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REM Working Paper 0387-2025

July 2025

REM – Research in Economics and Mathematics

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ISSN 2184-108X

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Deforestation Policies and the Architecture of Trade: A Network Perspective

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July 23, 2025

Abstract

This paper examines whether deforestation-related import regulations reshape the global trade network of forest-risk commodities such as soy, palm oil, timber, and paper. While existing research has focused on trade volumes and environmental outcomes, the structural effects of such policies on trade architecture remain underexplored. Using UN Comtrade data from 2004 to 2024 and a newly compiled dataset of import regulations, this study models global trade as a network of countries linked by bilateral flows. It applies a Difference-in-Differences framework to estimate how policy exposure affects country-level centrality, combined with community detection and modular realignment metrics to track changes in trade bloc configurations. Results show modest structural shifts. Treated importers often experience increased eigenvector centrality and reduced out-degree, especially under certification and market-based policies. However, effects are generally small and not consistently significant across all specifications. Modular realignment analysis reveals that only a few policies lead to measurable changes in trade community structure. The findings suggest that deforestation-related trade regulations can influence the architecture of global trade networks, but their structural impact depends heavily on policy design and enforcement. This paper contributes a novel network perspective to the literature on environmental trade governance.

Keywords:

Deforestation, Network Analysis, Modular Realignment, Global Supply Chain

1 Introduction

Deforestation remains one of the most pressing ecological challenges of our time, with profound implications for climate stability, biodiversity loss, and the livelihoods of millions of people who depend on forest ecosystems. Over the past three decades, the planet has lost more than 420 million hectares of forest, with tropical regions in South America, Southeast Asia, and Central Africa experiencing the most severe declines ([Food and Agriculture Organization of the United Nations](#)). Agricultural expansion especially for specific commodities such as soy, palm oil, timber, and paper accounts for over 80 percent of global deforestation ([Curtis et al.](#); [Pendrill et al.](#)). In response, a growing number of governments have introduced trade-based regulatory instruments ranging from due diligence frameworks to import restrictions in an effort to reduce the deforestation embedded in cross-border supply chains ([Union](#); [USA](#)).

While a substantial area of literature has explored the environmental effectiveness and economic implications of such regulations, far less attention has been paid to their structural consequences for the global trade system itself. This paper approaches the issue from a network-theoretic perspective, looking at the international trade of forest-risk commodities as a dynamic and interdependent system of relationships. Using network analysis offers a powerful set of tools to trace how policy shocks propagate through the system, potentially reshaping trade relations, rerouting flows, and reorganizing the modular structure of trade blocs. By moving beyond bilateral trade values, this perspective highlights how environmental policy can transform not only what is traded, but who trades with whom, and under what structural constraints.

This paper is built on three central research questions. While networks are often used to model global trade, including the trade of forest-risk commodities (FRC), do deforestation-related import policies reshape the trade network of FRC? If so, do their effects vary by policy type and do effects appear in community-level trade?

By addressing these questions, the paper contributes to the growing literature combining environmental governance and international trade by focusing on the structural effects of trade regulation. It begins with a review of the interdisciplinary literature on trade, deforestation, and network analysis. This is followed by a description of the data sources and the construction of the panel dataset. The next part outlines the methodological framework, including the use of centrality metrics, community detection, modular realignment, and robustness checks. The empirical results are then presented and interpreted, followed by a discussion of their broader implications. The paper concludes with a summary of findings and suggestions for future research.

2 Related Literature

Recent years have witnessed a surge in interdisciplinary studies that analyze the structural properties of global trade and environmental governance using tools from network science and input-output modeling. The integration of environmentally extended input-output (EEIO) analysis with complex network analysis has become a dominant methodological approach in efforts to uncover the embedded environmental impacts of international trade,

particularly in sectors linked to deforestation and climate change.

One of the most prominent trends in this literature is the increasing use of EEIO and multi-regional input–output (MRIO) models, often augmented by network-theoretic methods. For instance, [Zhu et al.](#) introduced the concept of “Global Value Trees” to demonstrate that global value chains tend to exhibit tree-like rather than linear structures. [Cerina et al.](#) advanced this line of inquiry by treating the World Input–Output Database as a network, applying clustering and centrality metrics to reveal community structures and the rise of Asian economies. Similarly, [Cornaro and Rizzini](#) proposed a multilayer network approach using the MD-HITS algorithm to uncover region-sector interdependencies in embodied energy flows, further highlighting the utility of network centrality metrics in global trade analysis.

Parallel to these developments in economic trade modeling, network analysis has also gained traction in the policy literature. [Carattini et al.](#) applied social network analysis to the architecture of international environmental agreements, identifying stylized structural features such as increased connectivity, regional clustering, and persistent asymmetries in global cooperation. [Wang and Zhang](#) contributed to this strand by modeling Chinese energy policy diffusion through both actor–collaboration and topic–network layers, demonstrating how centrality in policy and knowledge networks influences diffusion dynamics.

Several themes recur throughout this literature. First is the emphasis on network-driven diffusion whether in trade or environmental governance, structural position within a network and is often measured via centrality metrics that correlates strongly with influence and exposure ([Carattini et al.](#); [Zhu et al.](#); [Cerina et al.](#)).

A second theme is the embodiment of environmental externalities in trade flows. [Zhang, Liu, et al.](#) and [Cornaro and Rizzini](#) emphasize how deforestation and carbon emissions are transferred across borders through embedded trade in forest-risk commodities, using MRIO networks and centrality rankings to identify key polluters and gatekeepers.¹

A third emerging theme is the modularity of trade networks, where clustering and community detection algorithms reveal blocs of countries or sectors that are more tightly interconnected. These modular structures often align with geopolitical or commodity-specific trade patterns, offering new insights into trade resilience and policy spillover effects ([Cerina et al.](#); [Grassi, Riccaboni, et al.](#)).

Despite shared methodologies, the literature presents several areas of disagreement. One recurring debate concerns the appropriate level of granularity. EEIO studies frequently aggregate data at the country-sector level, which can obscure important firm- or product-level dynamics. [Cornaro and Rizzini](#) attempt to address this through a multilayer framework, though computational complexity remains a constraint.

A second point of tension is between topological representations. Some studies frame trade networks as hierarchical or tree-like structures ([Zhu et al.](#)), while others emphasize decentralized, small-world, or modular properties ([Cerina et al.](#); [Zhang, Liu, et al.](#)). These differing representations can lead to divergent policy implications, particularly regarding vulnerability and resilience.

¹In network analysis, a gatekeeper node connects different groups or communities, controlling the flow of goods, information, or influence between them

Finally, while some papers, such as [Wang and Zhang](#), highlight the dynamic nature of policy and topic diffusion, most EEIO-network studies remain static in nature, offering snapshots of trade at given points in time. This limits their ability to account for feedback effects, rerouting, or structural evolution following policy shocks.

Among the reviewed works, [Cerina et al.](#) emerges as particularly influential. Their study pioneered the application of community detection and centrality metrics to the World Input–Output Network, introducing the concept of modular structures in trade and showing how economic globalization has reshaped these communities. This paper serves as a methodological and conceptual foundation for many subsequent studies.

Similarly, [Carattini et al.](#) marks a turning point in the network analysis of environmental policy, shifting the focus from individual treaties to systemic patterns of cooperation and diffusion. These contributions helped establish network analysis as a legitimate and powerful tool in both trade and environmental governance research.

Despite the breadth of existing work, several gaps persist. First, while many studies quantify trade-embedded environmental impacts, few directly assess how environmental policies reshape the structure of trade networks themselves. Second, the majority of research remains static or descriptive, lacking tools to identify structural realignments over time or in response to exogenous shocks. Third, although community detection is used to uncover trade blocs, modular realignment following policy interventions is rarely examined.

This paper addresses these gaps by conducting a structural network analysis combined with modular realignment metrics to assess how deforestation-related import regulations reshape the architecture of global trade in forest-risk commodities. Building on the centrality-based community detection approach of [Grassi, Riccaboni, et al.](#), it introduces the use of Adjusted Rand Index and Normalized Mutual Information to quantify how trade community structures evolve pre- and post-policy implementation. This allows for a nuanced assessment of policy effectiveness and trade rerouting, moving beyond volume-based analyses to capture changes in network topology.

By focusing on structural reconfiguration, this research offers a novel contribution to the literature on environmental trade governance. It complements existing EEIO-based studies by examining not only who trades with whom, but how hierarchical positions and community affiliations shift in the wake of sustainability regulations.

3 Data

This study combines bilateral trade data from the UN Comtrade Database with a curated dataset of deforestation-related import policies. The integrated panel spans the years 2004 to 2024 and focuses on four commodity groups identified as primary drivers of tropical deforestation: soy, palm oil, timber, and paper. The resulting dataset enables a structural analysis of trade responses to environmental policy interventions.

3.1 Trade Data: UN Comtrade

The primary data source for international trade flows is the United Nations Comtrade Database [United Nations Statistics Division](#). UN Comtrade offers the most comprehensive and harmonized repository of official international trade statistics. The data are reported by national customs authorities and standardized by the UN Statistics Division. Each observation in the database represents the value and quantity of goods traded between a reporter (exporting country) and a partner (importing country), disaggregated by year, commodity code, and trade flow direction.

The sample covers annual trade data from 2004 to 2024, providing a 20-year panel across nearly all UN member states. This time frame encompasses major shifts in global commodity markets, the expansion of supply chain sustainability initiatives, and the adoption of several deforestation-related policies, enabling pre- and post-treatment comparison.

The analysis focuses on four key commodity groups:

- **Palm oil and derivatives:** Harmonized System (HS) code 1511.
- **Soybeans and derivatives:** HS 1201 (soybeans), HS 1507 (soybean oil and its fractions)
- **Timber and wood-based products:** HS 44 (wood and articles of wood).
- **Paper and pulp:** HS 48 (paper and paperboard).

These codes were selected based on their documented association with deforestation in the literature such as [Pendrill et al.](#) or [Curtis et al.](#) and their relevance to existing regulatory regimes.

To ensure consistency across reporting countries and years, all FOB (Free on Board) trade values are converted to constant USD using the World Bank deflator for trade values. Duplicate or conflicting records e.g., cases where both the importer and exporter report different values for the same transaction are resolved using a reporter-priority rule, prioritizing data provided by the exporter. Commodity codes are harmonized to the 6-digit HS 2012 standard to ensure compatibility across time.

For the network construction, bilateral trade flows are aggregated at the exporter, importer, year and commodity level. For each year, this produces a directed and weighted trade network $G_t = (V, E_t)$, where nodes V are countries and edges E_t represent the volume of trade from one country to another. The edge weights are interpreted as the intensity of trade relationships. This temporal sequence of graphs forms the basis for both the structural network metrics such as eigenvector centrality or in-degree and the modular realignment analysis.

