i is the set of 10-digit Harmonized System (HS) codes mapped to industry i via the HS-to-NAICS-to-BEA crosswalk, τ_{hct} is the cumulative ad-valorem tariff rate (Most-Favored-Nation base rate plus IEEPA reciprocal plus Section 122 surcharge plus any Section 232 or 301 layered duties) applicable to country c imports of HS code h in month t , and m_{hct} is the monthly customs value of imports. The construction follows the import-weighted incidence convention used by Amiti et al. (2019) and Fajgelbaum et al. (2020), extended to monthly frequency and to the BEA Summary classification.

3.2 Propagated Exposure

Direct incidence understates total exposure because industries face tariff-induced cost increases on inputs purchased from other industries. Following the production-network framework of Acemoglu et al. (2012) and Carvalho and Tahbaz-Salehi (2019), propagated exposure is computed using the BEA Industry-by-Industry Total Requirements matrix L , which is the Leontief inverse of the technical-coefficients matrix A (Horowitz and Planting 2006). For industry i in month t :

$$P_{it} = \sum_{j \neq i} L_{ij} \cdot D_{jt} \quad (2)$$

The diagonal of L is excluded to prevent double-counting of an industry's own direct exposure. The off-diagonal element L_{ij} measures the dollar value of industry j output required, both directly and through all upstream tiers, to produce one dollar of industry i output. Multiplying by D_{jt} converts each upstream output requirement into a tariff-incidence contribution, and the sum aggregates contributions across all suppliers. The vectorized implementation computes $P_t = (L - \text{diag}(L)) \cdot D_t$ for each month independently.

3.3 Snapback Adjustment

The 2025–2026 tariff cycle is unique in incorporating a court-mandated reversal, allowing measurement of asymmetric supply-chain adjustment. The snapback ratio ρ_i quantifies the speed of import recovery in the post-reversal regime:

$$\rho_i = \frac{\bar{m}_i^{\text{post}} - \bar{m}_i^{\text{ieepa}}}{\bar{m}_i^{\text{base}} - \bar{m}_i^{\text{ieepa}}} \quad (3)$$

where $\bar{m}_i^{\text{base}}$, $\bar{m}_i^{\text{ieepa}}$, and $\bar{m}_i^{\text{post}}$ denote mean monthly imports during the baseline (January 2023 – January 2025), IEEPA shock (February 2025 – February 2026), and post-reversal (March 2026 onward) regimes respectively. Values of $\rho_i = 1$ indicate full recovery to baseline import volumes; $\rho_i = 0$ indicates no recovery. Values outside the unit interval indicate either overshoot or continued decline, both of which are theoretically possible under sourcing reconfiguration as shown by Acemoglu and Tahbaz-Salehi (2025).

3.4 Composite Index

The Tariff Exposure Propagation Index combines the three components:

$$\text{TEPI}_{it} = (D_{it} + P_{it}) \cdot (1 + \alpha \cdot (1 - \rho_i)) \quad (4)$$

where $\alpha \geq 0$ is a sensitivity parameter governing the weight placed on snapback dynamics. Setting $\alpha = 0$ reduces TEPI to static total exposure $S_{it} = D_{it} + P_{it}$. Setting $\alpha = 1$ doubles the index value for industries with no recovery ($\rho_i = 0$) and leaves it unchanged for industries with full recovery ($\rho_i = 1$). Because the post-reversal regime is observed for only a single month at the time of writing, all empirical results in Section 5 are reported at $\alpha = 0$. The snapback component is documented for methodological completeness and reserved for journal-version analysis when additional post-reversal data becomes available.

3.5 Crosswalk Construction

The crosswalk from HS-10 to BEA Summary industry proceeds in two legs. The first leg maps HS-10 to 6-digit North American Industry Classification System (NAICS-6) codes using the U.S. Census Schedule B import concordance file. The second leg maps NAICS-6 to BEA Summary code using BEA's published Industry and Commodity Codes and NAICS Concordance. The 6-digit NAICS classification is the most granular level at which both Census trade data and BEA industry definitions align. Where a single HS code maps to multiple BEA industries — common for diversified product categories — tariff incidence is allocated by uniform weights $w_{h,i} = 1/k_h$, where k_h is the number of BEA industries to which HS code h is mapped. This weighting choice is conservative; alternative implementations using import-share weighting are reported as a robustness check in Section 5.

