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Research Article

Keywords:

Posted Date: November 16th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11433407/v1

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Additional Declarations: No competing interests reported.

Diversification without de-risking: Systematic supply risk, portfolio risk budgets and early warning of disruptions in U.S. imports

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Abstract Diversification is the central risk-management principle in finance, and since 2018 it has also become the central principle of U.S. trade policy. Whether diversifying a country's supplier base reduces its economic risk depends, as in an asset portfolio, on the volatility and co-movement of the positions, not on their number. This study treats U.S. goods imports as a portfolio of supplier-country exposures and applies the tools of portfolio risk management to monthly, seasonally adjusted Census data for January 2009–July 2026. We measure concentration and reallocation, decompose the volatility of aggregate imports into supplier risk contributions and systemic betas, and price the diversification benefit with the diversification ratio. We then build an explainable early-warning model, analogous to crisis and credit-risk early-warning systems, that forecasts supplier-level disruptions (falls of at least 10% in three-month-average imports) for 23 economies. Concentration fell sharply: China's share dropped from 22.3% in May 2015 to 8.0% in July 2026. Risk did not. Aggregate import volatility rose from 1.43% to 6.26% per month, the diversification ratio fell from 2.42 to 1.40, and Switzerland and Ireland, with 5.5% of imports, absorbed 32.0% of the portfolio's risk budget. Disruptions are predictable three months ahead, with an out-of-sample AUC of 0.787 against 0.745 for a persistence benchmark. Policy-driven common shocks have replaced idiosyncratic risk with systematic risk, so diversification by count cannot deliver resilience; economic security requires managing the covariance of supply.

Keywords portfolio diversification · systematic risk · risk budgeting · trade policy · supply-chain risk · import volatility · early-warning system · explainable machine learning

JEL Classification F14 · F13 · G11 · G32 · E32 · C53

1 Introduction

In finance, diversification is the one free lunch: combining imperfectly correlated assets lowers risk without lowering expected return (Markowitz 1952). Economic policy has borrowed the idea. Since the tariffs on Chinese goods in 2018–2019 (Amiti et al. 2019; Fajgelbaum et al. 2020), the pandemic supply shocks (Bonadio et al. 2021; Alessandria et al. 2023) and the broad tariff increases of 2025, U.S. trade policy has sought to reduce dependence on any single supplier country in the name of resilience (Baldwin and Freeman 2022; Grossman et al. 2023; Ahn and Tan 2025). Judged by concentration, the policy has worked. China supplied 21.6% of U.S. goods imports in 2017 but only 7.9% in the first seven months of 2026, Mexico has been the largest supplier since December 2022, and Taiwan and Vietnam each now supply more than 7%. A country's import base, however, is economically a portfolio of supplier exposures, and portfolio theory implies that the number of positions says little about risk. What matters is each position's volatility and, above all, its covariance with the rest of the portfolio.

This distinction between idiosyncratic and systematic risk is the core of our argument. Diversification across trade partners stabilises national income when partner shocks are independent (Koren and Tenreyro 2007; Caselli et al. 2020), and diversified U.S. import products adjusted more smoothly to the 2018–2019 tariffs (Ahn and Tan 2025). But diversification cannot remove systematic risk, and economic theory gives reasons to expect that systematic risk in supply has grown. When disruptions are possible, decentralised sourcing is inefficient because firms do not internalise the social value of resilience (Grossman et al. 2023), an externality that leaves supply networks fragile to aggregate shocks (Jiang et al. 2022; Elliott et al. 2022; Kancs 2024). Importer–exporter relationships are sticky, so reallocation is slow and costly (Grossman et al. 2024), and it can create new concentrations in transshipment hubs or in volatile high-value goods (Alfaro and Chor 2023; Freund et al. 2024). The firm-level counterpart is that supplier concentration constrains innovation and resists operational buffering (Hong et al. 2026), while lean, single-sourced procurement is structurally exposed to trade-war shocks (Liu 2025). Policy-driven shocks such as tariff announcements, moreover, hit many partners at once and are therefore systematic by construction.

Three literatures in economics and finance frame the question. The macroeconomics of production networks shows that idiosyncratic supplier shocks propagate and aggregate (Acemoglu et al. 2012; Barrot and Sauvagnat 2016; Boehm et al. 2019; Carvalho et al. 2021), and that large, granular partners drive aggregate volatility, much as large holdings dominate portfolio risk (Gabaix 2011; di Giovanni and Levchenko 2012). Supply-chain resilience is defined as the capacity to absorb and recover from disruptions (Christopher and Peck 2004; Sheffi and Rice 2005; Tang 2006; Ponomarov and Holcomb 2009), but its quantitative evidence is largely simulated (Hosseini et al. 2019; Ivanov 2020; Ivanov and Dolgui 2020), and supply-chain pressure is measured only in aggregate (Benigno et al. 2022). The trade-policy literature shows that tariffs were passed through to import prices (Cavallo et al. 2021) and reallocated trade to third countries (Fajgelbaum et al. 2024), following the China shock (Autor et al. 2013; Handley and Limão 2017), amid geoeconomic fragmentation (Aiyar et al. 2023; Gopinath et al. 2025), costly friend-shoring (Javorcik et al. 2024) and policy uncertainty that depresses investment and trade (Baker et al. 2016; Caldara et al. 2020). The closest study finds that supplier-country fundamentals precede the

erosion of U.S. import shares in sample but do not forecast out of sample once data-availability lags are respected (McCarthy and Alaghband 2026). Finally, the early-warning literature in financial economics predicts currency crises (Kaminsky et al. 1998) and recessions (Kauppi and Saikkonen 2008) with binary models in which tree ensembles now compete with logits (Döpke et al. 2017; Vrontos et al. 2021); related methods predict supplier disruptions from firm data (Baryannis et al. 2019; Brintrup et al. 2020), practitioners score supplier risk exposure (Simchi-Levi et al. 2014), and Shapley values make such models auditable (Lundberg and Lee 2017; Lundberg et al. 2020).

The gap lies where these literatures meet. Trade economics measures concentration and explains reallocation after the fact, but does not measure the risk of the realised import portfolio or attribute that risk to individual suppliers. Finance has precisely the tools for this, namely portfolio volatility, the diversification ratio (Choueifaty and Coignard 2008) and the Euler risk contributions used in risk budgeting (Maillard et al. 2010), but they have not been applied to a country's supplier base. Early-warning methods, standard for financial crises, have not been applied to bilateral trade flows or benchmarked against persistence models in real time. To our knowledge, no study prices the diversification benefit of a national import portfolio, decomposes its systematic and idiosyncratic risk by supplier, and forecasts supplier-level disruptions out of sample with transparent models. We ask three questions. **RQ1:** How has supplier-country concentration in U.S. goods imports evolved since 2009, and where has the sourcing that left China gone? **RQ2:** Has lower concentration reduced the risk of the import portfolio, and which suppliers absorb its risk budget? **RQ3:** Can disruptions in individual supplier relationships be forecast three to six months ahead, and which factors drive the warnings?