Policy Data

To identify and quantify the impact of deforestation-related regulations, a novel policy dataset was constructed by synthesizing multiple sources of legal, institutional, and NGO-based information. Legal data were sourced primarily from [European Union](#), the official legal portal of the European Union, which provides comprehensive access to EU legislation, policy proposals, and legal acts in all EU languages ([European Union](#)). For U.S.

regulations, the [U.S. National Archives and Records Administration](#) was used as the central repository of government-issued rules, proposed rules, and public notices, maintained by the U.S. National Archives and Records Administration ([U.S. National Archives and Records Administration](#)). In addition, national legal portals such as Brazil’s [Presidência da República do Brasil](#), Australia’s [U.S. National Archives and Records Administration](#), and Indonesia’s [Government of Indonesia](#) (Jaringan Dokumentasi dan Informasi Hukum) were consulted to obtain the full legal text and implementation details of country-specific forest-related trade policies ([Presidência da República do Brasil](#); [Australian Government](#); [Government of Indonesia](#)). This legal foundation was enriched with curated datasets and policy trackers maintained by environmental NGOs and academic institutions, including [Forest Trends](#), [Trase](#), [World Wide Fund for Nature](#), and [Chatham House](#). Further contextual and structural information was gathered from trade-focused policy briefs and datasets published by multilateral organizations such as the [World Trade Organization](#), [Organisation for Economic Co-operation and Development](#), [Food and Agriculture Organization of the United Nations](#), [United Nations Environment Programme](#), and [International Tropical Timber Organization](#).

A policy was included in the dataset only if it explicitly targeted at least one of the four focal commodities soy, palm oil, timber, or paper and if it was enforceable at the national level. Policies had to contain provisions that explicitly linked international trade or market access to forest-related criteria, such as sustainability, legality, or deforestation-free sourcing. Measures that focused solely on domestic land-use regulation without any trade implications were excluded, as were voluntary private-sector schemes unless directly embedded in binding national law [Organisation for Economic Co-operation and Development](#).

Each policy entry in the dataset was meticulously structured and includes detailed metadata on jurisdictional origin, legal identifiers, and formal titles, as well as a timeline of key dates for proposal, adoption, and enforcement. The dataset also records the commodity coverage of each regulation, indicating whether it targets soy, palm oil, timber, or paper. Mechanisms of enforcement vary across policies and include due diligence frameworks, mandatory certification requirements, import bans, tariff instruments, and systems for legality verification. The targeting logic of each policy was categorized based on whether restrictions were jurisdiction-wide, commodity-specific, or directed at particular firms or supply chains. For instance, the EU Timber Regulation (EUTR) [EU](#) prohibits placing illegally harvested timber on the EU market, requiring importers to conduct due diligence and maintain supply chain traceability. Another example is the amended U.S. Lacey Act (2008) [USA](#), which makes it unlawful to import wood products sourced in violation of foreign laws, and has led to seizures and re-routing of supply chains, especially from Southeast Asia.

In total, the dataset comprises sixteen distinct policies spanning a broad geographic and legal spectrum. These include the EU Deforestation Regulation (EUDR) [Union](#), the EUTR [EU](#), the EU FLEGT Action Plan [EU](#), the amended U.S. Lacey Act of 2008 [USA](#), Australia’s Illegal Logging Prohibition Act of 2012 [USA](#), Brazil’s Forest Code (Law 12.651/2012 [BRA](#), the Soy Moratorium in Brazil [BRA](#), the Ghana Timber Legality Assurance System [GHA](#), Indonesia’s ISPO certification scheme [IDN](#), Malaysia’s MSPO system

[MYS](#), and the UK’s Environment Act of 2021 [GBR](#) which regulates forest-risk commodities. In addition, several tariff-based import measures were included, such as India’s 2024 vegetable oil tariffs [IND](#), the EU’s palm oil ILUC exclusion and MFN tariff adjustments [EU](#), and Thailand’s MFN tariffs on soybeans and soymeal [THA](#). Each of these policies was reviewed to ensure its relevance to the empirical objectives of this study.

Based on this information, a binary treatment variable was created at the importer-commodity-year level. This indicator reflects whether a given trade flow was subject to a deforestation-related import regulation, taking into account the relevant partner country, targeted commodity, and timing of enforcement. Commodities were considered treated once a regulation became binding for that importer.

To capture the diversity in policy strength, targeting, and enforceability, all policies were grouped into a smaller number of analytically meaningful clusters. This step was necessary to avoid clusters with only one or two policies, which would weaken the power of the statistical analysis. The clustering was done by consolidating the original policy types into six broader categories based on enforcement structure and regulatory design. The resulting clusters are: (1) due diligence frameworks; (2) certification-based schemes; (3) voluntary partnership and bilateral agreements; (4) land use and forest protection laws with indirect trade implications; (5) import bans and other direct legal prohibitions; and (6) tariff-based instruments including product-specific duties and trade preferences. These clusters are used both to test heterogeneity in policy impact and to improve the robustness of causal identification by pooling similar interventions. Each implementation of a new policy is treated as a "shock". For example the implementation of the EUDR in 2023 [Union](#). Once adopted, this regulation created an immediate compliance requirement for EU importers of forest-risk commodities, especially palm oil and soy. Countries like Indonesia and Malaysia faced abrupt shifts in trade relationships as exporters scrambled to meet new traceability and deforestation-free criteria. These events are treated as structural shocks in the panel regression framework.

The resulting dataset is a high-dimensional, unbalanced panel that spans over 190 exporters and an equally large set of importers across 21 years. Each observation in this dataset contains multiple layers of information, including FOB trade values, HS-based commodity classifications, pre-computed network centrality measures such as eigenvector centrality, betweenness centrality, in-degree, out-degree, closeness, and PageRank, and community assignments derived from hierarchical clustering on centrality similarity. The dataset also includes policy treatment indicators, policy cluster assignments, and computed variables for direct and network-mediated policy exposure. Together, this richly layered dataset provides the empirical foundation for assessing how deforestation-related import policies reverberate through the structure of international trade.

4 Methodology

This study adopts a structural network analysis framework to investigate how deforestation-related import policies reshape the topology of global trade in forest-risk commodities. Rather than limiting the scope to changes in trade volume, the approach focuses on the evolving architecture of trade relationships between countries. To capture this, the methodology combines network visualization, multi-attribute centrality measures, and community detection with a Difference-in-Differences -inspired panel regression strategy. In addition, a modular realignment analysis is implemented to track whether the broader structure of trade blocs shifts in response to policy interventions, providing a complementary view of systemic change beyond node-level indicators.

The methodology unfolds in four main steps. First, annual undirected and weighted trade networks are constructed using the data described in the section before. Second, centrality measures and community detection are applied to each network to assess both the hierarchical position and trade bloc membership of countries. Third, static panel regressions estimate the effect of policy exposure on centrality outcomes, incorporating policy clusters to account for regulatory heterogeneity. Fourth, modular realignment metrics—specifically the Adjusted Rand Index and Normalized Mutual Information are used to quantify changes in community composition before and after each policy shock. These are interpreted as indicators of trade reorganization, with robustness checks including placebo timing and null model comparisons to assess the credibility of the observed effects.

4.1 Defining Networks

In this analysis, the international trade system is represented as a sequence of undirected, weighted networks, where nodes represent countries and edges capture bilateral trade relationships in deforestation-linked commodities. For investigating how those countries are interconnected through trade, how their connections evolve over time, and how environmental trade regulations such as import policies alter the structure of these relationships, this study uses a network analysis framework.

The construction of the networks is based on the bilateral trade data from the UN Comtrade Database. For each year between 2004 and 2024, a separate network is constructed that captures global trade in a selected set of forest-risk commodities. Each network is modeled as an undirected, weighted graph, where a trade connection is established between two countries if either one reports a trade relationship involving the relevant commodities. This reflects mutual trade linkages, without imposing directionality based on reporting convention. The weight assigned to each edge corresponds to the total Free on Board (FOB) trade value in USD exchanged between the countries in that year.

Formally, each network $G_t = (V_t, E_t)$ in year t consists of a set of nodes V_t , representing all countries engaged in trade of forest-risk commodities, and a set of undirected edges E_t , where an edge $\{i, j\}$ is included if countries i and j trade any of the relevant goods. The weight w_{ij}^t on each edge reflects the total value of these bilateral trade flows in year t .

Although the underlying trade flows are inherently directional, modeling the networks as undirected offers a clearer perspective on structural integration and interdependence between countries. This simplification is particularly useful for exploring how global trade architecture responds to policy shocks. Future extensions may consider reinstating directionality to examine asymmetries in trade exposure or regulatory burden.

4.1.1 Visualizing the Network

To gain insights into the structure and dynamics of global trade in forest-risk commodities, the annual networks is visualized using a geographic layout based on country coordinates. Visualizing the network on a world map facilitates an intuitive understanding of spatial trade patterns and the regional distribution of trade hubs. Countries are displayed as nodes, and edges are drawn proportional to the FOB trade value.

Additionally, the nodes are scaled by trade volume or centrality measures such as degree or eigenvector centrality, helping to identify prominent exporters and brokers within the network. Visualizations are also produced as dynamic sequences to track how trade linkages and centrality evolve over time, particularly in response to environmental trade regulations.

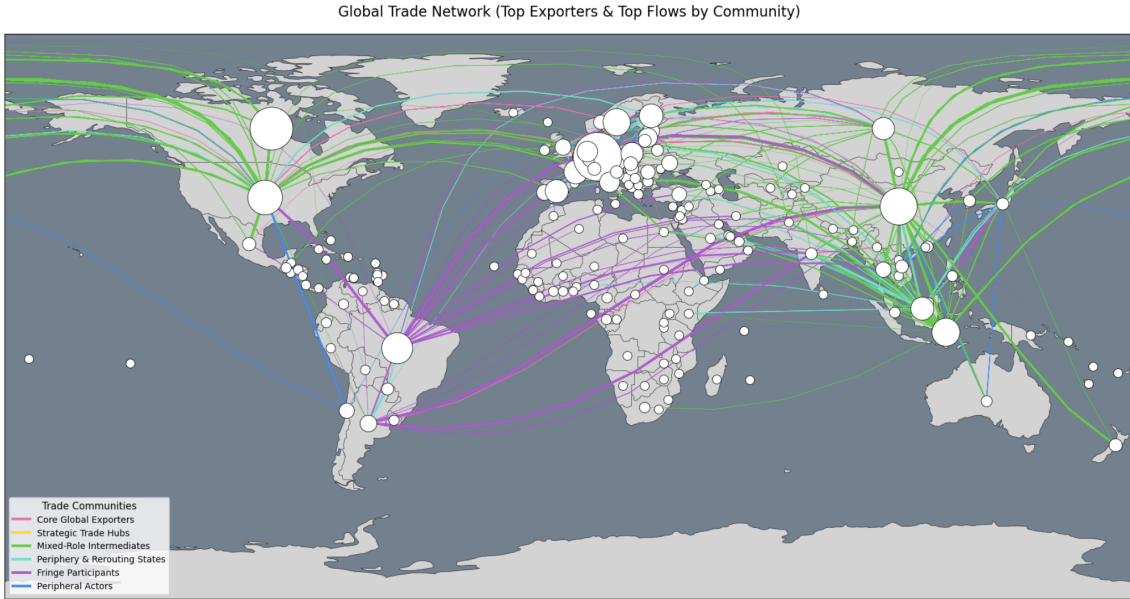


Figure 1: Global trade network of forest-risk commodities. Nodes represent exporting countries, scaled by their total trade volume (FOB value). Edges denote top 1% of trade flows, color-coded by the exporter's structural trade community.