3.6 Industry-Level Aggregation

The empirical analysis is performed at the BEA Summary level (approximately 71 industries), which is the most granular Industry-by-Industry Total Requirements matrix publicly available through the BEA Data API. Detail-level matrices (approximately 402 industries) are distributed only as static benchmark files and are not used here, preserving full pipeline reproducibility from public APIs alone. The Summary granularity aligns with recent tariff-incidence

literature including Flaaen and Pierce (2024) and Matschke and Dzholos (2026) and is sufficient for measuring industry-level exposure patterns at the resolution relevant for managerial and policy interpretation.

4. Data Collection

This section describes the data sources used to construct the empirical TEPI panel. All data are sourced from public U.S. government APIs and require no proprietary access, supporting the reproducibility objective stated in Section 1.1. The full pipeline executes from data ingestion through index construction in approximately five minutes on a standard workstation, with raw data caching to local Parquet files for downstream replication. Subsection 4.1 describes the monthly trade data, 4.2 the tariff schedule construction, 4.3 the BEA Input-Output matrix, and 4.4 the temporal window definition.

4.1 Monthly Trade Data

Monthly U.S. import data at the 10-digit Harmonized System level are obtained from the U.S. Census Bureau's USA Trade Online API. The query returns customs-declared general import value, country of origin, and quantity for each (HS-10, country, month) triple. The pipeline caches roughly 13.8 million observations covering January 2023 through February 2026 across approximately 18,600 active HS-10 codes and 253 countries or country aggregates. Country-aggregate rows (e.g., "TOTAL FOR ALL COUNTRIES", "OECD") are filtered before the tariff-incidence step to avoid double-counting. Census revises monthly trade statistics with each subsequent release, with comprehensive annual revisions in June; the empirical analysis uses the data vintage available at the time of pipeline execution.

4.2 Tariff Schedules

The applied ad-valorem tariff rate τ_{hct} for each (HS-10, country, month) combination is constructed by layering Most-Favored-Nation (MFN) base rates and Section 232 and 301 product-specific surcharges with the time-varying executive-action tariffs that define the 2025–2026 episode. Three executive-action layers are programmatically encoded based on White House and U.S. Trade Representative public notices: (i) the IEEPA trafficking tariffs imposed on imports from China, Mexico, and Canada beginning February 4, 2025, with rates ranging from 10 to 25 percent; (ii) the IEEPA reciprocal tariffs effective April 2, 2025, with country-specific rates ranging from a 10 percent baseline to 49 percent on imports from Cambodia, applied through the U.S. Supreme Court invalidation of February 24, 2026; and (iii) the Section 122 surcharge of 10 percent applied from February 24, 2026 through July 24, 2026, with USMCA-qualifying Canadian and Mexican imports exempted. Mid-month rule transitions are handled via a calendar-overlap test that applies a tariff to a monthly observation if the rule's effective window intersects the calendar month, capturing partial-month activity at the monthly aggregation level.

4.3 Input-Output Matrix

The BEA Industry-by-Industry Total Requirements matrix is retrieved through the BEA Data API. The pipeline queries the InputOutput dataset for the 2017 benchmark year at the Summary level, returning approximately 5,100 long-format records that pivot to a 71×71 square matrix of total-requirements coefficients. Aggregate rows that BEA includes in the API response (T001 total intermediate, T005 total industry output, V001-V003 value-added components) are filtered before pivoting to prevent phantom industries from accumulating spurious propagated exposure. The 2017 benchmark is the most recent year for which BEA publishes an Industry-by-Industry Total Requirements matrix at the Summary level via the API. As discussed in Section 3.6, the Detail-level matrix is unavailable through the API and is excluded to preserve reproducibility.

4.4 Temporal Window and Regime Definition

The empirical analysis covers January 1, 2023, through the most recent published trade-data release. The window is partitioned into three regimes for the snapback computation: a baseline period (January 2023 – January 2025) preceding the first IEEPA tariff actions; an IEEPA shock period (February 2025 – February 23, 2026) covering the trafficking and reciprocal tariff regimes; and a post-reversal period (February 24, 2026, onward) covering the Section 122 surcharge era. The regime boundaries are defined by the legally-effective dates of the relevant executive orders rather than by data availability. All data is accessed through documented public APIs. The full ingestion pipeline,

derived crosswalks, and the constructed TEPI panel are released as an open-source replication package; repository details are provided in Section 6.