The article makes four contributions. First, it builds a consistent monthly panel of U.S. imports by supplier that handles overlapping country groups and changing coverage. Second, it transfers portfolio risk measurement from finance to trade: aggregate import volatility is decomposed into supplier risk contributions and systemic betas, and the diversification benefit is measured directly, revealing that falling concentration and rising systematic risk have coexisted since 2022. Third, it develops a pseudo-real-time early-warning system for supplier disruptions, modelled on crisis and credit-risk forecasting, with dependence-robust inference and information-set ablation. Fourth, it makes the warnings transparent with SHAP attributions and a live watchlist, giving policy-makers, investors exposed to import-dependent firms and procurement managers a monthly measure of supply risk (Simchi-Levi et al. 2014; Liu 2025). Section 2 describes the methodology, Section 3 the results, Section 4 the discussion, and Section 5 concludes.

2 Methodology

Figure 1 summarises the design. Every number is produced by the Python code supplied with the article from a single public input file.

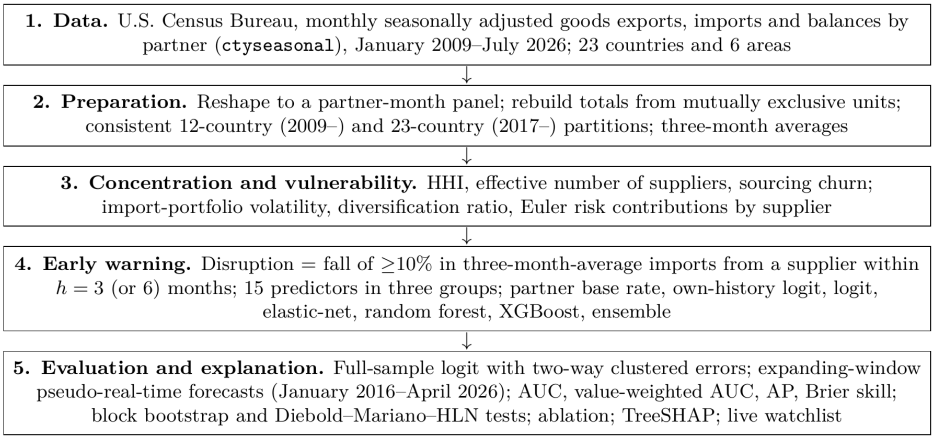


Figure 1 Research workflow

2.1 Data and preparation

The data are the U.S. Census Bureau's monthly, seasonally adjusted statistics on goods trade by country and area (the `ctyseasonal` file underlying the FT-900 release). They report exports (E), imports (M) and the balance for January 2009–July 2026 (211 months) and 29 partner units: 23 countries and six areas. Twelve countries are reported throughout; Hong Kong, Singapore and Taiwan are added in 2013, and Australia, Belgium, Ireland, Israel, Malaysia, the Netherlands, Switzerland and Vietnam in 2017. The identity $B = E - M$ holds exactly. Because areas overlap with countries, total imports are rebuilt from mutually exclusive units, $M_t = \sum_{i \in C_t} M_{it} + M_t^{AOC}$, where C_t is the set of listed countries and M_t^{AOC} the residual "All other countries". This reproduces published totals ($1,559.6 billion in 2009 and $3,263.9 billion in 2024). Concentration is measured on two partitions that each sum to M_t: a 12-country basis (2009–2026) and a 23-country basis (2017–2026), each with a rest-of-world unit. Shares use three-month moving averages, $\bar{M}_{it} = \frac{1}{3}\sum_{j=0}^{2} M_{i,t-j}$ and $s_{it} = \bar{M}_{it} / \sum_k \bar{M}_{kt}$.

2.2 Concentration and vulnerability measures

Concentration is measured by the Herfindahl–Hirschman index over identified suppliers (Hirschman 1945), the effective number of suppliers and sourcing churn, the share of imports that changes origin over twelve months:

$$HHI_t = 10{,}000 \sum_{i \neq RoW} s_{it}^2, \qquad N_t^{eff} = \frac{10{,}000}{HHI_t}, \qquad R_t = 50 \sum_i \left| s_{it} - s_{i,t-12} \right|. \tag{1}$$

The rest of world is treated as atomistic, so the HHI is a lower bound. Let $g_{it} = 100\,\Delta \ln M_{it}$ and $\boldsymbol{w}_t$ the supplier weights (average shares over a 24-month window). Because $\Delta \ln M_t \approx \sum_i w_{it} g_{it}$, total imports behave like a portfolio (Markowitz 1952), with volatility, diversification ratio (Choueifaty and Coignard 2008) and Euler risk contributions (Maillard et al. 2010):

$$\sigma_{p,t} = \sqrt{\boldsymbol{w}_t^{\top} \boldsymbol{\Sigma}_t \boldsymbol{w}_t}, \qquad DR_t = \frac{\sum_i w_{it} \sigma_{it}}{\sigma_{p,t}}, \qquad RC_{it} = \frac{w_{it} (\boldsymbol{\Sigma}_t \boldsymbol{w}_t)_i}{\sigma_{p,t}^2}, \tag{2}$$

where $\boldsymbol{\Sigma}_t$ is the covariance matrix of g_{it} over the window. DR_t equals one when all suppliers move together, and RC_{it} equals the supplier's share times its systemic beta $\beta_{it} = (\boldsymbol{\Sigma}_t \boldsymbol{w}_t)_i / \sigma_{p,t}^2$. A supplier is

vulnerability-intensive when its risk contribution exceeds its share (Koren and Tenreyro 2007; Caselli et al. 2020).

2.3 Disruptions and predictors

A supplier relationship is disrupted at horizon h if three-month-average imports fall by at least κ:

$$D_{it}^{(h)} = \mathbb{1}[\ln \bar{M}_{i,t+h} - \ln \bar{M}_{it} \leq \ln(1-\kappa)], \qquad \kappa = 0.10,\ h \in \{3,6\}. \tag{3}$$

For $h = 3$ this is a quarter-on-quarter fall of at least 10%, large enough to require rescheduling, buffer stocks or alternative sourcing; robustness checks use $\kappa = 0.05$ and 0.15. The primary design (23 countries, origins January 2011–April 2026) contains 3,320 country-months with 331 disruptions (10.0%; value-weighted 5.9%). Fifteen predictors, measured with data up to month t only, fall into three groups (Table 1): *own dynamics* (momentum, growth, surges, volatility and drawdown), *exposure* (share, share change, bilateral balance ratio, export growth and systemic beta) and *system conditions* common to all suppliers (total import momentum and growth, breadth of declines, the change in the HHI and churn).