Figure 1 illustrates the global trade network of forest-risk commodities, overlaid on a world map. Each node corresponds to an exporting country and is plotted at its geographical coordinates. Node size is proportional to the country's total trade value, capturing its economic weight in the global supply chain. To improve interpretability and focus on structurally significant flows, the 20 countries with the lowest trade volume were excluded and only the top 1% of trade flows are visualized.

To complement the main visualization, Appendix 8 presents separate network maps

for each detected trade community. These detailed visualizations isolate the subnetwork structure within each cluster, using the same geographical layout, visual scaling, and community-specific color scheme as in the main figure. This disaggregated view helps highlight intra-community trade intensity, geographic dispersion, and the role of central versus peripheral actors in each bloc. Each network graph is visualized without the thresholds used in the overall graph before.

4.1.2 Community Detection

In order to understand how policy shocks interact with the structural architecture of global trade, it is helpful to identify trade blocs that reflect shared trading patterns. Detecting these communities enables this analysis of both within-group and cross-group network responses to deforestation-related import policies. To detect structural communities within the trade network, the multi-attribute clustering method proposed by [Grassi, Riccaboni, et al.](#) is implemented. This method is designed to overcome the limitations of modularity-based or single-attribute clustering methods [Xiang et al.](#) by capturing countries' relative positions in the global trade system across multiple dimensions.

The procedure consists of four main steps. First, a set of centrality measures for each country in the network is being computed. The centrality measures used are degree centrality, which reflects the number of trade partners, betweenness centrality, which captures brokerage roles, closeness centrality, which measures average network distance, and eigenvector centrality, which identifies countries connected to other central nodes.

Second, all countries are ranked and a rank profile for each centrality measure is constructed. This yields a multi-dimensional representation of each country based on its structural position across different centralities.

The third step consists of computing a Spearman rank correlation matrix, capturing the pairwise similarity of countries' centrality profiles. This non-parametric similarity measure allows me to identify countries that play structurally similar roles in the network, regardless of magnitude.

Fourth and finally, agglomerative hierarchical clustering using the dissimilarity matrix derived from the Spearman correlations is applied. This process merges countries into a nested tree-like structure known as a dendrogram and is cut at a height selected through silhouette analysis and visual inspection of cluster stability (see Appendix Figure 7). In this context, a hierarchical structure refers specifically to a tree-shaped nested grouping, where countries are organized into increasingly larger modules that reflect different degrees of structural similarity in their centrality profiles. This differs from more general tree concepts and characterizes a specific form of nested clustering [Ravasz and Barabási](#).

The results for each cluster are visualized in 2. The numbers show how many countries, or nodes, belong to each cluster and that the distribution is relatively even. The results for each cluster are visualized in

Cluster 0 is labeled as Core Global Exporters and includes countries with consistently high export volumes in forest-risk commodities, such as Brazil, Indonesia, or the United States. These countries often serve as primary suppliers in global value chains. Cluster 1 is referred to as Strategic Trade Hubs and contains countries like the Netherlands or

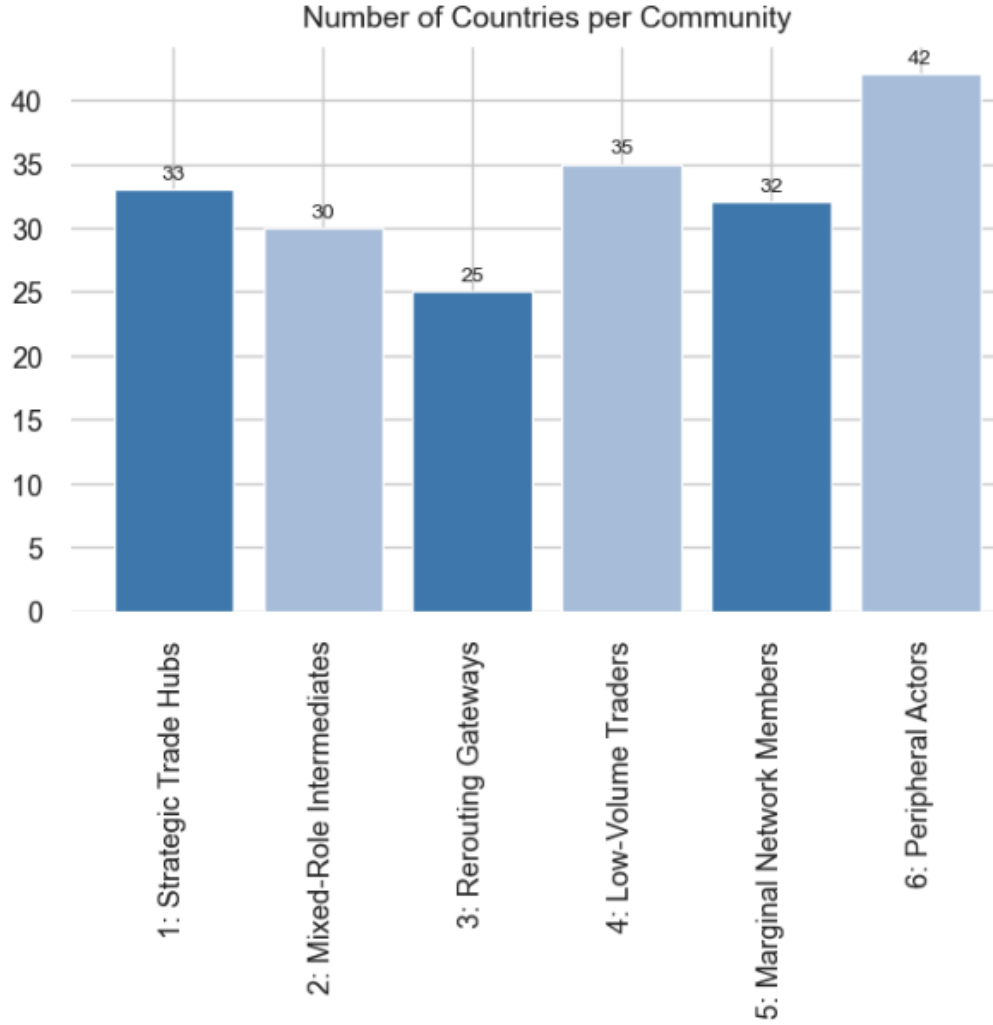


Figure 2: Number of Countries per detected Community

Singapore, which hold central positions due to their high connectivity and role in re-exporting, often without producing the commodities themselves. Cluster 2 is described as Mixed-Role Intermediates and comprises countries with hybrid roles both importing and exporting forest-risk goods which are often serving as regional connectors with moderate centrality. Cluster 3 is named Rerouting Gateways and includes countries that tend to absorb trade flows redirected due to policy changes or market disruptions, making them important in the analysis of trade diversion and leakage. Cluster 4 is defined as Low-Volume Traders and groups countries with limited participation in the trade network, either because of low demand or supply of the focal commodities. Finally, Cluster 5 is labeled as Peripheral Actors and refers to actors on the edge of the network with minimal connectivity or strategic importance, but whose inclusion ensures global coverage of trade dynamics.

This method is particularly well-suited for trade network analysis because it captures both direct trade intensity and broader topological roles. By combining multiple centrality dimensions, it avoids overemphasizing a single structural trait and provides more robust, interpretable groupings. As demonstrated in [Grassi, Riccaboni, et al.](#), multi-attribute clustering outperforms standard modularity approaches in generating communities that align with known geopolitical and economic blocs.

This can be explained when having a closer look into the interpretation of each network-specific measure used to cluster the country nodes. In-degree and out-degree centrality capture the number of unique import and export links a country maintains, reflecting its direct participation as a buyer or supplier in the network. Closeness centrality highlights countries that are more “centrally located” in terms of trade distance, suggesting strategic accessibility and reduced dependency on intermediaries. Betweenness centrality reveals broker positions meaning countries that disproportionately lie on the shortest trade paths and thus play critical roles in rerouting flows. Eigenvector centrality assigns higher values to countries that are connected to other influential partners, thus identifying globally embedded hubs in the trade architecture. PageRank, a flow-based measure, weights connections recursively and is especially useful for highlighting countries that are systemically important in sustaining trade flows across multiple commodity chains.

Figure 3 ranks the countries for each centrality measure and shows the top 10 in the respective category.

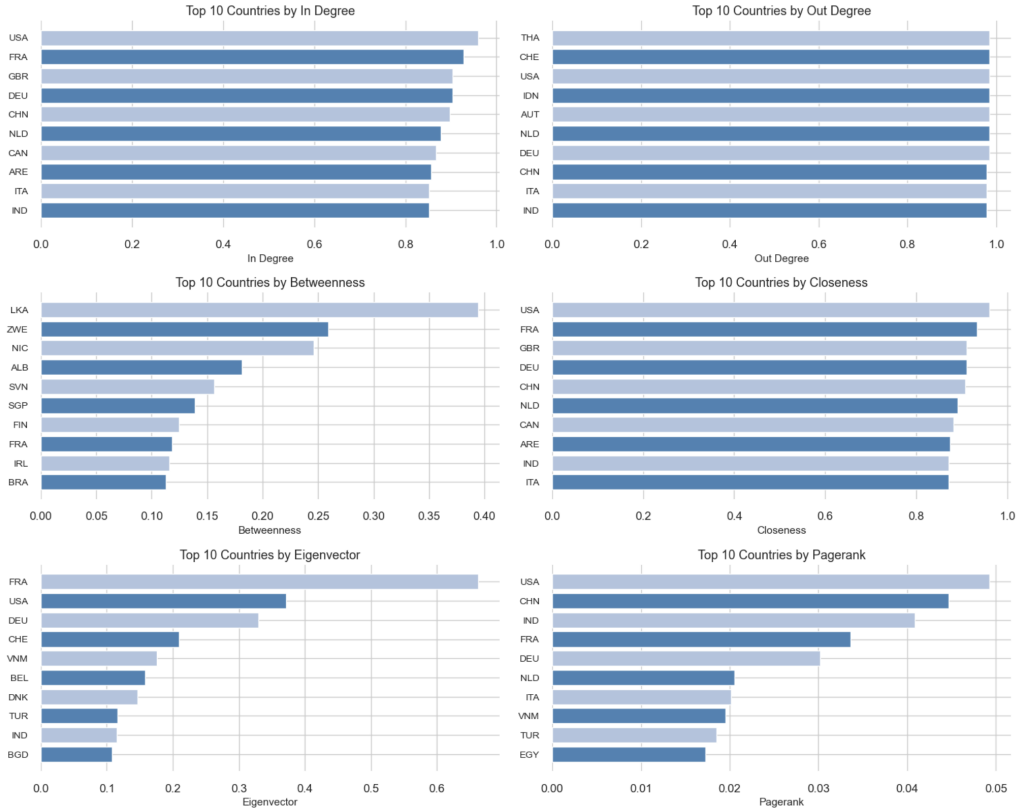


Figure 3: Top 10 Countries by Centrality Measures

France, which ranks highest in terms of eigenvector centrality, appears deeply embedded in the core of the trade network. This is not simply because of the number of its trade links, but because it trades with other central and well-connected countries. This highlights France’s integration into highly active trade circuits for forest-risk goods, likely driven by its role as both a consumer and an intermediate trade node, especially within the EU. Similarly, the USA appears consistently in the top three across in-degree, closeness, eigenvector, and PageRank centrality, reflecting its status as a major importer with globally diversified sourcing patterns and strong systemic influence. China and Germany also

score highly across most metrics, reaffirming their role as trade anchors with far-reaching direct and indirect connections.