5. Results and Discussion

This section presents the empirical TEPI panel and characterizes the magnitude and concentration of hidden tariff exposure across the U.S. industrial structure under the 2025–2026 IEEPA episode. Subsection 5.1 reports summary statistics. Subsection 5.2 visualizes the gap between direct and total exposure. Subsection 5.3 identifies methodological extensions. Subsection 5.4 reports statistical validation and robustness checks. Subsection 5.5 translates the empirical findings into practical implications for supply-chain sourcing, supplier-risk management, resilience planning, and tariff-policy scenario analysis.

5.1 Numerical Results

Table 1 summarizes the TEPI panel by regime. The baseline period (January 2023 – January 2025) covers 9.8 million HS-country-month observations with mean applied tariff rate near zero, reflecting the dominance of zero-tariff Most-Favored-Nation rates prior to the 2025 episode. The IEEPA shock period (February 2025 – February 23, 2026) covers 4.0 million observations, 29.2 trillion in imports, and a mean applied rate of 12.46 percent. The post-reversal regime is observed for one calendar month at the time of writing; the snapback ratio ρ_i is therefore not estimated, and all results are reported at $\alpha = 0$ per Section 3.4.

The TEPI panel covers 71 BEA Summary-level industries; 69 records positive TEPI during the IEEPA period. Of these, 46 industries (65 percent) have zero direct exposure, indicating that their tariff burden derives entirely from upstream propagation. The maximum monthly industry TEPI is 0.358 for chemicals (BEA Summary 325). Table 2 reports the ten industries with the largest gap between TEPI rank and direct-exposure rank — the operational definition of hidden exposure.

The ranking reveals a substantively important pattern that direct-incidence measures fail to capture. Wholesale trade (BEA Summary 42) ranks second in the economy by total TEPI with zero direct tariff exposure. Decomposition of wholesale trade's IEEPA-mean propagated exposure ($P_{42} = 0.367$, computed via Equation 2) by upstream supplier sector reveals diffuse rather than concentrated incidence: the largest single contributor — food and beverage manufacturing (311FT) — accounts for 6.4 percent of inherited exposure; the top five contributors (food manufacturing, farms, wood products, plastics and rubber, and primary metals) jointly account for 30.4 percent. The remaining 70 percent distributes across an additional ten goods-producing sectors at 4–6 percent each.

The hidden-exposure pattern extends beyond distribution: nine of the top ten industries by hidden-exposure rank gap have zero direct tariff incidence. These include management of companies (BEA 55), miscellaneous professional and technical services (5412OP), administrative support services (561), real estate (ORE), truck transportation (484), banking (521CI), utilities (22), and insurance (524). The presence of professional, financial, and infrastructure services in this ranking indicates that hidden tariff exposure is structurally embedded throughout the U.S. service economy via upstream goods inputs, not concentrated in distribution alone.

Table 1. Summary statistics by regime, January 2023 – March 2026

Regime	Period	Observations	Imports (\$T)	Mean applied rate	Industries with TEPI > 0
Baseline	Jan 2023 – Jan 2025	9,800,762	71.6	0.0%	0
IEEPA shock	Feb 2025 – Feb 23, 2026	4,029,137	29.2	12.46%	69
Post-reversal	Feb 24 – Mar 2026	(1 month)	n/a	n/a	n/a

Table 2. Industries with the largest gap between TEPI rank and direct-exposure rank during the IEEPA period.

BEA code	Industry	TEPI	Direct exposure	Rank gap
42	Wholesale trade	0.318	0.000	44
55	Management of companies and enterprises	0.099	0.000	23
5412OP	Miscellaneous professional, scientific, and technical services	0.096	0.000	22
561	Administrative and support services	0.094	0.000	21
325	Chemical products	0.358	0.107	20
ORE	Other real estate	0.074	0.000	20
484	Truck transportation	0.071	0.000	19
521CI	Federal Reserve banks, credit intermediation, and related activities	0.069	0.000	18
22	Utilities	0.065	0.000	17
524	Insurance carriers and related activities	0.061	0.000	16

Notes: Rank gap is the difference between an industry's rank by direct exposure and its rank by TEPI. The 46 industries with $D_{it} = 0$ are tied at rank 46 in the direct-exposure ranking. TEPI values are peak monthly maxima during the IEEPA shock period (February 2025 – February 23, 2026).