Table 1 Early-warning predictors: definitions and descriptive statistics (3,320 country-months)

Predictor	Definition	Mean	SD	P1	P99
Own dynamics					
Import momentum (3m)	$100\,\Delta_3 \ln \bar{M}_{it}$	0.86	16.70	−44.0	40.5
Import growth (12m)	$100\,\Delta_{12} \ln \bar{M}_{it}$	3.81	24.73	−74.3	78.7
Import surge	$100\,[\ln M_{it} - \ln \frac{1}{12}\sum_{j=1}^{12} M_{i,t-j}]$	0.76	20.24	−76.9	46.1
Import volatility	SD of $100\,\Delta \ln M_{it}$, 12 months	10.77	10.99	1.4	64.5
Drawdown from 12m peak	$100\,[\ln \bar{M}_{it} - \max_{j<12} \ln \bar{M}_{i,t-j}]$	−10.29	22.82	−131.9	0.0
Exposure					
Import share	$100\,\bar{M}_{it}/\bar{M}_t$	4.36	5.06	0.1	21.1
Share change (12m)	Δ_{12} share (pp)	0.00	0.78	−3.1	2.5
Bilateral balance ratio	$100\,(\bar{X}_{it} - \bar{M}_{it})/(\bar{X}_{it} + \bar{M}_{it})$	−16.47	32.90	−83.9	75.0
Export growth (12m)	$100\,\Delta_{12} \ln \bar{X}_{it}$	4.58	18.31	−41.2	55.4
Systemic beta	$\widehat{\mathrm{cov}}(g_{it}, g_t)/\widehat{\mathrm{var}}(g_t)$, 24 months	0.82	1.58	−3.9	5.9
System					
U.S. import momentum (3m)	$100\,\Delta_3 \ln \bar{M}_t$	0.89	4.77	−15.2	14.7
U.S. import growth (12m)	$100\,\Delta_{12} \ln \bar{M}_t$	3.56	9.60	−19.1	27.3
Breadth of declines	% of countries with $\Delta_3 \ln \bar{M}_{it} < 0$	41.15	18.28	0.0	80.0
Concentration change (12m)	$\Delta_{12} HHI_t$	−24.98	60.10	−180.0	92.7
Sourcing churn (12m)	R_t	3.57	2.03	1.1	9.7

Notes: $\bar{M}$, $\bar{X}$: three-month averages of imports and exports; g: monthly log growth $\times 100$; P1, P99: 1st and 99th percentiles.

2.4 Models and evaluation

The association between predictors and disruptions is first estimated with a pooled logit, $\Pr(D_{it}^{(3)} = 1 \mid \boldsymbol{x}_{it}) = \Lambda(\alpha + \boldsymbol{x}_{it}^{\top}\boldsymbol{\beta})$, on winsorised and standardised predictors, with and without country fixed effects.

Standard errors are clustered by country and month (Cameron et al. 2011); all variance inflation factors are below 6. Six models are then compared out of sample: (1) a partner base rate, each supplier's disruption frequency shrunk towards the pooled rate; (2) an own-history logit on the five own-dynamics predictors, the analogue of an autoregressive benchmark; (3) a logit on all predictors; (4) an elastic-net logit (Zou and Hastie 2005) tuned by time-ordered cross-validation; (5) a random forest with 500 trees (Breiman 2001); and (6) XGBoost with 300 trees of depth 3 (Chen and Guestrin 2016). An equal-weight ensemble averages models (4)–(6). Hyperparameters were fixed in advance.

Forecasts are produced at every origin from January 2016 to April 2026 (2,564 country-months, 294 disruptions). At origin t, models are trained only on country-months whose outcome is observed by t, with winsorisation, standardisation and cross-validation confined to the training window, and are re-estimated quarterly. Discrimination is measured by the AUC (Fawcett 2006) and an import-share-weighted AUC, rare-event precision by average precision (Saito and Rehmsmeier 2015), and accuracy by the Brier skill score relative to the base rate (Brier 1950). Uncertainty comes from a 12-month moving-block bootstrap over forecast months (Künsch 1989), and Brier losses are compared with the Diebold–Mariano test (Diebold and Mariano 1995) with the Harvey et al. (1997) correction and a Newey–West variance (Newey and West 1987). An information-set ablation re-estimates the models on nested predictor groups. Warnings are explained with exact TreeSHAP values (Lundberg and Lee 2017; Lundberg et al. 2020), and the models are finally applied to July 2026 data to produce a live watchlist.

3 Results

3.1 Concentration and sourcing diversification (RQ1)

U.S. goods imports more than doubled from $1,559.6 billion in 2009 to $3,414.5 billion in 2025, while the supplier base became markedly less concentrated (Fig. 2, Table 2). On the 12-country basis, the HHI peaked at 921 in May 2015, when China's share also peaked at 22.3%, then fell to 500 in May 2025 and stood at 582 in July 2026; the effective number of suppliers rose from 12.6 to 17.2. The 23-country basis shows the same pattern (910 in early 2017, 702 in July 2026). Deconcentration came in two waves matching the two tariff episodes. China's annual share fell from 21.6% in 2017 to 13.5% in 2024 and 7.9% in January–July 2026, and Mexico overtook China as the largest supplier in December 2022.

Between 2017 and 2026 China lost 13.7 percentage points, while Vietnam (2.0% to 7.2%), Taiwan (1.8% to 8.0%) and Mexico (13.4% to 17.1%) together gained 15.2 points (Fig. 3). Twelve-month changes in China's share are negatively correlated with those of Mexico ($\rho = -0.51$), Taiwan (-0.39) and Vietnam (-0.25), the "China plus one" pattern documented with product data (Alfaro and Chor 2023; Fajgelbaum et al. 2024; Freund et al. 2024). Reallocation was also fast: sourcing churn averaged 2.4% a year before 2020, peaked at 10.4% in June 2020 and returned to similar levels in 2025.