Interestingly, countries such as Sri Lanka and Zimbabwe emerge with unexpectedly high betweenness centrality, indicating that while they may not dominate trade volumes, they function as key bridges or rerouting points between otherwise disconnected regions or clusters. This is particularly relevant for understanding how policy shocks in core import markets e.g. EU or US due diligence regulations might propagate through the network, potentially rerouting flows through such intermediaries.

In the context of this study, such communities offer a meaningful lens to understand the transmission of trade shocks. Since countries with similar centrality profiles are more likely to respond similarly to disruptions or reroute flows among each other, community-based analysis enhances the empirical identification of rerouting channels. It also allows me to disaggregate between within-community and between-community propagation effects, offering deeper insight into the systemic impact of import policy interventions.

Moreover, this approach is computationally tractable and replicable, making it suitable for application to annual snapshots over two decades of global trade. It supports a dynamic perspective on how trade communities evolve, merge, or fragment in response to external shocks such as deforestation regulations.

From a modeling perspective, the identification of trade communities adds valuable structure to the network shock propagation framework. By distinguishing between within-community and between-community transmission of policy shocks, I can assess not only whether there are indicators if trade flows are rerouted but also the systemic boundaries along which they are redirected. This deepens the interpretability of the results by linking rerouting behavior to the underlying topology of the global trade system. It also enables testing whether shocks remain contained within tightly integrated blocs or diffuse across structural boundaries, providing a nuanced understanding of the resilience and adaptability of trade relationships.

4.2 Investigating Effects of Policy Shocks on the Trade Network

As mentioned before, this study investigates how deforestation-related import policies reshape the global trade network. After creating the network and detecting structural communities, I aim to identify persistent changes in network topology—particularly in country centrality and trade bloc affiliations—before and after policy implementation. This approach emphasizes long-run structural reconfiguration rather than short-run trade responses, using static snapshots of the network to assess policy effects on hierarchy and cohesion.

To that end, three complementary structural analysis approaches are implemented, each designed to answer a specific dimension of the research questions. The first estimates the average structural effect of deforestation-related import policies across all treated country pairs. The second adds structural granularity by controlling for trade communities and estimating community-specific treatment responses. The third disaggregates treatment effects into within-community versus between-community changes to

trace the direction of structural reorganization.

The general static regression model follows a Difference-in-Differences framework:

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot \text{TreatedPost}_{it} + \varepsilon_{it} \quad (1)$$

This model estimates how a network outcome Y_{it} , such as a centrality measure, evolves for treated countries after a policy is enacted, relative to untreated countries. The components are defined as follows:

- Y_{it} : The outcome variable of interest for importer country i in year t . This could be, for example, eigenvector centrality or log trade volume.
- α_i : Country fixed effects that control for all time-invariant heterogeneity across countries (e.g. geography, size, baseline trade behavior).
- δ_t : Year fixed effects that absorb global shocks or shared temporal trends (e.g. financial crises, commodity price cycles).
- TreatedPost_{it} : A binary interaction term equal to 1 if country i is in the post-policy period at time t ; 0 otherwise.
- β : The coefficient of interest, estimating the average structural effect of policy implementation across treated countries.
- ε_{it} : The error term, clustered at the country level to address serial correlation and heteroskedasticity.

The second specification introduces trade community structure to test for heterogeneous effects across detected communities. One formulation includes interaction terms for community-specific treatment effects:

$$Y_{it} = \alpha_i + \delta_t + \sum_g \beta_g \cdot \text{TreatedPost}_{it} \cdot \mathbf{1}_{\{i \in g\}} + \varepsilon_{it} \quad (2)$$

where g indexes communities and β_g captures treatment effects specific to each trade bloc. $\mathbf{1}_{\{i \in g\}}$ is an indicator function that equals 1 if country i belongs to trade community g , and 0 otherwise. This specification allows the model to estimate how deforestation-related import policies affect countries differently depending on their structural community within the trade network.

The third and most granular static analysis decomposes the treatment effect by network boundaries. This allows me to estimate how much of the observed change is due to internal restructuring within communities versus shifts across community lines:

$$Y_{it} = \alpha_i + \delta_t + \theta_{\text{within}} \cdot \text{TreatedPost}_{it}^{\text{within}} + \theta_{\text{between}} \cdot \text{TreatedPost}_{it}^{\text{between}} + \varepsilon_{it} \quad (3)$$

where:

- Y_{it} is the network outcome of interest (e.g., centrality score) for country i in year t ,
- α_i captures country fixed effects accounting for unobserved, time-invariant heterogeneity,

- δ_t captures year fixed effects accounting for global shocks and temporal trends,
- $\text{TreatedPost}_{it}^{\text{within}}$ is an indicator for treatment effects occurring within the same community,
- $\text{TreatedPost}_{it}^{\text{between}}$ is an indicator for treatment effects transmitted across community boundaries,
- θ_{within} and θ_{between} are the coefficients capturing rerouting effects within and between communities,
- ε_{it} is the error term clustered at the appropriate level.

Together, these three modeling layers provide a robust framework to detect, disaggregate, and interpret how environmental trade policy shocks reverberate through the global trade network. By comparing outcomes across different specifications, the assessment does not only look at whether the network structure responds to regulation, but also how that response varies by structural embeddedness and trade bloc alignment.

4.2.1 Heterogeneous Effects by Policy Cluster

To capture regulatory heterogeneity, the analysis extends the static regression framework by incorporating policy clusters. Policies are grouped into four distinct categories based on their legal design and enforcement mechanisms:

1. certification and regulatory instruments,
2. due diligence and transparency requirements,
3. voluntary agreements and soft law initiatives, and
4. market instruments, including tariffs and import restrictions.

These clusters enable the estimation of heterogeneous treatment effects and allow for a structured comparison across different types of deforestation-related regulatory approaches.

Formally, the regression model is re-estimated separately for each policy cluster k as follows:

$$Y_{ict}^k = \alpha_i + \delta_t + \beta^k \cdot \text{TreatedPost}_{ict}^k + \varepsilon_{ict}^k \quad (4)$$

where:

- Y_{ict}^k denotes the network outcome of interest (such as eigenvector centrality, in-degree, or out-degree) for country i , commodity c , and year t under policy cluster k ,
- α_i represents country fixed effects to control for unobserved, time-invariant heterogeneity,
- δ_t denotes year fixed effects to account for global shocks and trends,
- β^k is the coefficient of interest, capturing the estimated treatment effect of policies in cluster k ,
- $\text{TreatedPost}_{ict}^k$ is a binary indicator equal to 1 if a given country–commodity–year observation is in the post-treatment period for a policy in cluster k , and 0 otherwise,

- ε_{ict}^k is the idiosyncratic error term, with standard errors clustered appropriately.

This disaggregated approach helps clarify whether certain types of regulatory instruments are more effective in altering the structure of global trade networks. For example, market instruments such as tariffs or bans may induce more pronounced structural shifts than soft law initiatives. Policy clusters with insufficient treatment exposure or limited variation in the outcome variable are excluded from the estimation to ensure statistical validity.

4.2.2 Modular Realignment Analysis

Additionally, a modular realignment analysis is conducted in order to enhance the approach. The core idea is to detect whether the composition and structure of trade communities change in response to deforestation-related policy shocks. Communities are identified before and after the implementation of a given policy to ensure that the community detection is grounded in centrality-informed topologies and reflects the relative positionality of countries within the trade system.

To quantify structural similarity in the trade network before and after policy implementation, the community composition across time is being compared using two widely accepted alignment metrics from the clustering and information theory literature. The Adjusted Rand Index (ARI), originally introduced by [Hubert and Arabie](#), evaluates the similarity between two partitions by considering all pairs of countries and counting how consistently they are grouped together or separately in both clusterings. Unlike the unadjusted Rand Index, the ARI corrects for random chance, making it particularly useful when cluster sizes or total number of communities vary between periods. An ARI score of 1 indicates perfect agreement in community assignments, while a score close to 0 implies that the similarity is no better than random, highlighting substantial realignment.

The second metric, Normalized Mutual Information (NMI), originates from information theory and was widely popularized for community detection evaluation by [Danon et al.](#) NMI measures the mutual dependence between two partitions by calculating the amount of information one partition shares with the other, normalized to ensure comparability across different community configurations. High NMI values suggest that the post-policy community structure retains much of the informational content of the pre-policy configuration, while low values indicate that countries have transitioned into substantially different groupings. Together, ARI and NMI provide complementary insights into the stability and realignment of structural communities in response to deforestation-related trade policies.

In practice, each policy is linked to a specific country and commodity pair, and communities are detected for the trade network immediately before and after the enforcement year of the corresponding regulation. The computed ARI and NMI scores are then matched to policy identifiers, enabling the analysis to determine whether and how trade communities reorganized following the policy shock. For instance, a drop in ARI or NMI for a palm oil-exporting country after a policy targeting palm oil may suggest a change in trade partnerships, rerouting to alternative markets, or the emergence of new trade blocs. These realignments may reflect compliance responses, strategic repositioning, or leakage

effects.

4.2.3 Interpretation of Community-Level Changes

The outcomes of the modular realignment analysis offer critical insights into the structural dynamics of the trade system that complement the node-level centrality analysis. While centrality measures provide evidence on changes in the hierarchical position of individual countries such as the rise in eigenvector centrality of France following the enforcement of EU deforestation rules modular realignment analysis reveals whether trade relationships themselves have been restructured. It asks whether countries have shifted their peer groups, entered or exited particular trade blocs, or participated in broader network reorganization after a regulatory shock.