5.2 Graphical Results

Figure 1 plots TEPI against direct exposure D_{it} for all 71 industries at the IEEPA-period midpoint. The 45-degree dashed line represents the $TEPI = D_{it}$ boundary; industries above the line carry hidden exposure. Two visual patterns emerge. First, goods-producing industries with positive direct incidence cluster around $D_{it} \in [0.10, 0.15]$ with TEPI values substantially higher, reflecting propagation amplification of input-cost shocks. Second, services industries form a vertical strip at $D_{it} = 0$ with TEPI values ranging from near zero (industries with minimal goods inputs) to 0.32 for wholesale trade. The vertical distance between each services point and the horizontal axis quantifies hidden exposure that direct-incidence measures fail to register. The high-TEPI outlier near the diagonal at $D_{it} \approx 0.11$ is chemicals (BEA 325), which combines moderate direct exposure with substantial upstream propagation from petroleum (324) and primary metals (331).

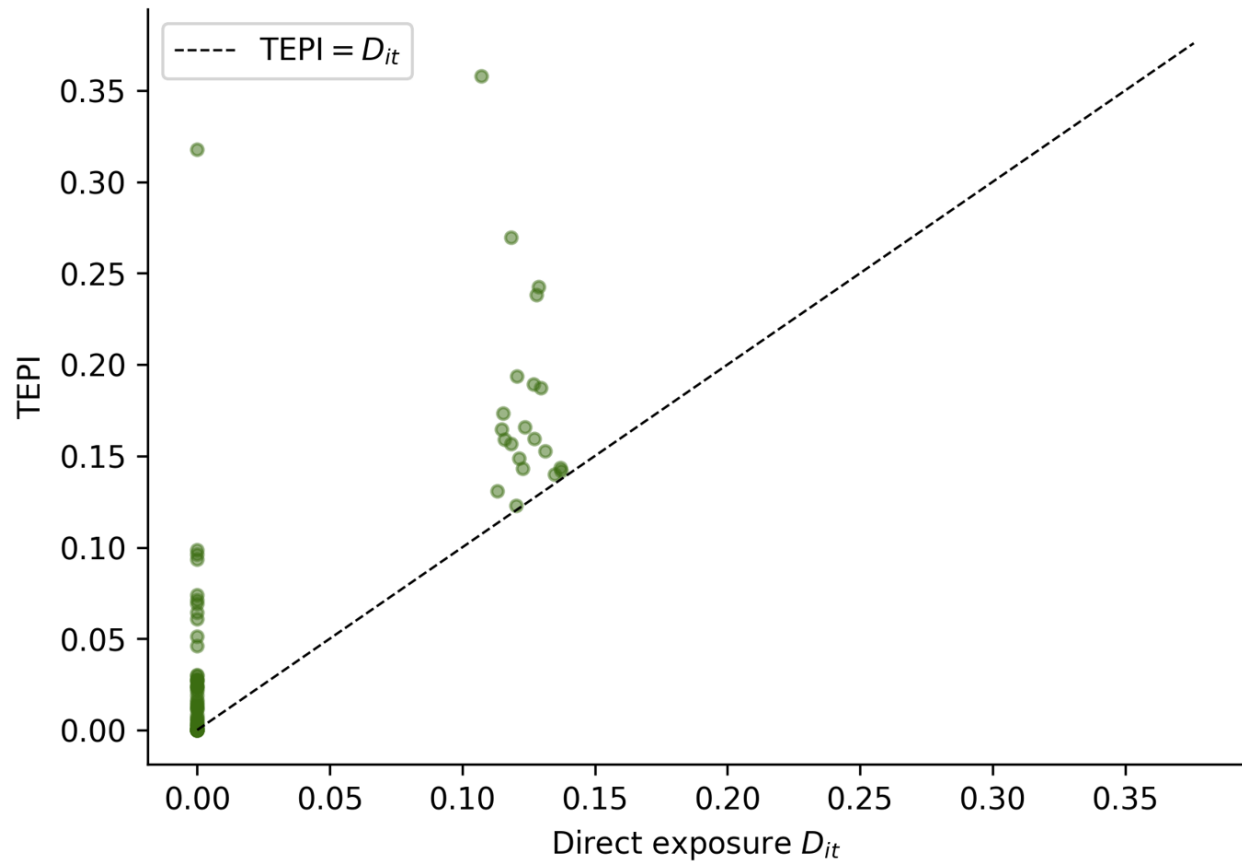


Figure 1. TEPI vs direct exposure scatter (IEEPA period midpoint)