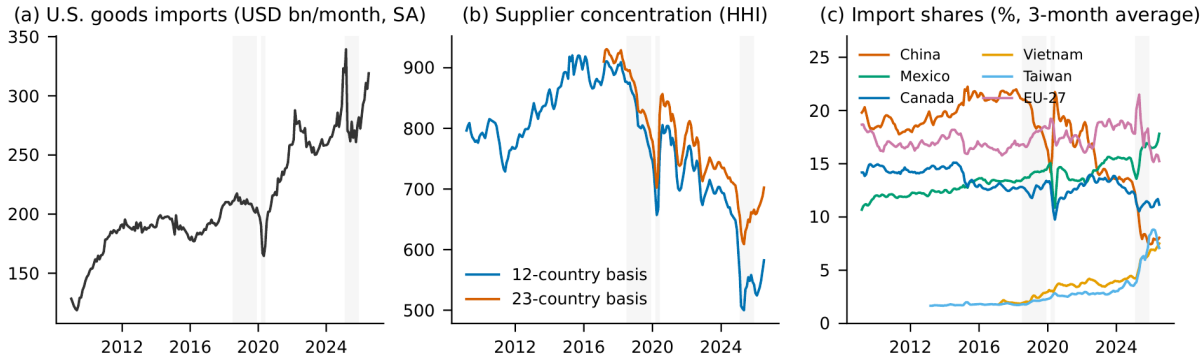


Figure 2 U.S. goods imports and supplier concentration, January 2009–July 2026. (a) Total goods imports (SA). (b) HHI on the 12- and 23-country bases. (c) Shares of selected suppliers (three-month averages). Shaded: Section 301 tariffs, COVID-19 collapse, 2025 tariff shock

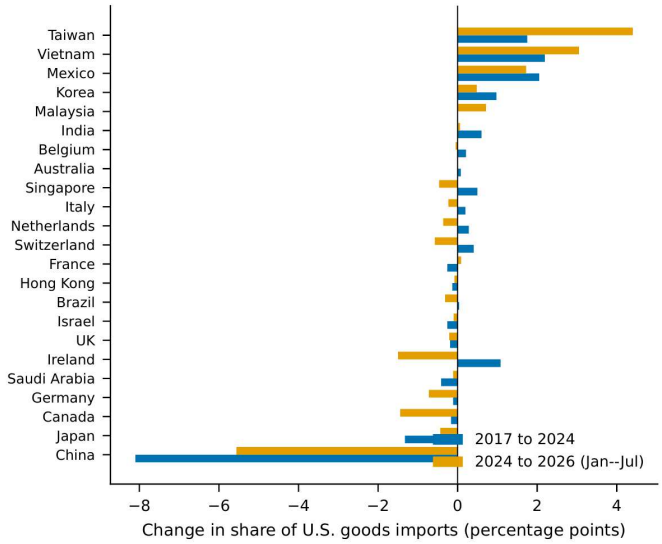


Figure 3 Change in each supplier's share of U.S. goods imports (percentage points), 2017 to 2024 and 2024 to January–July 2026

Table 2 Supplier concentration, sourcing churn and import-portfolio risk by period

	12-country		23-country								
Period	HHI	N^{eff}	HHI	N^{eff}	CR1	CR4	China	R	σ_p	$\sum w\sigma$	DR
2009–2012	785	12.8	–	–	China (18.7)	51.1	18.7	2.5	1.92	4.02	2.11
2013–2016	872	11.5	–	–	China (20.5)	53.1	20.5	2.4	2.12	4.24	2.00
2017–2019	858	11.7	879	11.4	China (20.4)	52.6	20.4	2.2	1.43	3.43	2.42
2020–2021	747	13.4	791	12.7	China (18.1)	48.9	18.1	5.2	4.12	8.61	2.12
2022–2024	701	14.3	744	13.5	Mexico (14.9)	47.8	14.8	3.0	2.87	5.31	1.86
2025–2026	542	18.5	656	15.3	Mexico (16.1)	40.6	8.8	6.6	5.38	7.47	1.42

Notes: Period means. CR1: largest supplier and share (%); CR4: four largest suppliers (%); China: China's share (%); R: churn (%); σ_p, $\sum w\sigma$, DR: portfolio volatility, weighted supplier volatility (% per month) and diversification ratio, 24-month windows.

3.2 Diversification without resilience (RQ2)

Lower concentration has not made the import portfolio less risky (Fig. 4). In 2017–2019, portfolio volatility averaged 1.43% per month and the diversification ratio 2.42, so the supplier mix removed more than half of supplier-level volatility. By July 2026 volatility had risen to 6.26% and the ratio had fallen to 1.40 (minimum 1.28 in April 2025). Over the whole sample the HHI and portfolio volatility are negatively correlated ($\rho = -0.66$). Two mechanisms explain this. Supplier shocks became larger, as weighted supplier volatility roughly doubled (Table 2), and they became more correlated, because tariff announcements hit many partners at once and so removed the benefit of independent shocks (Koren and Tenreyro 2007; Caselli et al. 2020).

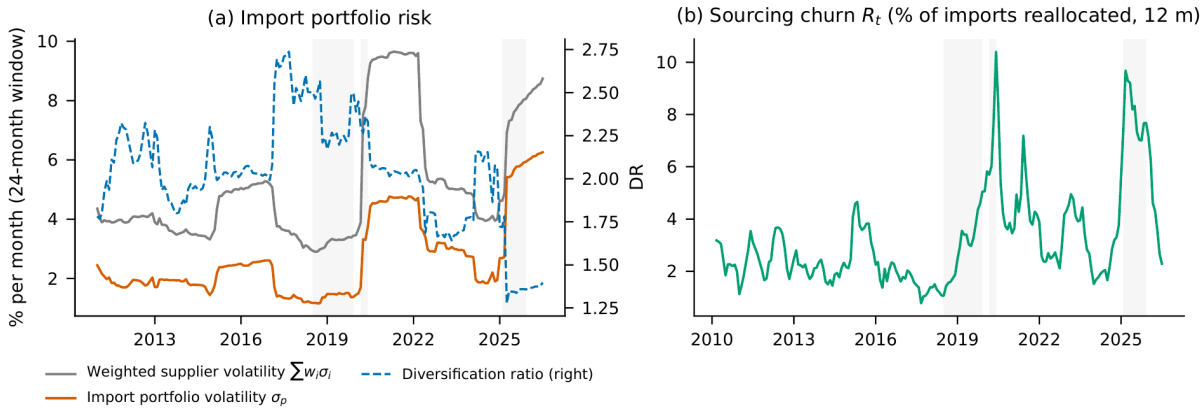


Figure 4 (a) Rolling 24-month import-portfolio risk: weighted supplier volatility, portfolio volatility σ_p and diversification ratio (right axis). (b) Sourcing churn R_t (12-country basis)

The risk decomposition (Table 3) shows where vulnerability now sits. In the two years to July 2026, Switzerland and Ireland supplied 5.5% of imports but generated 32.0% of portfolio risk, up from 8.5% in 2018–2019. Their flows, widely attributed to gold and pharmaceutical shipments, have monthly standard deviations near 50% and systemic betas above 5. With China, they account for 42.9% of risk, while China's own contribution fell from 27.3% to 10.9%. The new hubs are risk-light: Vietnam (share 5.9%, risk 1.2%), Taiwan (6.1%, 0.1%) and Mexico (16.1%, 9.5%). Diversification towards them lowered risk, but volatile flows in a few specialised products added more risk than it removed, so a supplier's share is a poor guide to its contribution to vulnerability.