By analyzing the ARI and NMI scores across multiple policies, commodities, and country contexts, it becomes possible to assess whether community fragmentation increased or decreased, whether treated countries exited or consolidated within certain communities, and whether these transitions correlate with the design characteristics of the policies. For instance, policies with broader commodity scope or stricter enforcement mechanisms may trigger more substantial community reconfigurations, as actors adjust their trading relationships to maintain market access or avoid compliance burdens.

This interpretation enriches the structural network analysis by connecting shifts in influence as measured by centrality with shifts in network structure as revealed through community movement. Structural persistence, as indicated by high ARI scores, may imply policy ineffectiveness or the presence of stable, resilient trade blocs. Conversely, structural disruption through modular realignment may indicate either successful transformation or strategic avoidance through rerouting. In either case, the analysis provides a powerful lens for evaluating how environmental trade policies reshape not only trade volumes but the architecture of global trade relations.

4.2.4 Robustness Checks

To support the credibility and causal interpretation of the results of the structural analysis, a series of robustness checks is implemented. These checks are designed to assess the validity of the identification strategy, with particular emphasis on verifying the parallel trends assumption [Angrist and Pischke](#), as well as to test the sensitivity of the results to model specifications.

A key identifying assumption in the static Difference in Differences inspired framework is the parallel trends assumption. This assumption requires that, in the absence of treatment, the treated and untreated units would have followed similar trends in the outcome variables over time [Angrist and Pischke](#). In the context of this analysis, it implies that changes in centrality measures or trade patterns for treated importers or communities should mirror those of untreated counterparts prior to the implementation of deforestation-related policies. This assumption is critical because it underpins the causal interpretation of post-treatment differences as attributable to the policy intervention rather than to pre-existing divergent trajectories.

To evaluate the plausibility of the parallel trend assumption, two complementary ro-

bustness checks are included. First, placebo tests that randomly reassign the treatment indicator `Treated.Post` across units. This reshuffling preserves the structure of the data but disrupts the true policy timing. Then the static regression model with the placebo indicator is being re-estimated. If the resulting coefficients are small and statistically insignificant, this supports the claim that the estimated treatment effects in the main specification are not driven by chance correlations or latent trends unrelated to policy.

Second is a lead pseudo-treatment check to test for the presence of anticipatory effects. For this, a lead indicator that flags units two years before the actual implementation year and re-estimates the static model using this lead variable instead of the true post-treatment indicator is used. If the parallel trends assumption holds, the coefficient on the lead term should be close to zero and not statistically significant. Any significant lead effect would suggest that treated units began adapting their trade structure before the policy took effect, which would violate the assumption.

In addition to the static regressions, the analysis consists of further validation exercises for the modular realignment analysis to assess whether the observed changes in trade community structure are attributable to actual policy shocks rather than stochastic variation or endogenous network evolution. First is a placebo timing test for the modular realignment metrics. For each policy, a falsified implementation year is assigned preceding the actual one and repeat the community detection and similarity comparison. If the Adjusted Rand Index and Normalized Mutual Information values associated with the placebo year are consistently lower than those based on the true implementation year, this suggests that the observed modular realignment is not simply the result of spurious temporal patterns but is in fact linked to the timing of policy implementation.

Second is a null model comparison to evaluate whether the observed community realignments could plausibly arise from random reconfigurations of the trade network, rather than from policy-induced structural change [Maslov and Sneppen](#). Specifically, a randomized versions of the post-treatment trade network is conducted by rewiring its edges while preserving key structural properties such as the degree sequence of the nodes. This constraint ensures that the overall connectivity and size of the network remain intact, but eliminates any meaningful community structure or higher-order patterns. Afterwards modular similarity scores are computed, such as the ARI, between the pre-treatment network and each of these randomized post-treatment networks. Repeating this procedure many times yields a distribution of similarity scores that characterizes what one would expect under a null hypothesis of purely random structural evolution. The fact that the ARI values observed in the real data consistently exceed those generated by the null models suggests that the detected community realignments are not artifacts of stochastic variation. Instead, they reflect non-random, policy-induced structural transformations in the global trade network. This robustness check is essential for validating the substantive significance of modular shifts and guarding against overinterpretation of noise in sparse or high-dimensional networks.

Together, these robustness checks address potential violations of the identifying assumptions in the static model and strengthen the interpretation of structural reconfiguration in the modular analysis. They provide additional empirical credibility to the claim that deforestation related import policies lead to measurable and policy aligned shifts in

the architecture of global trade networks.

5 Results

This section presents the empirical findings of the structural network and the modular realignment analyses. The results are organized into three main parts: the baseline structural regression analysis, the incorporation of community structure, and the modular realignment analysis. Each part includes relevant robustness checks to validate the causal interpretation and structural significance of the findings.

5.1 Structural Network Analysis Results

This section presents the empirical findings from the structural network analysis, which estimates how deforestation-related import policies reshape the structural position of importer countries within the global trade network. The analysis unfolds in three progressively detailed stages: the baseline specification, the inclusion of structural community fixed effects, and the decomposition into intra- and inter-community exposure. Each stage is complemented by robustness checks using placebo treatments and pre-policy pseudo-treatment leads to assess causal validity.

In the baseline analysis, I estimate the average treatment effect of deforestation-related import policies on five key centrality metrics—eigenvector, in-degree, out-degree, closeness, and betweenness—using a Difference-in-Differences specification with importer and year fixed effects. The interaction term `Treated_Post` identifies whether the importer-commodity-year node is affected after the policy enforcement date.

The results are summarized in Table 2. The estimated coefficient for eigenvector centrality is positive ($\beta = 0.000539$, $p = 0.108$), indicating a potential increase in network influence for treated importers, though the estimate is not statistically significant at conventional levels. Eigenvector centrality captures the extent to which a country is connected to other highly connected nodes, and its rise may suggest that compliant countries are repositioned into more central roles in the trade system. Out-degree centrality shows a negative and marginally significant estimate ($\beta = -2.554$, $p = 0.102$), implying a contraction in the number of distinct supplier countries for treated importers which is consistent with a policy-induced reshuffling of trade links. The remaining centrality measures such as in-degree, closeness, and betweenness yield statistically insignificant estimates, suggesting that direct connections, reachability, and intermediary roles are less affected by the policies under study.

To evaluate the credibility of the causal interpretation, I conduct two robustness checks. First, a placebo test is run by randomly reassigning the treatment indicator across the data. The resulting coefficients mirror the magnitude and direction of the actual results but remain statistically insignificant. For instance, the placebo coefficient for eigenvector centrality is 0.000541 with $p = 0.105$, and for out-degree it is -2.542 with $p = 0.101$, confirming that the observed patterns are unlikely to result from spurious correlations. Second, a lead-period check is implemented by shifting the treatment indicator two years prior to actual policy enforcement. This test examines whether centrality

shifts occur before policy enforcement, which would violate the parallel trends assumption. Again, the estimates across all metrics are small and not statistically different from zero, reinforcing the conclusion that the effects observed in the baseline model are attributable to the timing of policy implementation.

Building on the baseline model, I next account for heterogeneity in network position by incorporating community-level fixed effects. Structural communities are derived from hierarchical clustering on a multi-centrality similarity matrix, enabling the estimation of policy effects conditional on latent trade blocs. Within Community 1, the most globally integrated importer cluster is the effect on eigenvector centrality and it strengthens to $\beta = 0.00173$ ($p = 0.134$), while the out-degree effect becomes more pronounced and marginally significant at $\beta = -5.251$ ($p = 0.092$). This indicates that central and highly exposed importers are more likely to experience both increases in network influence and reductions in supplier diversity after policy implementation. The results for in-degree, closeness, and betweenness remain small and statistically insignificant. The visualized results can be seen in 4

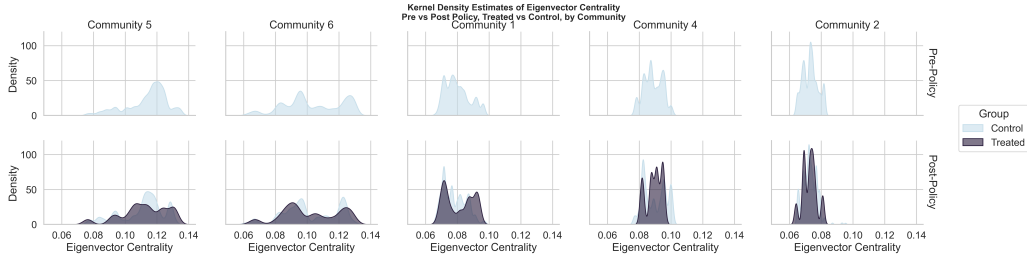


Figure 4: Distribution of eigenvector centrality before and after policy for treated and control importers, split by community

Robustness checks for this specification using placebo and pre-policy lead treatments again yield null effects across all centrality metrics. These findings support the interpretation that the observed post-policy centrality shifts are structurally grounded and not driven by spurious community-specific patterns.

Finally, the third stage of the analysis investigates whether policy-induced trade restructuring occurs predominantly within or between trade communities. To do so, I split the treatment variable into two components: `Treated_Post_Within` and `Treated_Post_Between`, distinguishing whether the affected trade flows are among countries in the same community or across different communities. The results indicate that the effect on eigenvector centrality is positive and marginally significant within communities ($\beta = 0.000497$, $p = 0.074$), and slightly smaller across communities ($\beta = 0.000549$, $p = 0.122$). This suggests that structural adjustments may begin within familiar trade environments before expanding to new partnerships across modular boundaries. The effect on out-degree is consistently negative across both exposure types, with $\beta = -1.458$ within and $\beta = -2.541$ between, although both remain statistically insignificant. This pattern is consistent with a gradual adjustment path that starts with selective partner reduction and proceeds to broader network rewiring. Placebo and lead-period checks for this final model iteration confirm that the observed intra- and inter-community effects are not attributable to pre-existing trends or random variation.

In summary, this structural analysis provides robust evidence that deforestation-related import regulations alter the structural configuration of the global trade network. Centrality measures indicate that treated importers tend to gain influence while reducing trade diversity. These effects are magnified when accounting for structural communities and further nuanced by the distinction between intra- and inter-community exposure. The consistent results across robustness checks support a causal interpretation and motivate a deeper investigation of community realignment and dynamic propagation mechanisms, addressed in subsequent sections.