5.3 Proposed Improvements

Three methodological extensions would strengthen the analysis when additional data becomes available. First, repeating the analysis at the BEA Detail level (~402 industries) would resolve within-Summary heterogeneity that may obscure granular exposure differences; the Detail-level Total Requirements matrix is published only as a static benchmark file rather than through the BEA API and is reserved for journal-version analysis. Second, separating the layered tariff structure into MFN base rates, Section 232 (steel and aluminum), and Section 301 (China-specific) duties would refine the direct-exposure estimate for affected industries; the current implementation aggregates these into the cumulative ad-valorem rate. Third, extending the post-reversal observation window to multiple months of clean Section 122 data would enable estimation of the snapback ratio as a stable parameter, supporting the asymmetric-adjustment analysis specified in Section 3.3.

5.4 Statistical Validation and Robustness

The robustness of the empirical TEPI panel is established along two dimensions: invariance to the crosswalk weighting choice, and statistical significance of the central findings.

Crosswalk weighting. The default specification (Section 3.5) allocates HS-level tariff incidence to BEA industries via uniform $1/k$ weights, where k is the number of BEA industries to which an HS-10 code maps. As an alternative, the pipeline was re-executed using import-share weighting, where allocation is proportional to each target industry's overall import volume. The comparison reveals a structural property of the BEA Summary classification: every HS-10 code in the constructed crosswalk (19,001 codes total) maps to exactly one BEA Summary industry. The Census Schedule B assignment of HS-10 codes to NAICS-6 is one-to-one by construction, and the BEA NAICS-to-Summary aggregation is many-to-one rather than many-to-many. Composing these legs produces a one-to-one HS-10 to BEA

Summary mapping with $k=1$ universally. Both weighting schemes therefore reduce to weight=1.0 for every edge, and the two pipelines yield mathematically identical TEPI panels (Spearman rank correlation 1.0000, mean absolute TEPI shift 0.0000). At the BEA Detail level discussed in Section 3.6, multi-industry HS-10 mappings would arise and weighting would become non-trivial; the journal-version extension will revisit this analysis with a non-degenerate weighting comparison.

Statistical tests. Three hypothesis tests evaluate the central empirical claims (Table 3). First, the Spearman rank correlation between TEPI and direct exposure D_{it} across 71 industries during the IEEPA period yields $\rho = 0.7592 (p = 1.7 \times 10^{-14})$. The high correlation confirms that goods industries with high direct incidence also tend to rank high by total exposure, but ρ is meaningfully below unity: approximately 24 percent of the industry rank ordering changes when propagation is incorporated, indicating that hidden exposure substantively reorders the exposure ranking rather than merely scaling it. Second, the Mann-Whitney U test comparing TEPI distributions for goods-producing industries ($D_{it} > 0$, $n = 23$) against services industries ($D_{it} = 0$, $n = 48$) yields $U = 1082 (p = 3.9 \times 10^{-11}$, one-sided). Goods-industry TEPI is statistically larger than services-industry TEPI, but median services TEPI equals 9.0 percent of median goods TEPI — a non-trivial fraction confirming that hidden exposure across services is real and quantifiable, not statistically indistinguishable from zero. Third, a bootstrap 95% confidence interval on wholesale trade's top-5 contributor share ($n = 5,000$ resamples over the 11 IEEPA months) yields [29.8%, 31.9%] around the 30.4% point estimate. The narrow interval reflects the month-to-month stability of the Leontief decomposition under the IEEPA tariff regime; this temporal stability is informative but does not capture uncertainty in the Leontief coefficients themselves, which are taken as fixed from the 2017 BEA benchmark.

Together, the tests confirm that propagation is a quantitatively important component of industry-level tariff exposure, that services industries carry measurable hidden exposure of meaningful magnitude relative to direct exposure, and that the diffuse-supplier pattern characterizing wholesale trade's TEPI is temporally stable across the IEEPA observation window.