3.3 Disruptions and their correlates

Disruptions cluster in time and across suppliers (Fig. 5). The rate was 0.0% in 2013 but 29.0% of country-months in 2020 and 26.8% in 2025. Large manufacturing suppliers are rarely disrupted (Mexico and Korea, 1.6%), while commodity-dominated suppliers are disrupted often (the Netherlands, 30.7%; Saudi Arabia, 34.8%).

The full-sample logit (Table 4) shows that disruptions follow run-ups. A one-standard-deviation increase in three-month momentum raises the odds of a disruption by a factor of 1.45 and in twelve-month growth by 1.86, while a high latest month lowers them (0.55). Risk is therefore highest once a

Table 3 Supplier vulnerability (23-country basis), sorted by current risk contribution

	Share (%)				RC (%)			
Supplier	2018–19	Now	Vol.	β	2018–19	Now	Bal.	Disr.
Switzerland	1.7	2.4	49.6	6.85	3.9	16.1	−7.8	19.3
Ireland	2.4	3.1	55.2	5.12	4.5	15.9	−61.2	15.9
China	19.6	9.6	11.6	1.14	27.3	10.9	−47.1	8.2
Canada	12.7	11.4	6.4	0.86	19.3	9.8	−6.8	4.9
Mexico	13.9	16.1	4.7	0.59	3.9	9.5	−22.1	1.6
Germany	5.0	4.5	10.1	1.09	3.3	4.9	−30.2	3.8
Korea	3.0	4.0	9.7	0.94	2.5	3.7	−30.6	1.6
Australia	0.4	0.7	39.9	5.04	0.3	3.4	22.5	21.6
France	2.2	1.9	17.4	1.73	−0.5	3.4	−15.6	6.5
India	2.2	2.9	9.8	1.09	3.0	3.1	−35.7	3.8
UK	2.5	1.9	11.2	1.62	4.4	3.1	18.9	5.4
Netherlands	1.1	0.9	27.1	1.98	3.6	1.8	51.6	30.7
Italy	2.2	2.2	8.9	0.61	2.9	1.3	−28.9	2.2
Malaysia	1.6	1.9	8.3	0.65	1.5	1.2	−35.7	5.7
Brazil	1.2	1.1	13.2	1.04	3.5	1.2	16.0	11.4
Vietnam	2.3	5.9	5.3	0.20	−0.0	1.2	−85.1	2.3
Singapore	1.1	1.1	29.4	1.02	1.1	1.1	11.7	16.2
Belgium	0.7	0.8	27.4	0.60	−2.3	0.5	13.3	23.9
Japan	5.7	4.2	5.2	0.06	−0.9	0.2	−25.8	4.3
Israel	0.8	0.6	21.2	0.33	1.2	0.2	−20.5	9.1
Taiwan	2.0	6.1	11.4	0.01	0.7	0.1	−57.6	2.2
Saudi Arabia	0.7	0.3	30.3	−0.20	2.3	−0.1	17.2	34.8
Hong Kong	0.2	0.1	74.9	−1.08	0.2	−0.2	77.1	22.1
Rest of world	14.7	16.4	3.1	0.46	14.4	7.5	–	–

Notes: Share: average share in the 24 months to December 2019 and to July 2026; Vol.: SD of monthly import growth (%); β: systemic beta; RC: risk contribution (negative values hedge); Bal.: bilateral balance ratio; Disr.: disruption frequency (%).

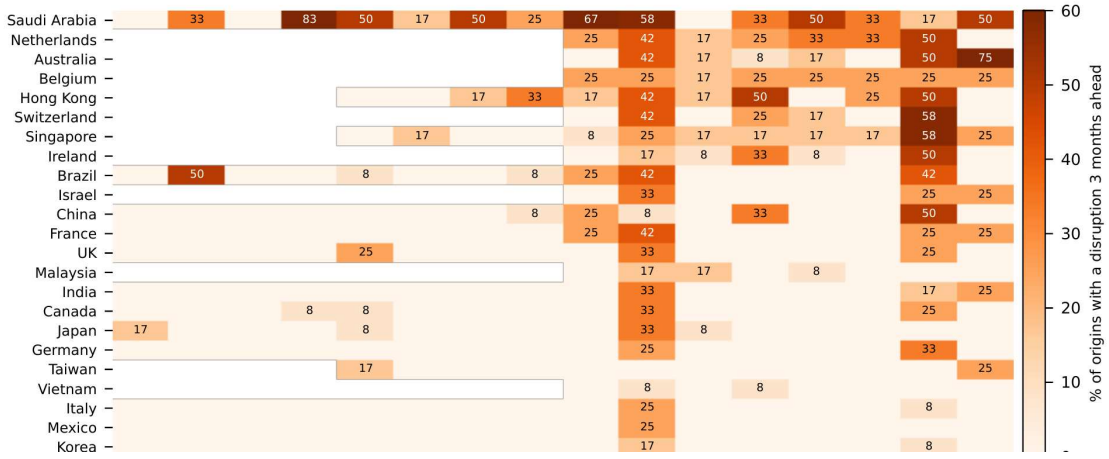


Figure 5 Import disruptions by supplier and year: percentage of origins at which three-month-average imports fell by at least 10% over the following three months

run-up starts to reverse, the signature of front-loading ahead of tariff changes. Growing U.S. exports to the partner lower the odds (0.75); sourcing churn raises them (1.30) and a rising HHI lowers them (0.68), so rapid deconcentration is itself a warning sign. With country fixed effects, a wider bilateral U.S. deficit raises the odds (0.47 for the balance ratio). Clustered standard errors are up to 3.0 times the conventional ones.

Table 4 Full-sample logit for disruption three months ahead ($h = 3$, $\kappa = 0.10$)

	Pooled		Country fixed effects	
Predictor	Coef. (SE)	OR	Coef. (SE)	OR
Import momentum (3m)	0.37*** (0.11)	1.45	0.34*** (0.09)	1.40
Import growth (12m)	0.62*** (0.13)	1.86	0.46*** (0.11)	1.59
Import surge	−0.59*** (0.12)	0.55	−0.70*** (0.14)	0.50
Import volatility	0.43 (0.32)	1.54	0.20 (0.28)	1.22
Drawdown from 12m peak	0.15 (0.38)	1.16	0.22 (0.21)	1.25
Import share	−0.22 (0.27)	0.80	0.30 (0.48)	1.35
Share change (12m)	−0.17 (0.13)	0.84	−0.13* (0.07)	0.88
Bilateral balance ratio	0.17 (0.16)	1.18	−0.75*** (0.24)	0.47
Export growth (12m)	−0.28*** (0.07)	0.75	−0.10 (0.08)	0.90
Systemic beta	0.09 (0.08)	1.09	0.05 (0.09)	1.05
U.S. import momentum (3m)	0.00 (0.10)	1.00	0.11 (0.13)	1.11
U.S. import growth (12m)	−0.19 (0.14)	0.82	−0.31** (0.16)	0.73
Breadth of declines	−0.00 (0.14)	1.00	0.01 (0.15)	1.01
Concentration change (12m)	−0.39** (0.16)	0.68	−0.41*** (0.15)	0.66
Sourcing churn (12m)	0.26** (0.12)	1.30	0.45*** (0.12)	1.57
Observations; pseudo-R^2; AUC	3,320; 0.206; 0.805		3,320; 0.295; 0.873	