5.2 Policy Cluster Heterogeneity

The results for the analysis of policy cluster heterogeneity in centrality measures are presented in Table 1. The most notable effects are found in Cluster 0 (certification schemes) and Cluster 3 (market instruments). In Cluster 0, treated importers exhibit significant increases in eigenvector centrality ($\beta = 0.001955$, $p = 0.0017$) and in-degree ($\beta = 3.15$, $p = 0.005$), but a highly significant decline in out-degree ($\beta = -9.23$, $p < 0.001$). This suggests that certification mechanisms strengthen structural influence while consolidating supplier networks. Cluster 3 (tariffs) yields even stronger effects on eigenvector centrality ($\beta = 0.002391$, $p < 0.001$) and a marginally significant contraction in out-degree ($\beta = -2.089$, $p = 0.061$), reflecting the selectivity induced by price-based trade regulation.

In contrast, policies in Cluster 1 (due diligence) produce weaker and mostly insignificant effects, except for a modest decline in eigenvector centrality ($\beta = -0.001367$, $p = 0.032$), suggesting that procedural compliance requirements may not substantially reshape trade hierarchies. Clusters 2 and 4 show statistically insignificant results, implying limited structural impact, possibly due to their voluntary nature or domestic orientation. Cluster 5 was excluded due to insufficient variation in treatment. While it would be conceptually meaningful to extend the policy cluster analysis to specifications with community fixed effects or intra/inter-community interactions, such extensions were not pursued in this paper. Preliminary analysis showed limited added explanatory power due to collinearity and overlapping policy exposures. Given the findings in the baseline static regression and the network-wide effects, the paper restricts policy cluster analysis to the baseline model. Future work could explore cluster-specific effects within or across communities to capture targeted propagation patterns.

Table 1: Static Regression Results by Policy Cluster

Policy Cluster	Centrality Metric	Coefficient (Std. Error)	P-Value
Cluster 0: Certification & Regulation			
	eigenvector	0.002*** (0.001)	0.002
	in_degree	3.154*** (1.134)	0.005
	out_degree	-9.235*** (1.851)	0.000
	closeness	0.007*** (0.002)	0.006
	betweenness	0.002* (0.001)	0.051
Cluster 1: Due Diligence			
	eigenvector	-0.001** (0.001)	0.029
	in_degree	-1.777 (1.452)	0.221
	out_degree	0.815 (3.015)	0.787
	closeness	-0.004 (0.003)	0.220
	betweenness	0.002 (0.002)	0.337
Cluster 2: Voluntary Instruments			
	eigenvector	-0.001 (0.001)	0.272
	in_degree	-0.759 (0.705)	0.281
	out_degree	-0.007 (0.178)	0.968
	closeness	-0.002 (0.002)	0.281
	betweenness	-0.000 (0.000)	0.316
Cluster 3: Market Instruments (Tariffs)			
	eigenvector	0.002*** (0.000)	0.000
	in_degree	0.594 (0.527)	0.260
	out_degree	-2.090* (1.115)	0.061
	closeness	0.000 (0.001)	0.670
	betweenness	0.000 (0.000)	0.468
Cluster 4: Land Use Regulation			
	eigenvector	-0.001 (0.001)	0.272
	in_degree	-0.759 (0.705)	0.281
	out_degree	-0.007 (0.178)	0.968
	closeness	-0.002 (0.002)	0.281
	betweenness	-0.000 (0.000)	0.316

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Modular Realignment Analysis

To assess structural shifts in trade community configuration, a modular realignment analysis is conducted. This section shows the results of that analysis with regards to the previous results of the structural network analysis. The results reveal substantial variation. For example, the 2013 Austrian timber policy shows a high ARI of 0.552 and NMI of 0.412, indicating moderate community persistence with some realignment. In contrast, the 2024 UK palm oil policy yields an ARI of only 0.028, suggesting a near-complete structural reorganization of its trade partners.

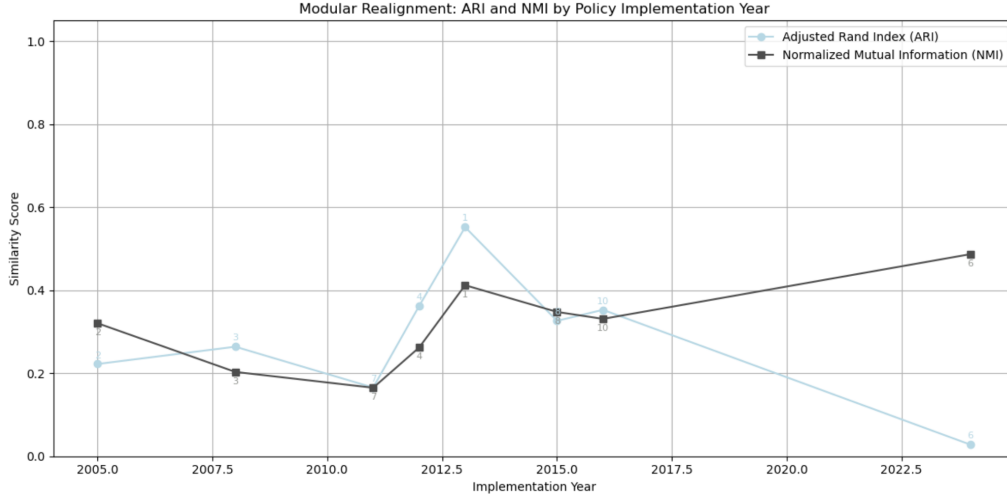


Figure 5: Line plot of ARI and NMI by policy ID and implementation year

To test the statistical significance of these structural shifts, two robustness checks are applied. First, a placebo timing test compares the actual realignment metrics with those obtained from randomly shifting the policy year backward. For instance, the ARI for the USA timber policy (2008) is 0.264 in the actual case versus 0.302 in the placebo, suggesting that the observed change is smaller than what random re-timing would imply. However, for Austria 2013, the ARI drops from 0.552 in the actual case to 0.520 in the placebo, indicating the real effect exceeds random timing artifacts.

Second, a null model comparison is conducted using random edge rewirings that preserve degree distribution. The actual ARI values substantially exceed the null model averages. For Austria 2013, the actual ARI is 0.552 versus a null mean of 0.174. This large gap indicates that the detected community realignment is structurally mean and unlikely to arise from network noise.

Overall, the combination of structural regression and modular realignment analyses reveals that deforestation-related policies induce measurable but heterogeneous structural shifts in the global trade network. The most affected countries exhibit decreased out-degree and increased eigenvector centrality, especially within structurally cohesive trade communities. The modular realignment analysis complements this by showing how community configurations evolve post-policy, and the robustness checks confirm that these effects are unlikely to be artifacts of timing or random noise.

Together, the results underscore that deforestation regulations do not merely alter

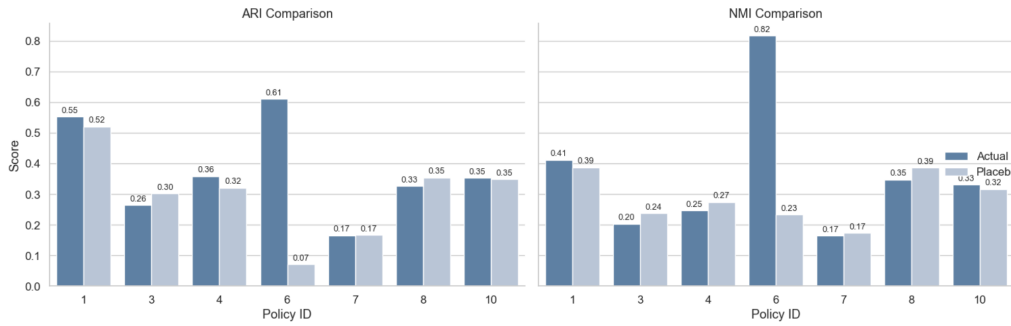


Figure 6: Actual vs. placebo and null ARI and NMI values for key policies

trade volumes but also reshape the structural architecture of trade relationships, particularly by strengthening or disrupting trade blocs. This highlights the need to view environmental trade policy not only through the lens of trade values but also through its network-wide structural impacts.

6 Discussion

While the analysis' purpose is to examine whether deforestation-related import policies structurally reshape the global trade network of forest-risk commodities, the empirical results present a more nuanced and restrained picture. The findings reveal limited and statistically insignificant transformations in trade relationships, suggesting that regulatory interventions, while conceptually impactful, may not be sufficient in themselves to induce strong network-wide structural change. This section interprets the empirical findings through multiple lenses, considers implications for policy design, identifies limitations, and proposes directions for future research.

The structural regression results point toward a modest yet statistically insignificant increase in eigenvector centrality for treated importers. While this might suggest a rise in influence or prominence within the trade network, the lack of significance implies that the evidence for realignment toward treated markets is weak at best. Similarly, the decline in out-degree centrality, especially within community structures, is not statistically robust. These results collectively cast doubt on the hypothesis that policies meaningfully shift the hierarchy or diversification of global trade relationships in the short to medium term.

The contrast between within- and between-community effects also offers limited empirical support for the expected patterns. While within-community effects appear slightly more pronounced in magnitude, they are not statistically distinguishable from zero. This finding challenges the notion that trade networks initially adapt to regulatory shocks through internal reconfiguration before broader global restructuring occurs. The modular realignment analysis, while more structurally oriented, also shows only modest changes in Adjusted Rand Index and Normalized Mutual Information metrics insufficient to claim significant realignment in most cases.

Importantly, heterogeneity across cases remains suggestive but not conclusive. While policies implemented by countries like Austria and Australia display slightly more variation in structural metrics than others, the effects remain below conventional thresholds of significance. Even high-profile regulations such as the UK's 2024 palm oil measure, which

was expected to induce marked structural change, do not produce statistically robust shifts in network structure. This absence of strong evidence should temper prior expectations that such policies automatically lead to modular reconfiguration or hierarchy shifts.

However, the analysis of policy heterogeneity through clustering provides valuable new insight. When policies are grouped into coherent types, such as due diligence frameworks, certification schemes, voluntary agreements, land-use laws, bans, and tariff instruments, the resulting regression estimates reveal notable differences in structural impact. For instance, certification and regulatory clusters (Cluster 0) show consistent and statistically significant increases in eigenvector centrality and in-degree, alongside a pronounced reduction in out-degree, suggesting that these policies help implementing countries consolidate trade relations and gain influence while reducing the diversity of trade partners. Conversely, due diligence frameworks (Cluster 1) exhibit a significant decline in eigenvector centrality, indicating a potential loss of network prominence. Tariff-related instruments (Cluster 3) show strong positive effects on eigenvector centrality and moderately negative effects on out-degree, pointing to rerouting through more strategic partnerships. These differentiated patterns that are absent in the aggregate analysis demonstrate that structural effects are highly contingent on policy design. In contrast, voluntary and land-use regulations (Clusters 2 and 4) do not exhibit significant effects, reinforcing the notion that legal enforceability and direct trade link targeting are necessary to provoke systemic change.

