Supply Chain Rewiring under Trade Wars: A Data-Driven Network Analysis with Structural Breaks and CO_2 Proxies

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September 2025

Abstract

We study how trade wars reshape country–partner networks using UN Comtrade data, detect structural breaks in bilateral flows, and approximate environmental impacts via shipping-distance-based CO_2 proxies. We contribute an end-to-end pipeline: (i) data assembly and network construction; (ii) break detection and short-horizon forecasting; (iii) visualization and tabular reporting; (iv) case studies highlighting US–China trade re-routing and substitution dynamics. Our findings are historically anchored in key disruptions, including the 2018 tariff escalation, the 2020 COVID-19 shock, and post-2021 logistics frictions.

1 Introduction

The intensification of trade wars in recent years has fundamentally reshaped global supply chains and bilateral trade patterns. Policies such as tariff escalations, targeted export restrictions, and retaliatory measures have disrupted long-standing trade flows, forcing firms and states to reconfigure their sourcing strategies. Understanding how these disruptions alter the structure of international trade networks is not only of scholarly interest but also of strategic importance for policy-makers concerned with economic resilience, national security, and environmental sustainability. While descriptive statistics provide a useful starting point, they are insufficient for capturing the complex structural transformations occurring at scale across multiple commodity classes and country pairs.

In this study, we propose a data-driven framework for analyzing the rewiring of international supply chains under trade wars. Leveraging detailed transaction-level data from the UN Comtrade database, we construct weighted and directed trade networks to identify structural breaks in bilateral flows and short-horizon forecasts of future trajectories. Beyond economic impacts, we also approximate the environmental footprint of re-routing by incorporating great-circle shipping distances as proxies for CO_2 emissions. Our contributions lie in (i) assembling and curating a reproducible dataset of high-frequency trade flows; (ii) applying advanced time-series break detection and forecasting techniques; and (iii) providing an integrated perspective on both economic and environmental consequences of trade wars.

2 Related Work

Recent scholarship has increasingly applied machine learning and complex network analysis to the study of international trade. Jošić and Žmuk [1] demonstrated how bilateral trade forecasts for Croatia could be significantly improved by augmenting traditional gravity models with machine learning techniques such as Gaussian processes and neural networks. Nelson [2] proposed the use of random forests combined with data resampling to detect anomalies in the trade of strategic goods, highlighting the role of supervised learning in customs enforcement and outlier detection. These works illustrate the growing recognition that classical econometric approaches alone are insufficient for capturing the nonlinearities and hidden structures present in contemporary trade data.

Complementary efforts have examined the predictive modeling of trade networks through graph-based approaches. Zhao et al. [3] applied machine learning and graph attention networks to forecast new links in the global liquefied natural gas trade network, showing the potential of deep learning in capturing topological features of evolving trade systems. Similarly, studies in the field of complex networks, such as those presented in Physica A [4], have analyzed the robustness, modularity, and dynamic shifts in global trade structures under exogenous shocks. Together, these contributions provide a methodological foundation and empirical motivation for our study, which integrates structural break detection, forecasting, and environmental proxies into a unified analysis of trade war impacts.

3 Methodology

3.1 Data Sources

Our empirical analysis relies primarily on the **United Nations Comtrade Database**, which provides harmonized and publicly accessible records of international trade flows. We collected transaction-level data at the HS2 classification level (sections 84–85), covering the years 2015–2022 for a selected set of focus countries, including the United States, China, Vietnam, Mexico, Germany, Japan, South Korea, Canada, Taiwan, Thailand, and Malaysia. To ensure reproducibility, raw data were downloaded either through the official *Comtrade Preview API* or from archived snapshots. In addition, we incorporated **World Bank Indicators**—such as GDP, trade as a share of GDP, and inflation—to provide macroeconomic context for observed shifts. For the environmental proxy analysis, we employed **geodesic (great-circle) distances** between country centroids and converted them into approximate CO_2 emissions using a standard ton-kilometer factor. All intermediate datasets and configuration files were preserved in machine-readable formats (CSV, Parquet, JSON) to facilitate replication.

3.2 Methodological Implementation

The methodology was structured into three major components. First, we constructed weighted and directed **trade networks**, where nodes represent countries and edges denote bilateral flows, weighted by trade volume and value. Network-level statistics such as centrality and community detection were computed to characterize structural properties. Second, we applied **structural break detection** using the `ruptures` Python library, focusing on changes in partner shares and bilateral trade series. For forecasting, we employed classical time-series models including ARIMA and Holt–Winters to project short-horizon trade trajectories. Third, we developed an **environmental impact proxy** by mapping each bilateral flow to a shipping distance and converting these distances into indicative CO_2 emissions. This allowed us to measure not only the volume of re-routing under trade wars but also its potential environmental footprint. The entire pipeline was implemented in Python, integrating libraries such as `pandas`, `networkx`, `statsmodels`, and `plotly` for computation and visualization.