Notes: Standardised predictors; standard errors clustered by country and month. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

3.4 Out-of-sample early warning (RQ3)

Three months ahead, every model ranks disruptions better than the partner base rate (AUC 0.670; bootstrap $p \leq 0.035$), as Table 5 and Fig. 6 show. The own-history logit is already a strong benchmark (0.745). The ensemble achieves the highest AUC, 0.787 [0.705, 0.875], and is the only model whose gain over the own-history benchmark is significant ($p = 0.020$) and whose Brier skill interval excludes zero (0.085 [0.011, 0.154]). Gains in squared error are modest: no Diebold–Mariano test rejects equal Brier loss against the base rate at 5% (ensemble $p = 0.096$), and the unpenalised logit has negative skill despite a reasonable AUC, so regularisation or averaging is needed.

The gains are largest where they matter most. On the value-weighted AUC, the random forest (0.784) and ensemble (0.759) clearly beat the own-history logit (0.683), and among the ten largest suppliers the ensemble reaches 0.752 against 0.666 (Table 6). Predictability depends on the shock: the ensemble AUC is 0.889 in 2016–2019 and 0.841 in 2022–2024, but only 0.566 during the 2020–2021 pandemic, when an exogenous collapse of almost all flows could not be anticipated. In 2025–2026 it is 0.729: at the 74

Table 5 Out-of-sample early-warning performance, forecast origins January 2016–April 2026

Model	AUC [95% CI]	VW-AUC	AP	Brier	BSS	DM_{base}	DM_{own}
$h = 3$: 2,564 country-months, 294 disruptions (11.5%)							
Partner base rate	0.670 [0.56, 0.80]	0.588	0.221	0.0974	0.000	–	–
Own-history logit	0.745 [0.65, 0.85]	0.683	0.354	0.0951	0.024	−0.34	–
Logit	0.736 [0.64, 0.84]	0.667	0.336	0.1052	−0.080	1.00	1.75
Elastic-net logit	0.738 [0.64, 0.84]	0.651	0.335	0.0946	0.029	−0.61	−0.11
Random forest	0.786 [0.70, 0.87]	0.784	0.282	0.0920	0.056	−1.15	−0.66
XGBoost	0.772 [0.69, 0.86]	0.739	0.335	0.0931	0.044	−0.85	−0.43
Ensemble	**0.787 [0.71, 0.87]**	0.759	0.343	0.0891	0.085	−1.68	−1.41
$h = 6$: 2,495 country-months, 375 disruptions (15.0%)							
Partner base rate	0.653 [0.56, 0.75]	0.587	0.248	0.1246	0.000	–	–
Own-history logit	0.681 [0.56, 0.79]	0.594	0.319	0.1244	0.002	−0.01	–
Logit	0.637 [0.53, 0.75]	0.543	0.277	0.1482	−0.189	1.46	1.97
Elastic-net logit	0.643 [0.53, 0.75]	0.538	0.269	0.1293	−0.038	0.80	0.99
Random forest	0.686 [0.59, 0.79]	0.621	0.282	0.1240	0.005	−0.19	−0.22
XGBoost	0.665 [0.56, 0.76]	0.591	0.288	0.1302	−0.045	1.04	0.81
Ensemble	0.678 [0.57, 0.78]	0.595	0.294	0.1231	0.012	−0.35	−0.35

Notes: AUC with 95% moving-block bootstrap interval; VW-AUC: import-share-weighted AUC; AP: average precision; BSS: Brier skill score relative to the base rate; DM: Diebold–Mariano–HLN statistics on monthly Brier loss against the base rate and the own-history logit (negative favours the model).

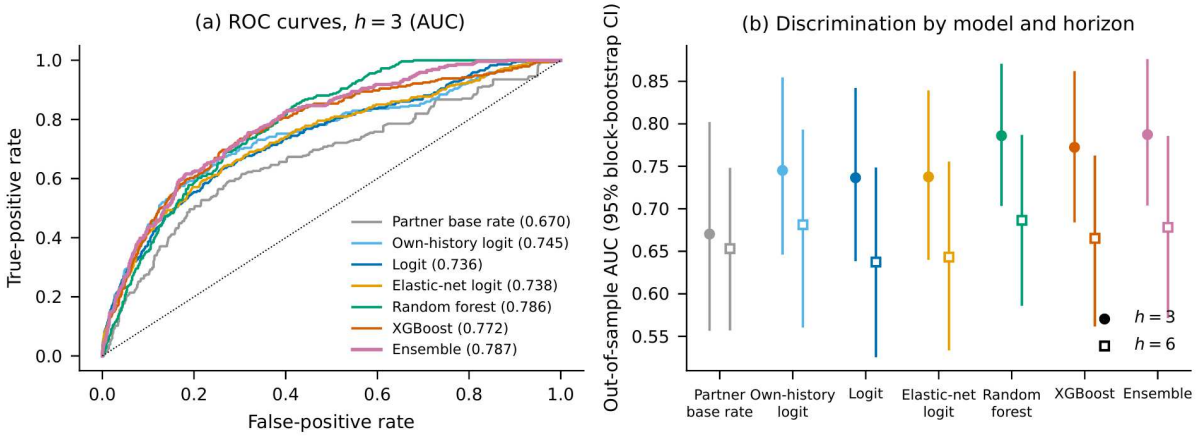


Figure 6 Out-of-sample discrimination. (a) ROC curves at $h = 3$. (b) AUC with 95% block-bootstrap intervals at $h = 3$ (filled) and $h = 6$ (open)

disruptions with 2025 origins, the mean predicted probability was 37.8% against 25.8% for non-events. For China, the probability rose from 1.9% in December 2024 to 35.3% in May 2025, ahead of the April–June collapse (Fig. 8). At six months predictability fades (ensemble 0.678, own-history 0.681), so the framework is a short-horizon monitoring tool. In the ablation, adding system conditions to own dynamics raises the XGBoost AUC from 0.744 to 0.767 and all predictors to 0.772, while the linear elastic-net stays at 0.736–0.739, indicating non-linear interactions between a supplier's run-up and system-wide churn.

3.5 Drivers of warnings, watchlist and robustness

SHAP attributes 54% of the model's explanatory weight to own dynamics, 27% to system conditions and 19% to exposure (Fig. 7). Import volatility is the most important predictor (23.6%), followed by surges (12.3%), the change in concentration (11.9%) and momentum (9.5%). High volatility, recent run-ups, falling concentration and high churn raise predicted risk, and the weight of system conditions rose from 26% in 2016–2019 to 32% in 2025–2026 as trade policy became the dominant source of shocks.