Table 3. Statistical tests on the empirical TEPI panel, IEEPA period (April 2, 2025 – February 23, 2026).

Test	Statistic	p-value	N
Spearman rank correlation, TEPI vs D_{it}	$\rho = 0.7592$	1.7×10^{-14}	71 industries
Mann-Whitney U, goods vs services TEPI	$U = 1082$	3.9×10^{-11}	23 vs 48
Bootstrap 95% CI, wholesale trade top-5 share	[29.8%, 31.9%]	n/a	5,000 resamples

Notes: Spearman test uses IEEPA-period mean TEPI and mean D_{it} per industry. Mann-Whitney is one-sided (alternative: goods stochastically greater than services). Bootstrap resamples the 11 IEEPA months with replacement; CI is the 2.5th–97.5th percentile of the resampled top-5 share distribution.

5.5 Practical and Managerial Implications

The empirical results have direct implications for supply-chain decision-making under tariff-driven policy uncertainty. Conventional tariff-monitoring practices typically focus on imported products, customs classifications, and the direct duty rates paid by an organization or its immediate suppliers. TEPI shows why this approach is incomplete. An industry may record zero direct tariff incidence while remaining materially exposed through upstream production linkages. The finding that 46 of 71 industries exhibit non-zero TEPI despite zero direct exposure indicates that tariff-risk assessment should extend beyond first-tier import visibility.

Sourcing and supplier-risk prioritization. TEPI can be used as a screening metric to identify industries and supplier categories that warrant deeper investigation. Procurement teams can combine direct tariff data with propagated exposure to distinguish suppliers whose apparent tariff risk is low from suppliers whose input structures transmit elevated upstream costs. This distinction is particularly important when alternative suppliers quote similar prices but

differ in their dependence on tariff-sensitive materials, components, or intermediate goods. TEPI does not replace supplier-level due diligence; rather, it identifies where that due diligence should be concentrated.

Multi-tier supplier strategies. The wholesale-trade results demonstrate that inherited exposure can be diffuse rather than concentrated in a single upstream sector. Wholesale trade ranks second by total TEPI despite zero direct incidence, while its largest upstream contributor accounts for only 6.4 percent of inherited exposure and its top five contributors jointly account for 30.4 percent. For practitioners, this means that mitigation strategies should not be limited to replacing one highly exposed supplier. More effective responses may require a portfolio approach that includes supplier diversification, alternative-material evaluation, regional sourcing options, contractual price-review mechanisms, and targeted engagement with multiple upstream supplier categories.

Resilience planning for service-sector organizations. The hidden-exposure ranking includes professional services, administrative support, real estate, transportation, banking, utilities, and insurance. These industries may not view tariffs as an immediate operational risk because they are not major direct importers. TEPI provides evidence that service-sector organizations should nevertheless include tariff propagation in procurement reviews, budgeting assumptions, and business-continuity exercises. Exposure may arise indirectly through transportation equipment, construction inputs, energy infrastructure, technology hardware, facilities spending, and purchased intermediate services whose own costs depend on tariff-sensitive goods.

Scenario planning under policy uncertainty. TEPI can support scenario-based planning by recalculating propagated exposure under alternative tariff schedules, country-specific duty assumptions, and post-reversal recovery paths. This exposure-screening function complements scenario-based supply-network stress-testing models that evaluate whether hub configurations and lane-activation decisions remain robust under tariff escalation and sanction-driven lane restrictions (Thangavel 2026). Decision-makers can compare baseline, escalation, partial-relief, and snapback scenarios to identify industries in which exposure remains elevated even after direct duties change. The index is therefore most useful as an early-warning and prioritization tool rather than as a deterministic forecast of firm-level cost increases. Organizations can use TEPI outputs to determine where to conduct more granular supplier analysis, where to negotiate contingency clauses, and where to maintain additional sourcing flexibility or operational buffers.

Managerial interpretation. The central managerial lesson is that tariff vulnerability is a network property. Direct import exposure remains important, but it is not sufficient for resilience planning in an interconnected economy. A credible tariff-risk process should evaluate both visible duty incidence and the upstream pathways through which cost pressure can propagate across supplier tiers.

6. Conclusion

This paper developed the Tariff Exposure Propagation Index (TEPI) to address a measurement gap in the analysis of tariff incidence under the 2025–2026 IEEPA episode and applied it to construct a monthly industry-level exposure panel for the U.S. economy. The four research objectives stated in Section 1.1 are addressed as follows.