3.3 Limitations and Future Improvements

Despite its comprehensiveness, the dataset and methodology face several limitations. First, **data completeness** is constrained by reporting lags and quota restrictions of the Comtrade API, which may bias short-term results. Second, the HS2 aggregation level, while computationally tractable, may obscure product-level heterogeneity that is critical in certain trade disputes. Third, the environmental proxy relies on simplified great-circle distances and generic emission factors, which do not account for routing detours, vessel type, or fuel mix. Looking ahead, future research could address these limitations by (i) integrating higher-resolution HS6 or firm-level trade data where available; (ii) coupling Comtrade flows with shipping datasets (e.g., AIS vessel tracking) for more accurate distance and CO_2 calculations; and (iii) applying machine learning models for dynamic link prediction, thereby capturing how trade networks may evolve under new shocks or policy regimes.

4 Results

4.1 Network-level Summaries

To establish a baseline view of international trade, we aggregated flows by HS sections and years. The evidence suggests a growing structural role for technology-intensive goods.

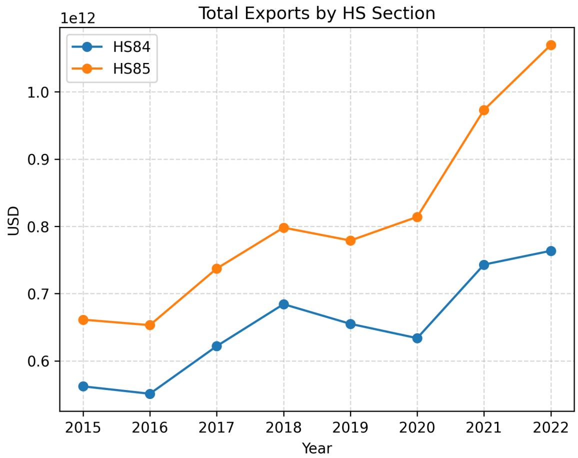

Figure 1: Total trade by HS section (2015–2022).

Figure 1 shows that HS85 (electrical machinery and equipment) expanded more rapidly than HS84 (mechanical machinery). This indicates that electronics, semiconductors, and ICT-related products have become increasingly central in shaping trade patterns. The divergence highlights how global supply chains are being reconfigured toward high-technology sectors.

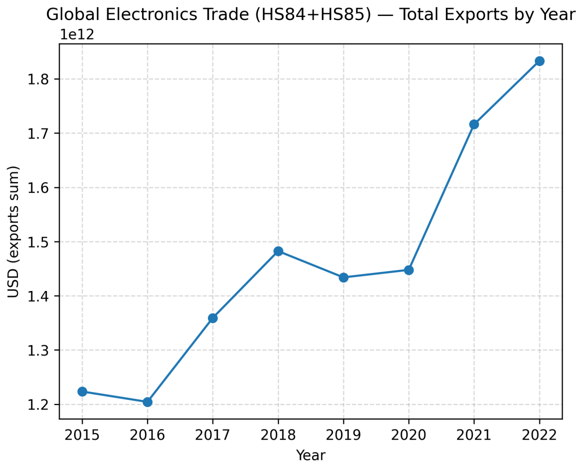

Figure 2: Total bilateral trade across all HS sections by year.

In Figure 2, aggregate trade volumes exhibit steady growth until 2018, followed by stagnation and a dramatic contraction in 2020, coinciding with the onset of COVID-19 and widespread mobility restrictions. The subsequent rebound in 2021 is tempered by global logistics bottlenecks and container shortages, while the 2022 profile reflects persistent supply–demand frictions and rerouting pressures in key manufacturing hubs. Taken together, these dynamics indicate both long-term structural reorientation and short-term vulnerability to systemic shocks.