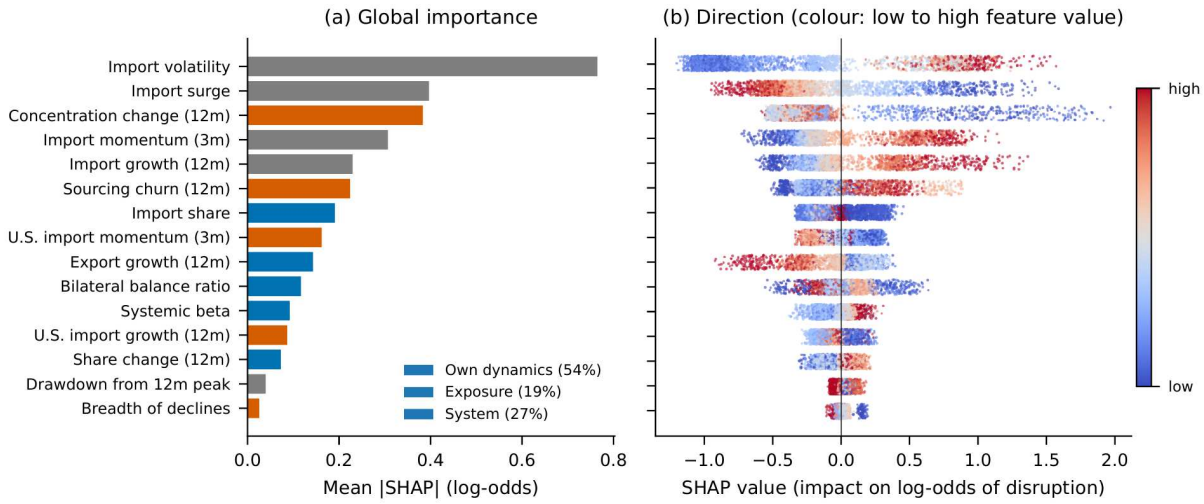


Figure 7 TreeSHAP explanation of the XGBoost model ($h = 3$). (a) Mean absolute SHAP value by predictor and group. (b) SHAP values for every country-month, coloured by predictor value

Applied to July 2026 data, the models flag small, volatile suppliers as most at risk by October 2026 (Table 7): Israel (28.5%), Hong Kong (25.7%) and Singapore (17.7%). Among large suppliers Taiwan stands out (13.1%), while Mexico (3.1%), Canada (2.3%) and China (2.6%) carry low near-term risk. The model ranking is stable across designs (Table 6): with $\kappa = 0.05$ or 0.15 the ensemble and random forest still lead, and excluding the 2020 origins raises the ensemble AUC to 0.840.

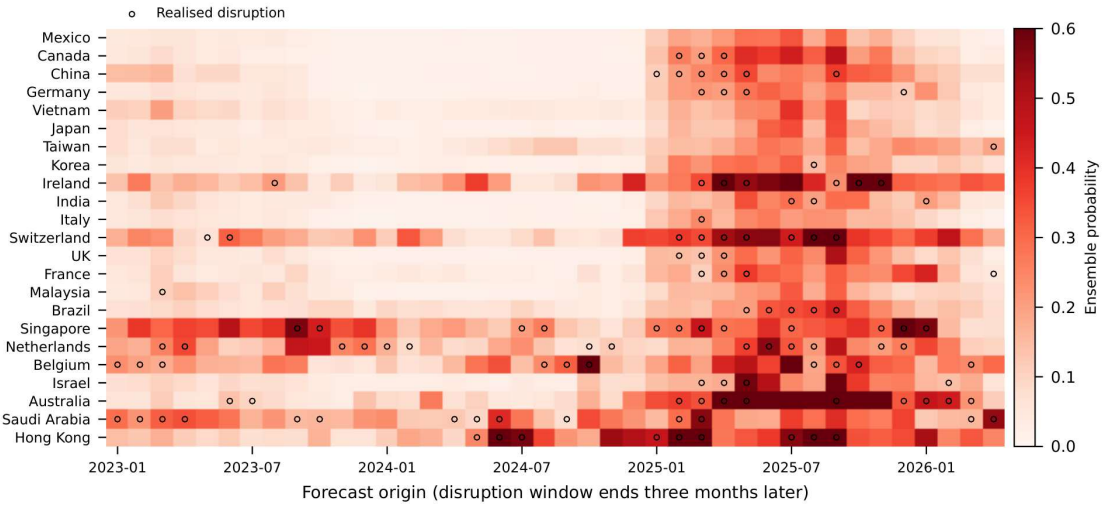


Figure 8 Early-warning dashboard: out-of-sample ensemble probability of a disruption within three months, by supplier and origin (2023–2026). Circles mark realised disruptions

Table 6 Robustness: out-of-sample AUC under alternative designs

Design	Rate	Base	Own	Logit	EN	RF	XGB	Ens.
Primary: 10% fall, $h = 3$	11.5	0.670	0.745	0.736	0.738	0.786	0.772	0.787
5% fall, $h = 3$	20.2	0.635	0.680	0.696	0.692	0.699	0.696	0.706
15% fall, $h = 3$	7.2	0.677	0.755	0.738	0.725	0.788	0.770	0.777
10% fall, $h = 6$	15.0	0.653	0.681	0.637	0.643	0.686	0.665	0.678
Excluding 2020 origins	9.4	0.754	0.811	0.799	0.797	0.830	0.833	0.840
Ten largest suppliers	6.1	0.567	0.666	0.666	0.649	0.782	0.714	0.752

Notes: Rate: disruption rate in the evaluation sample (%). Base: partner base rate; Own: own-history logit; EN: elastic-net; RF: random forest; XGB: XGBoost; Ens.: ensemble.

Table 7 Live watchlist: probability (%) of a disruption between July and October 2026 (12 highest of 23 suppliers)

Supplier	Ens.	XGB	Share	Mom. 3m	Gr. 12m	Surge	Main SHAP drivers
Israel	28.5	46.6	0.6	14.0	33.0	2.3	Volatility, growth (12m)
Hong Kong	25.7	18.9	0.1	42.6	49.5	43.2	Volatility, growth (12m)
Singapore	17.7	15.7	0.9	23.9	2.9	3.7	Volatility, momentum (3m)
Ireland	13.5	8.5	1.7	12.9	−39.8	−6.9	Volatility, momentum (3m)
Taiwan	13.1	20.6	7.1	−14.0	27.9	5.8	Volatility, growth (12m)
Switzerland	12.4	12.6	1.4	3.6	−28.5	15.1	Volatility, import share
Australia	11.6	8.6	0.5	2.4	−21.7	−8.8	Volatility, systemic beta
Saudi Arabia	10.3	9.4	0.1	−111.9	−70.1	−149.0	Surge, volatility
Belgium	10.1	7.0	0.8	5.1	6.4	12.1	Volatility, balance ratio
Netherlands	8.7	6.7	0.7	−5.3	−41.7	−14.1	Volatility, surge
France	8.3	7.4	1.7	−14.8	5.0	−9.7	Volatility, surge
Malaysia	6.2	3.7	2.4	14.1	41.1	23.6	Growth (12m), momentum (3m)

Notes: Ens.: mean of elastic-net, random forest and XGBoost re-estimated on all outcomes; XGB: XGBoost; Share: import share (%).