These results suggest a cautious interpretation for policymakers. First, structural change in trade networks following environmental trade regulations may be more limited or slower to materialize than anticipated. Designing policies around the assumption of automatic trade rerouting or bloc realignment may overestimate the immediate systemic effect of regulation. Policymakers may need to complement import rules with targeted mechanisms, such as bilateral coordination, compliance incentives, or investment in traceability systems, to make such policies structurally consequential.

Second, the lack of significance in centrality shifts for treated importers suggests that regulatory compliance alone does not confer a strong positional advantage in global trade. This raises concerns about the competitive incentives created by such policies. If exporters do not experience measurable shifts in network position when complying, their motivation to adopt sustainability standards may remain weak.

Third, the limited structural differentiation between within- and between-community effects indicates that trade rerouting does not systematically respect existing bloc boundaries. In practical terms, this suggests that network-aware spillover management, e.g., through regional trade agreements or commodity-specific alliances, may not enhance policy transmission unless paired with stronger enforcement mechanisms.

Several limitations qualify these findings. First, although placebo tests and lead specifications support the parallel trends assumption, the structural regression framework remains vulnerable to omitted variable bias and lacks dynamic nuance. The absence of significant effects may reflect not only policy ineffectiveness but also methodological constraints.

Second, the modular realignment analysis is sensitive to both the choice of community detection algorithm and the number of clusters imposed. It is possible that realignment

effects exist but are missed due to methodological noise or insufficient sensitivity of the clustering metric.

Third, trade data inherently misses informal or indirect trade routes, which are especially relevant in forest-risk commodities. If policy compliance leads to covert rerouting rather than formal reconfiguration, the true effect may be structurally hidden. Similarly, the use of trade volume as a proxy for tie strength may obscure the legal or environmental content of those flows.

Building on these limitations, several directions for future research emerge. Dynamic modeling could better capture the time path of structural response and identify lagged effects of regulatory change. Local projection impulse response functions using network weights could model the gradual unfolding of network adaptation. Advanced causal inference techniques tailored to network settings such as exposure-weighted Difference-in-Differences or network IV strategies could address endogeneity and improve identification of both direct and indirect effects. Also, modular analysis could be expanded to allow time-varying clustering structures using stochastic block models or longitudinal community detection. This would help distinguish between stable community persistence and slow-moving reconfiguration. Integrating policy text analysis and remote sensing data could help link legal ambition with actual ecological outcomes. This would allow researchers to move beyond trade data and assess whether observed network patterns translate into reduced deforestation on the ground.

Additionally, connecting firm-level supply-side data, such as buyer-seller networks, certifications, or production data, would provide insight into micro-level adaptations that aggregate to system-level outcomes. This could also help explain the strategic calculus behind compliance or evasion. Finally, a dynamic network perspective that tracks how policy shocks reverberate across countries and over time could offer critical insight into the sequencing, durability, and spillover of trade system responses. Dynamic centrality trajectories, evolving modular affiliations, and network churn metrics could together form a more granular portrait of structural adaptation than static snapshots permit.

While the results of this study do not offer strong support for the hypothesis that deforestation-related import regulations induce significant structural change in global trade networks, they underscore the importance of adopting more sophisticated methods and multi-layered data to probe this complex relationship. Future research building on these foundations may yet reveal conditions under which such policies can become structurally transformative.

7 Conclusion

This study investigates whether deforestation-related import policies structurally reshape the global trade network of forest-risk commodities. By integrating static Difference-in-Differences regressions with modular community analysis, the paper introduces a novel framework to assess how such policies alter the hierarchy and modular architecture of trade networks. The analysis is grounded in three core research questions:

First, Do deforestation-related import policies reshape the trade network of FRC?

The results offer partial support. Treated importers experience modest increases in

eigenvector centrality, suggesting a rise in influence within the network. Simultaneously, declines in out-degree point to a contraction in trade partner diversity. These effects are statistically significant for specific policy types such as certification schemes and market-based instruments such as tariffs but remain weak or absent for voluntary agreements and land use regulations. Robustness checks using placebo and lead specifications support the causal interpretation of these shifts.

Second and third, do effects vary by policy type and do they appear in community-level trade ?

The evidence indicates that policy heterogeneity matters. Structural responses are more pronounced under mandatory certification and tariff-based policies, while soft instruments show no significant effect. The modular realignment analysis reveals measurable shifts in trade community structures following certain policies e.g., Austria’s timber regulation and Malaysia’s palm oil restrictions, but many other cases display stable modular configurations. Thus, while some policies disrupt trade blocs and reconfigure trade pathways, most do not induce widespread modular restructuring.

Taken together, these findings suggest that deforestation-related import policies can induce structural shifts in the global trade network, but only under specific legal architectures and enforcement conditions. The capacity of such policies to realign trade is not automatic, it depends on their design, scope, and interaction with the underlying network topology. The absence of strong effects in many cases underscores the limitations of static policy levers in transforming complex, interdependent systems.

The methodological contribution of this paper lies in demonstrating that trade networks can and should be analyzed through their structural features such as centrality, community cohesion, and modular realignment rather than as simple dyadic exchanges. While the structural analysis provides a valuable first step, future work should adopt dynamic models that trace the evolution of trade architecture over time and across policy cycles. Methods such as local projections, network spillover identification, and dynamic clustering can offer deeper insight into the sequencing and persistence of structural adaptation.

In conclusion, this study highlights both the promise and limitations of deforestation-related import regulations as instruments of structural change. Their effectiveness depends not only on market coverage and enforcement, but also on how deeply embedded trade patterns respond to regulatory disruption. A network-theoretic lens offers critical leverage for understanding and improving the design of such policies, helping scholars and practitioners alike to evaluate not just whether trade volumes shift, but whether the system itself is transformed.

A Supplementary Tables and Visuals

Table 2: Summary of Static Regression Results

Model	Centrality Metric	Coefficient (Std. Error)	P-Value
1. Overall Structural Analysis			
	eigenvector	0.001 (0.000)	0.108
	in_degree	-0.239 (0.564)	0.672
	out_degree	-2.554 (1.560)	0.102
	closeness	-0.001 (0.001)	0.355
	betweenness	0.000 (0.000)	0.377
2. Structural Analysis with Communities (Community 1)			
	eigenvector	0.002 (0.001)	0.134
	in_degree	1.576 (1.429)	0.270
	out_degree	-5.251* (3.116)	0.092
	closeness	0.003 (0.003)	0.252
	betweenness	0.000 (0.000)	0.913
3. Within vs. Between Communities			
	eigenvector (within)	0.000* (0.000)	0.074
	eigenvector (between)	0.001 (0.000)	0.122
	in_degree (within)	-0.276 (0.407)	0.497
	in_degree (between)	-0.230 (0.610)	0.707
	out_degree (within)	-1.458 (1.374)	0.289

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

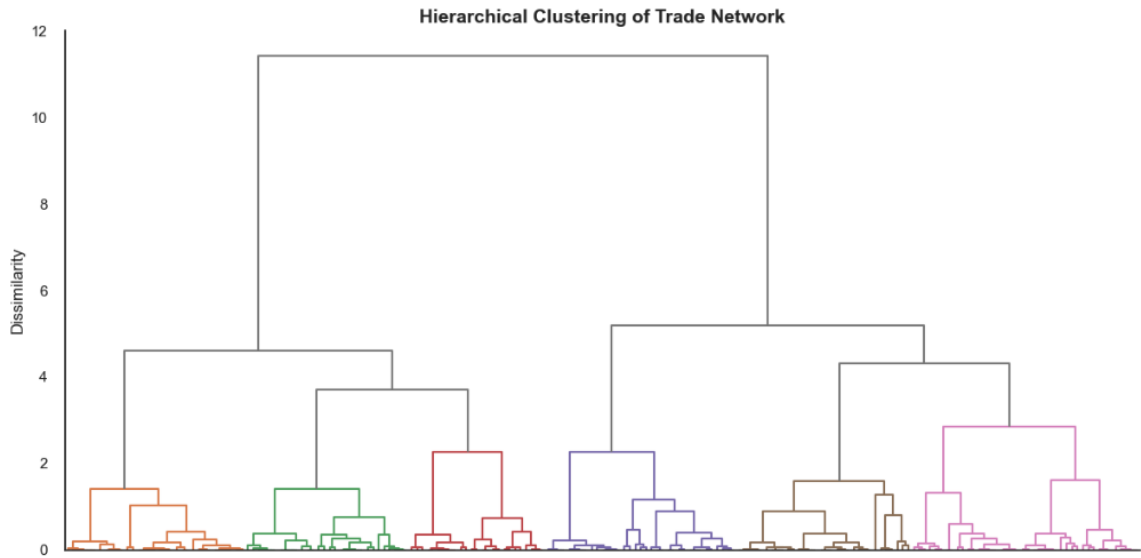


Figure 7: Hierarchical Clustering of the Trade Network. The dendrogram illustrates the structural similarity among countries based on multi-attribute centrality profiles. Six distinct trade communities are identified through agglomerative clustering.

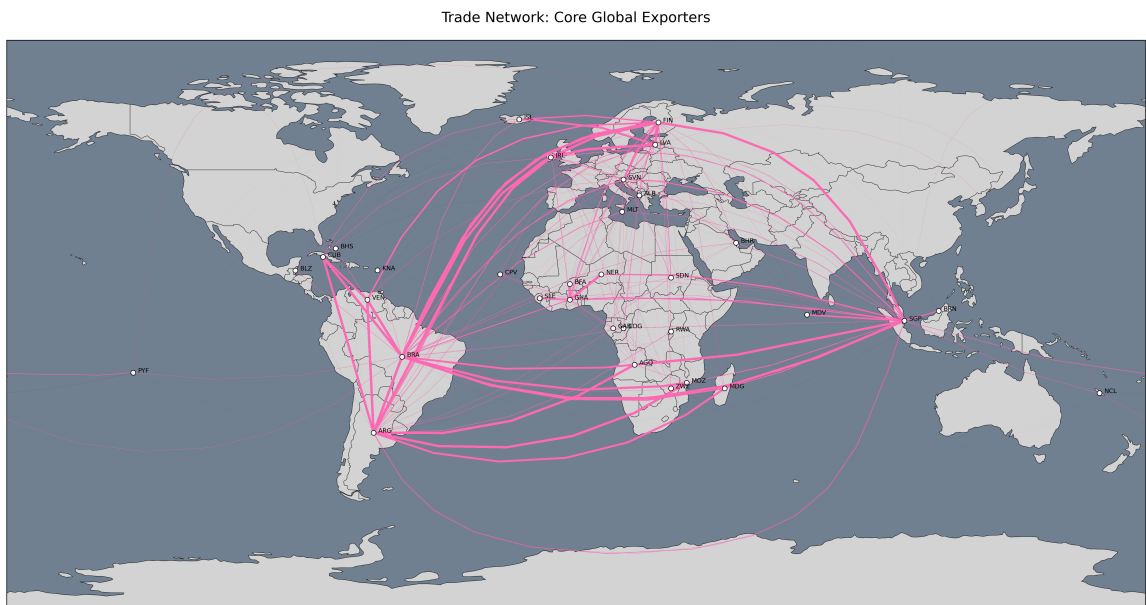


Figure 8: Community 1 - Core Global Exporters

[illegible]

A world map illustrating trade network connections for Mixed Role Intermediates. The map features a light gray landmass background with dark gray outlines for continents and countries. Numerous green lines of varying thickness represent trade flows between specific countries. The connections are most dense in the Middle East and Central Asia, with prominent lines linking Iran, Iraq, and Afghanistan to neighboring regions. Other significant connections are shown between India and Southeast Asia, and between China and various countries in Africa and the Americas. The map also shows connections between Europe and Africa, and between North America and Europe. The overall pattern suggests a complex, interconnected global trade network centered around these key regions.