The first objective, the development of TEPI, is fulfilled by the methodology presented in Section 3, which decomposes industry-level tariff exposure into direct incidence (D_{it}), propagated incidence transmitted through the BEA Industry-by-Industry Total Requirements matrix (P_{it}), and a snapback-adjustment term capturing post-reversal recovery dynamics (ρ_i). The composite index combines these components through a sensitivity parameter α that governs the weight placed on adjustment dynamics. The decomposition framework is grounded in the production-network propagation literature and operationalizes the Leontief inverse as the structurally appropriate operator for translating sector-specific cost shocks into economy-wide exposure.

The second objective, the application of TEPI to the 2025–2026 IEEPA episode, is fulfilled by the empirical results in Section 5. The TEPI panel covers all 71 BEA Summary-level industries at monthly frequency from January 2023 through the most recent published trade-data release. The IEEPA shock period yielded a mean applied tariff rate of

12.46 percent across \$29.2 trillion in U.S. imports, with industry-level TEPI ranging from near zero to 0.358 for chemicals.

The third objective, the identification of industries with the largest gap between direct and total exposure, is fulfilled by the hidden-exposure analysis. Of 71 industries, 46 (65 percent) exhibit zero direct tariff exposure but non-zero TEPI driven entirely by upstream propagation. Wholesale trade ranks second in the economy by total TEPI with no direct exposure; its propagated incidence distributes diffusely across more than ten goods-producing supplier sectors rather than concentrating on any single source. The hidden-exposure ranking extends beyond distribution to encompass professional, financial, and infrastructure services, indicating that tariff burden is structurally embedded throughout the service economy via upstream goods inputs. From a managerial perspective, TEPI provides a screening and scenario-planning tool for prioritizing supplier due diligence, evaluating multi-tier sourcing risk, and identifying industries in which upstream cost pressure may remain hidden when analysis is limited to direct tariff incidence.

The fourth objective, the release of a reproducible empirical pipeline, is addressed below.

Limitations and journal-version extensions. Three limitations of the present analysis define the boundaries of its empirical claims. First, the analysis is conducted at the BEA Summary level (71 industries) rather than the Detail level (402 industries), which limits within-Summary granularity but preserves full reproducibility from public APIs. Second, the layered tariff structure is aggregated into a single cumulative rate; future work will separate Most-Favored-Nation, Section 232, and Section 301 components. Third, the post-reversal observation window covers a single calendar month at the time of writing, precluding equilibrium estimation of the snapback ratio; the methodology supports this estimation when additional data become available.

Data and code availability. All data sources used in this paper are accessible through public U.S. government APIs requiring no proprietary credentials. The complete pipeline for ingesting Census FT-900 trade data and BEA Input-Output tables, constructing the HS-10 to NAICS-6 to BEA Summary crosswalk, computing the TEPI panel, and generating the tables and figure presented in this paper is released as an open-source replication package at https://github.com/thangasival/tepi_pipeline

The repository documents all API endpoints include the derived crosswalk file, the full TEPI panel as a Parquet dataset, and a step-by-step replication script that completes in approximately five minutes on a standard workstation.