4 Discussion

The results separate two quantities that policy debate treats as one: concentration and risk. For RQ1, U.S. sourcing diversified substantially and quickly. China's share fell by almost two thirds from its peak, and Mexico, Vietnam and Taiwan absorbed the difference, in line with product-level evidence on tariff-induced reallocation (Fajgelbaum et al. 2024; Freund et al. 2024). For RQ2, this diversification did not reduce the risk of the import portfolio. Since 2022 aggregate import volatility has risen and the diversification ratio has fallen, because the composition of risk shifted from idiosyncratic to systematic: tariff announcements moved many suppliers at once, and a few volatile, high-value flows with systemic betas above 5 came to absorb a third of the risk budget. In finance terms, the portfolio added positions but its average correlation rose, so the diversification benefit shrank. For RQ3, supplier-level disruptions are forecastable three months ahead from public monthly data, most for large suppliers and in tranquil periods and least for exogenous shocks, consistent with the limited out-of-sample predictability of supplier-country fundamentals (McCarthy and Alaghband 2026).

Three economic implications follow. First, concentration indices are a poor proxy for economic security. An index of supplier weights ignores volatilities and covariances, and in U.S. data concentration and risk moved in opposite directions. This extends the portfolio view of trade diversification (Koren and Tenreyro 2007; Caselli et al. 2020) from cross-country comparisons of income volatility to the monitoring of one country's realised supply risk. Second, the results show when diversification fails. Diversification insures against independent, exporter-specific shocks (Grossman et al. 2023; Ahn and Tan 2025), but it cannot insure against shocks that are common to suppliers, such as broad tariff changes, or against risk concentrated in a few volatile product lines. Resilience should therefore be judged by exposure to systematic shocks rather than by the number of suppliers (Baldwin and Freeman 2022). Third, the evidence is consistent with the externality view of supply-chain fragility: because individual importers optimise sourcing without internalising aggregate risk, the economy can end up diversified in count but exposed in covariance (Jiang et al. 2022; Elliott et al. 2022; Kancs 2024). At firm level, the parallel finding is that upstream dependence resists operational buffering (Hong et al. 2026).

The findings have implications for policy, markets and management. For policy-makers, the case for intervention rests on an externality, so the target should be aggregate risk rather than concentration. Statistical agencies can publish supplier risk contributions and diversification ratios each month alongside concentration indices, and policies that subsidise diversification should favour suppliers whose shocks are weakly correlated with the rest of the import base. For investors and lenders, supplier-country risk contributions and disruption probabilities are inputs for assessing import-dependent firms and sectors, in the same way that country-risk and crisis indicators inform asset allocation. For managers, the framework turns the exposure indices proposed for procurement into an operational signal (Simchi-Levi et al. 2014; Liu 2025): a supplier whose imports have surged, whose flows are volatile and whose environment is churning warrants larger safety stocks or a qualified second source (Christopher and Peck 2004; Sheffi and Rice 2005). Methodologically, the strength of the persistence benchmark and the poor forecasts of the best-fitting unpenalised logit show that, as in financial forecasting, early-warning claims should be tested out of sample against simple benchmarks.

5 Conclusions

This article asked whether diversifying U.S. goods imports away from China has made the supply of imports more resilient and whether supplier-level disruptions can be anticipated. Monthly Census data for January 2009–July 2026 give three answers. Concentration fell substantially, with the HHI dropping from 921 to 582 and China's share from 22.3% to 8.0%. Lower concentration did not reduce vulnerability: portfolio volatility rose from 1.43% to 6.26% per month and the diversification ratio fell from 2.42 to 1.40, while Switzerland and Ireland, with 5.5% of imports, accounted for 32.0% of risk. Disruptions are predictable three months ahead, with an ensemble AUC of 0.787 that beats a strong own-history benchmark and adds most for the largest suppliers. Because policy-driven common shocks have turned idiosyncratic supply risk into systematic risk, economic resilience should be measured by exposure to the covariance of supply, not by the number of suppliers.

Limitations. The analysis has several limitations. The data are aggregate goods trade by partner, so product composition, which matters most for critical inputs, cannot be observed, and the attribution of Swiss and Irish volatility to gold and pharmaceuticals rests on outside sources. Partner-level flows do not reveal transshipment or Chinese value added embedded in third-country imports, so measured diversification may overstate true diversification (Alfaro and Chor 2023; Freund et al. 2024). Country coverage changes over time and the rest of world is treated as atomistic, so the HHI is a lower bound and results for the eight countries added in 2017 rest on a shorter history. The data are current, not real-time, vintages; disruptions are falls in value that mix price and quantity effects; and the sample contains few independent shock episodes, so the modest Brier skill and wide bootstrap intervals should be read with care.

Future directions. Future work could apply the framework to product-level (HS6 or HS10) imports to measure concentration, risk contributions and disruptions for critical goods directly. It could add real-time external information, such as trade-policy uncertainty (Caldara et al. 2020), supply-chain pressure (Benigno et al. 2022) and supplier-health scores (McCarthy and Alaghband 2026), to test whether it improves on trade data alone, and use value-added trade data to separate genuine diversification from rerouting. Finally, linking warnings to cost-sensitive thresholds, inventory policies and the optimal degree of diversification under ambiguity (Grossman et al. 2023; Kancs 2024) would show how much an early warning is worth to procurement and policy decision-makers.

Statements and declarations

Author contribution

Abdullah Al Shohan, Md Mazharul Islam, Fatema Tuj Johra, Md Jakaria Islam, and Md Farhad Hossain contributed equally to the conceptualization, methodology, data curation, software, validation, investigation, formal analysis, visualization, writing, review and editing, supervision, and project administration of the study. All authors have read and approved the final manuscript and agree to be accountable for all aspects of the work.

Data Availability

The data are public: U.S. Census Bureau, Foreign Trade Division, file `ctyseasonal` (`https://www.census.gov/foreign-trade/balance/index.html`).

Acknowledgments

Authors are grateful to one and all who, directly or indirectly, have lent their helping hand and thoughtful responses of this study.

Funding

This research received no specific grant from any funding agencies in the public, commercial, or not-for-profit sectors.

Ethics, Consent to Participate, and Consent to Publish

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

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