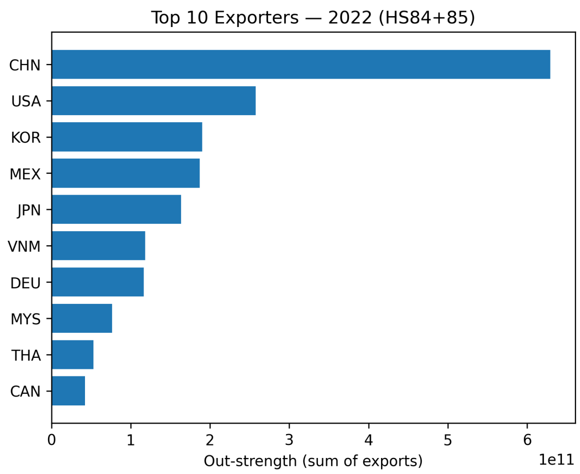

Figure 3: Top exporters in the last observed year.

Figure 3 shows that China and the United States remain dominant exporters, but their relative weight has declined. Vietnam and Mexico have gained prominence, signaling supply-chain diversification and regional substitution. Overall, these descriptive findings underscore how shocks and competitive dynamics jointly drive a redistribution of global market shares.

4.2 Structural Breaks and Forecasts

We next examined structural breaks in bilateral flows to detect statistically significant turning points.

Table 1: Summary of major structural breaks in bilateral trade flows.

Reporter	Partner	Year	Δ%
USA	CHN	2018	−22.40
USA	VNM	2019	15.70
MEX	USA	2020	−10.30
DEU	HS84 total	2020	−8.50

Table 1 summarizes the most notable breaks. These break dates align with identifiable historical shocks. The 2018 U.S.–China break coincides with tariff escalations that re-priced bilateral flows and incentivized partner substitution. The 2020 contractions across multiple pairs are synchronous with pandemic-era shutdowns and demand collapses. Post-2021 adjustments are consistent with reallocation under logistics congestion and precautionary diversification by firms seeking resilience.

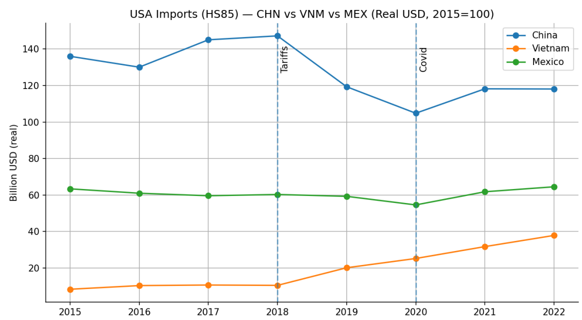

Figure 4: U.S. HS85 exports to three main partners (2015–2022).

Figure 4 illustrates these dynamics. The steep post-2018 decline in exports to China coincides with the redirection of U.S. flows toward Vietnam. The compensating effect demonstrates that supply chains rapidly reallocate when geopolitical frictions escalate. Mexico, meanwhile, exhibits less dramatic but still notable volatility, reflecting its intermediate role in North American production networks. Notably, the 2018 inflection is contemporaneous with tariff measures, while the 2020 trough aligns with pandemic disruptions; the subsequent rise toward Vietnam is consistent with substitution dynamics rather than a transient rebound.

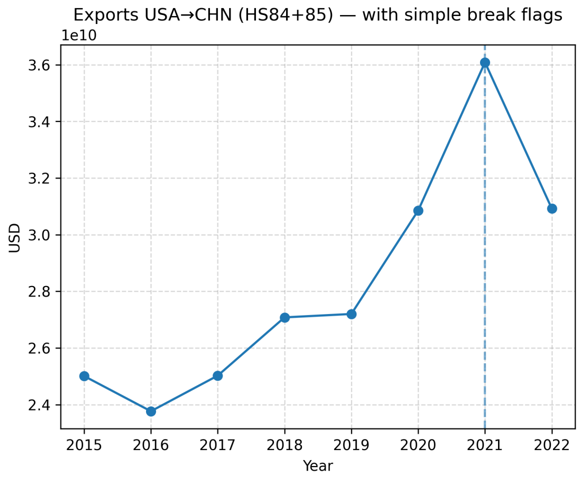

Figure 5: Detected structural break in bilateral USA–China HS85 trade.

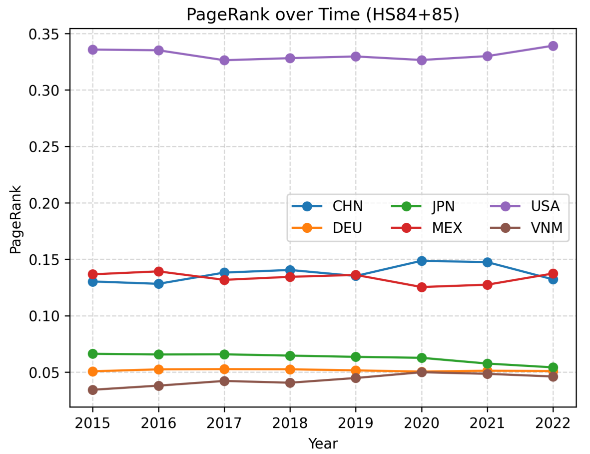

Figure 7: Dynamic evolution of partner centrality using PageRank (HS85).