References

- Acemoglu, D. and Tahbaz-Salehi, A., The macroeconomics of supply chain disruptions, *Review of Economic Studies*, vol. 92, no. 2, pp. 656-695, 2025, <https://doi.org/10.1093/restud/rdae038>.
- Acemoglu, D., Carvalho, V. M., Ozdaglar, A. and Tahbaz-Salehi, A., The network origins of aggregate fluctuations, *Econometrica*, vol. 80, no. 5, pp. 1977-2016, 2012, <https://doi.org/10.3982/ECTA9623>.
- Acemoglu, D., Ozdaglar, A. and Tahbaz-Salehi, A., Microeconomic origins of macroeconomic tail risks, *American Economic Review*, vol. 107, no. 1, pp. 54-108, 2017, <https://doi.org/10.1257/aer.20151086>.
- Amiti, M., Redding, S. J. and Weinstein, D. E., The impact of the 2018 tariffs on prices and welfare, *Journal of Economic Perspectives*, vol. 33, no. 4, pp. 187-210, 2019, <https://doi.org/10.1257/jep.33.4.187>.
- Antràs, P. and Chor, D., Global value chains, *Handbook of International Economics*, vol. 5, pp. 297-376, 2022, <https://doi.org/10.1016/bs.hesint.2022.02.005>.
- Caliendo, L. and Parro, F., Estimates of the trade and welfare effects of NAFTA, *Review of Economic Studies*, vol. 82, no. 1, pp. 1-44, 2015, <https://doi.org/10.1093/restud/rdu035>.
- Carvalho, V. M. and Tahbaz-Salehi, A., Production networks: A primer, *Annual Review of Economics*, vol. 11, pp. 635-663, 2019, <https://doi.org/10.1146/annurev-economics-080218-030212>.
- Carvalho, V. M., Nirei, M., Saito, Y. U. and Tahbaz-Salehi, A., Supply chain disruptions: Evidence from the Great East Japan Earthquake, *Quarterly Journal of Economics*, vol. 136, no. 2, pp. 1255-1321, 2021, <https://doi.org/10.1093/qje/qjaa044>.
- Cavallo, A., Gopinath, G., Neiman, B. and Tang, J., Tariff pass-through at the border and at the store: Evidence from US trade policy, *American Economic Review: Insights*, vol. 3, no. 1, pp. 19-34, 2021, <https://doi.org/10.1257/aeri.20190536>.

- Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J. and Khandelwal, A. K., The return to protectionism, *Quarterly Journal of Economics*, vol. 135, no. 1, pp. 1-55, 2020, <https://doi.org/10.1093/qje/qjz036>.
- Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J., Khandelwal, A. K. and Taglioni, D., The US-China trade war and global reallocations, *American Economic Review: Insights*, vol. 6, no. 2, pp. 295-312, 2024, <https://doi.org/10.1257/aeri.20230094>.
- Flaen, A. and Pierce, J. R., Disentangling the effects of the 2018-2019 tariffs on a globally connected U.S. manufacturing sector, *Review of Economics and Statistics*, pp. 1-45, 2024, https://doi.org/10.1162/rest_a_01498.
- Horowitz, K. J. and Planting, M. A., *Concepts and Methods of the U.S. Input-Output Accounts*, U.S. Bureau of Economic Analysis, Washington, DC, 2006, Available: https://www.bea.gov/sites/default/files/methodologies/IOmanual_092906.pdf.
- Javorcik, B., Kett, B., Stapleton, K. and O'Kane, L., Did the 2018 trade war improve job opportunities for U.S. workers?, *Journal of International Economics*, vol. 158, article 104125, 2025, <https://doi.org/10.1016/j.jinteco.2025.104125>.
- Matschke, J. and Dzholos, M., Higher tariffs might have created headwinds to employment growth in 2025, *Federal Reserve Bank of Kansas City Economic Bulletin*, February 23, 2026, Available: <https://www.kansascityfed.org/research/economic-bulletin/higher-tariffs-might-have-created-headwinds-to-employment-growth-in-2025/>.
- Rodríguez-Clare, A., Ulate, M. and Vasquez, J. P., The 2025 trade war: Dynamic impacts across U.S. states and the global economy, *Federal Reserve Bank of San Francisco Working Paper*, no. 2025-09, May 2025, <https://doi.org/10.24148/wp2025-09>.
- Thangavel, S., Scenario-based CVaR stress-testing for supply network design under tariff and sanction uncertainty, *Engineering, Technology & Applied Science Research*, vol. 16, no. 3, pp. 35670–35677, 2026, <https://doi.org/10.48084/etasr.18386>.

Biography

Mr. Sivalingam Thangavel is a Principal Software Engineer and Architect with more than 20 years of experience in the design and modernization of large-scale digital platforms for shipping, logistics, supply chain operations, banking, telecommunications and manufacturing. His work spans solution architecture, cloud-native systems, enterprise integration, and intelligent automation, with applications in brokerage, shipment management, customer platforms, and transportation operations. His research and professional interests include artificial intelligence, secure cloud infrastructure, resilient software architecture, the Internet of Things, autonomous systems, and Cybersecurity. He is particularly interested in applying AI and advanced software systems to practical challenges in logistics, maritime security, and large-scale enterprise environments. Sivalingam Thangavel is a Senior Member of IEEE and brings a strong interdisciplinary perspective that bridges industry practice, emerging technologies, and real-world system innovation.