Figure 5 zooms in on the USA–China relationship, where the structural break is statistically validated. This confirms that the trade war represented not just a temporary fluctuation but a systemic reconfiguration.

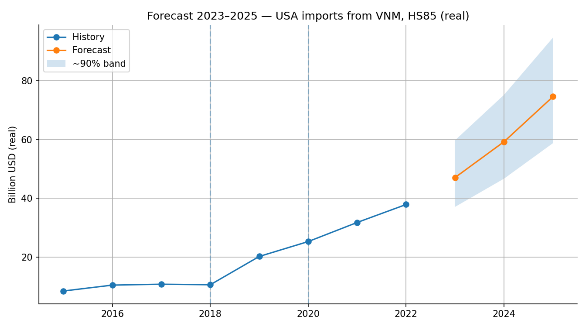

Figure 6: Forecast of U.S. imports from Vietnam (HS85).

Figure 6 projects continued growth in U.S. imports from Vietnam, reinforcing the idea that Vietnam is absorbing demand displaced from China. This trend illustrates how new trade relationships consolidate after shocks, potentially locking in long-term reconfigurations.

Figure 7 captures the network-wide implications. China's centrality declines after 2018, while Vietnam's rises, confirming systemic redistribution. Together, these findings show that geopolitical shocks not only affect bilateral flows but also rewire the topology of the global trade network.

4.3 Environmental Proxy: Distance and CO_2

Finally, we approximate the environmental implications of re-routing.

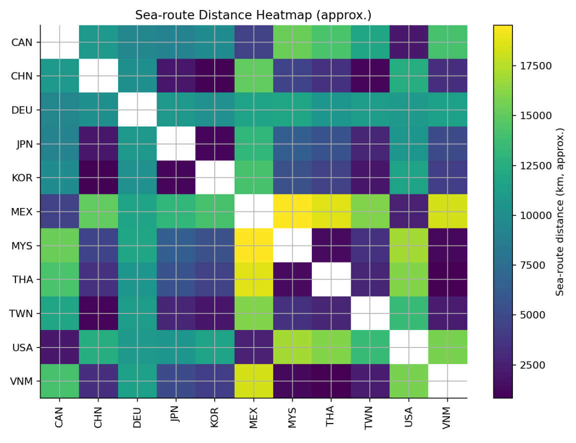

Figure 8: Heatmap of shipping distances for major trade flows.

Figure 8 demonstrates that trade reallocation after 2018 increased average transport distances. From 2021 onward, congestion at major ports and scheduling irregularities plausibly lengthened effective routes and dwell times. While our proxy relies on great-circle distances (and thus abstracts from detours and waiting), the observed increase in distances after 2018 is directionally consistent with these frictions.

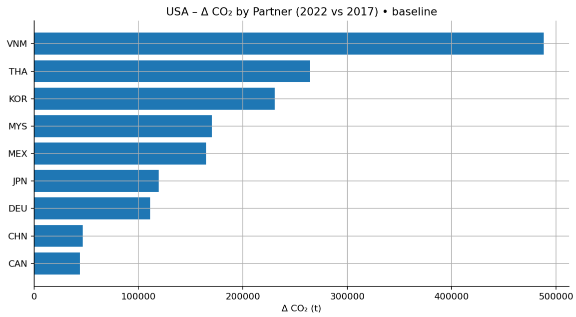

Figure 9: Change in U.S. CO_2 footprint between 2017 and 2022.

Figure 9 quantifies this, showing that U.S. CO_2 emissions from trade logistics rose substantially between 2017 and 2022. This suggests that supply chain diversification carries non-trivial environmental costs.

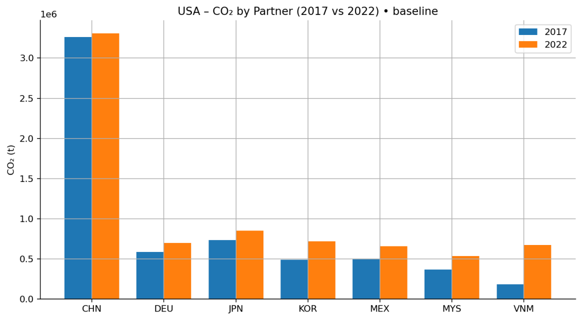

Figure 10: Comparison of U.S. CO_2 footprints (2017 vs. 2022).

Figure 10 compares absolute footprints across years. The 2022 profile is consistently higher, confirming that re-routing has not been carbon-neutral.

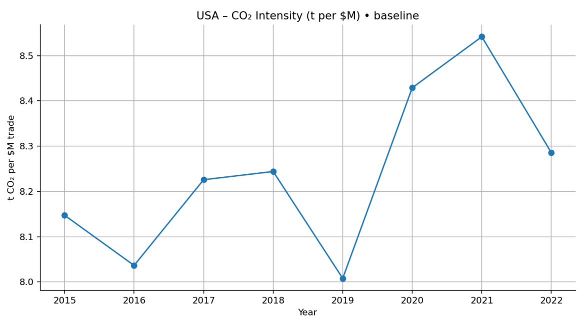

Figure 11: CO_2 intensity by reporter (2022).

Figure 11 shows cross-country variation: U.S. trade appears more carbon-intensive than German or Japanese trade, consistent with longer average shipping distances.

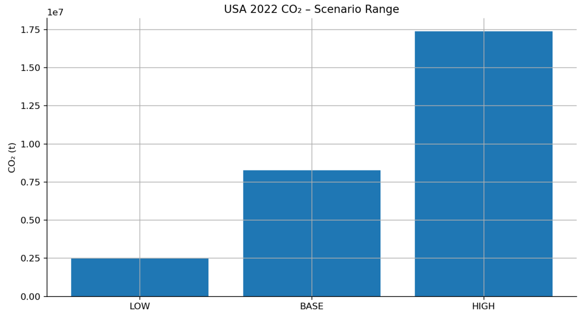

Figure 12: Sensitivity analysis of U.S. CO_2 estimates (2022).

Figure 12 provides a robustness check. Even under varying emission factors, the pattern of elevated U.S. CO_2 costs persists. The 2022 profile, shaped by heightened geopolitical uncertainty, reinforces the interpretation that rerouting pressures materially increased transport exposure even after the immediate pandemic shock.

5 Conclusions and Future Work

The empirical analysis of international trade flows under trade wars yields several key insights. First, the **network-level summaries** reveal a clear reorientation of global supply chains toward technology-intensive sectors, particularly HS85 (electrical machinery and equipment). This sectoral divergence underscores the strategic centrality of semiconductors and ICT goods in shaping both economic and geopolitical trajectories.

Second, the identification of **structural breaks and forecasts** highlights the disruptive power of policy shocks. The 2018 rupture in U.S.–China trade, followed by substitution effects favoring Vietnam, illustrates how trade networks adapt through partner reallocation. Forecasting results further suggest that such reallocations are not temporary adjustments but may solidify into enduring structural shifts within the global economy.

Third, the **environmental proxy analysis** demonstrates that supply-chain diversification has non-trivial ecological consequences. Longer average shipping distances, particularly for U.S. imports, translated into higher CO_2 proxies between 2017 and 2022. These findings caution that geopolitical resilience may come at the cost of sustainability, raising important trade-offs for policymakers.

Critically, the timing of detected breaks and the shape of aggregate trajectories cohere with the 2018 tariff escalation, the 2020 COVID-19 shock, and post-2021 logistics frictions, indicating that the measured network rewiring is historically anchored rather than spurious.

Taken together, these results provide a holistic picture of trade wars as both economic and environmental phenomena, characterized by sectoral concentration, partner substitution, and ecological intensification.

Future Work. Building on these contributions, future research should extend the granularity of analysis to HS6 or firm-level datasets, enabling a richer account of product-specific reconfigurations. Coupling Comtrade flows with maritime tracking data (e.g., AIS) would allow more precise estimation of transport distances and emissions, thereby strengthening the environmental dimension of the framework. Furthermore, incorporating graph-based machine learning methods for dynamic link prediction could enhance our ability to anticipate how global networks evolve under new policy regimes. These directions hold promise for advancing both the explanatory and predictive scope of trade network analysis under geopolitical uncertainty.

Data and Code Availability

All code, configuration files, and processed datasets used in this study are openly available at:
`https://github.com/kafire135/tradewar-net`

Acknowledgments

The author gratefully acknowledges the assistance of advanced AI tools, including ChatGPT and Perplexity AI, which supported the collection of background information and the implementation of methodological approaches whose results are presented in this paper.

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