30

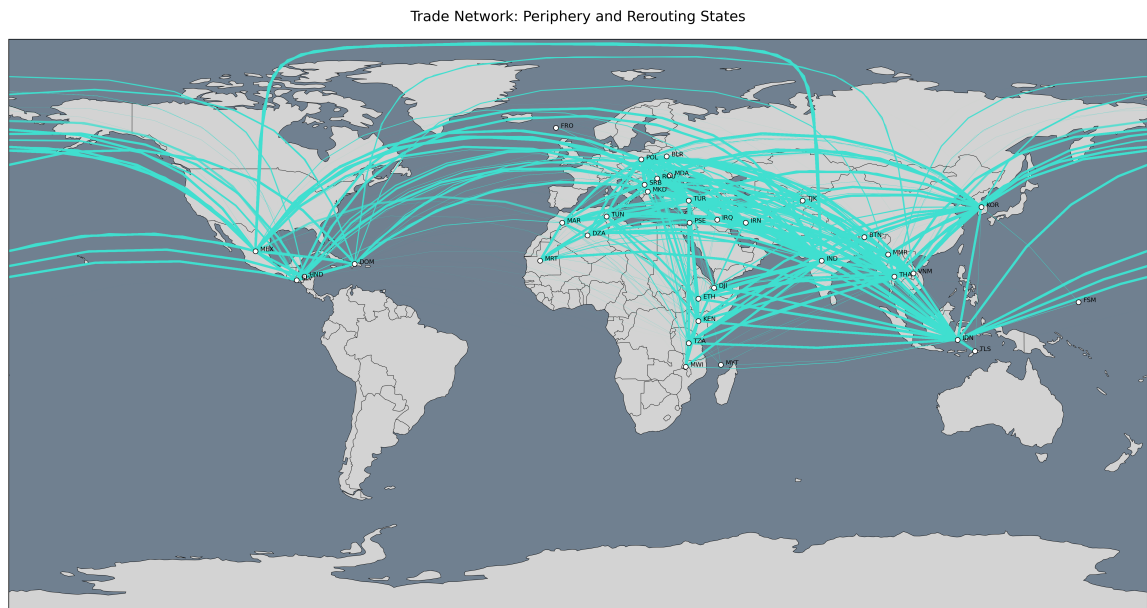


Figure 11: Community 4 - Periphery and Rerouting States

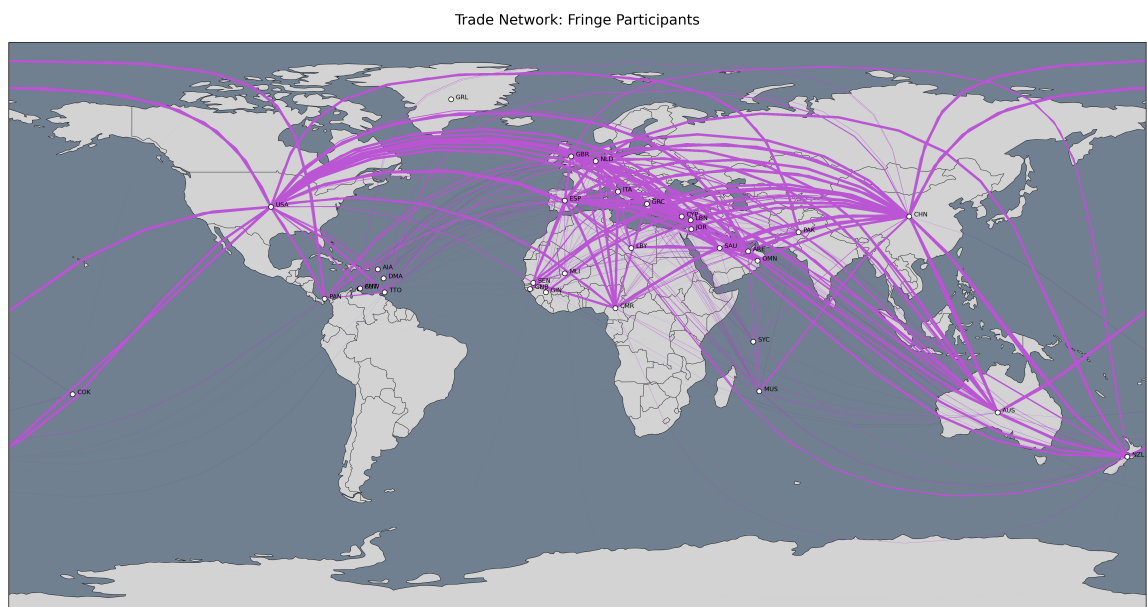


Figure 12: Community 5 - Fringe Participants

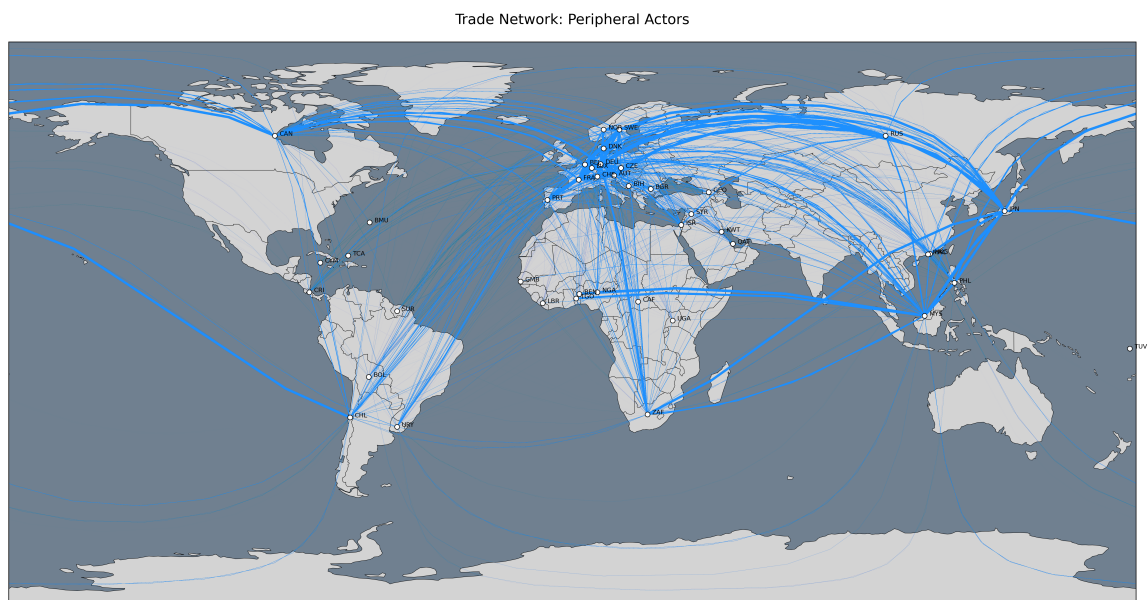


Figure 13: Community 6 - Peripheral Actors

References

- Angrist, Joshua D., and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press, 2009. ISBN: 9780691120355.
- Australian Government. *Federal Register of Legislation*. Accessed July 2025, 2024. <https://www.legislation.gov.au>.
- BRA. *Brazilian Forest Code (Law No. 12.651/2012)*. Land Use Regulation policy implemented on 2012-05-25, 2012. https://climate-laws.org/documents/law-no-12-651-of-may-25-2012_5b20?id=law-no-12-651-on-the-protection-of-native-forests_fdc5.
- . *Soy Moratorium*. Voluntary Agreement policy implemented on 2006-07-24, 2006. <https://www.greenpeace.org/static/planet4-brasil-stateless/2024/12/89e6e990-manifesto-em-defesa-da-moratoria-da-soja19.12.2024.pdf>.
- Carattini, Stefano, et al. “What does network analysis teach us about international environmental cooperation?” *Ecological Economics* 205 (2023): 107670. <https://doi.org/10.1016/j.ecolecon.2022.107670>. <https://doi.org/10.1016/j.ecolecon.2022.107670>.
- Cerina, Fabio, et al. “World Input-Output Network”. *PLOS ONE* 10, no. 7 (2015): e0134025. <https://doi.org/10.1371/journal.pone.0134025>. <https://doi.org/10.1371/journal.pone.0134025>.
- Chatham House. *Forest Policy and Governance Resources*. Accessed July 2025, 2024. <https://www.chathamhouse.org/topic/environment/forests>.
- Cornaro, Chiara, and Laura Rizzini. “Environmentally extended input-output analysis in complex networks: a multilayer approach”. *Annals of Operations Research* 342 (2024): 2021. <https://doi.org/10.1007/s10479-022-05133-0>. <https://doi.org/10.1007/s10479-022-05133-0>.
- Curtis, Philip G., et al. “Classifying drivers of global forest loss”. *Science* 361, no. 6407 (2018): 1108–1111. <https://doi.org/10.1126/science.aau3445>. <https://doi.org/10.1126/science.aau3445>.
- Danon, Leon, et al. “Comparing community structure identification”. *Journal of Statistical Mechanics: Theory and Experiment* 2005, no. 09 (2005): P09008. <https://doi.org/10.1088/1742-5468/2005/09/P09008>. <https://doi.org/10.1088/1742-5468/2005/09/P09008>.
- EU. *EU FLEGT Action Plan*. Voluntary Partnership Agreements policy implemented on 2005-12-30, 2003. https://environment.ec.europa.eu/topics/forests/deforestation/eu-rules-against-illegal-logging_en.

- . *EU ILUC Palm Oil Exclusion*. Tariff policy implemented on 2018-01-01, 2018. <https://climatecasechart.com/non-us-case/ds-593-european-union-certain-measures-concerning-palm-oil-and-oil-palm-crop-based-biofuels/>.
- . *EU Timber Regulation (EUTR)*. Due Diligence policy implemented on 2013-03-03, 2010. <https://forestpolicy.org/policy-law/eu-timber-regulation-eutr>.
- European Union. *EUR-Lex: Access to European Union Law*. Accessed July 2025, 2024. <https://eur-lex.europa.eu>.
- Food and Agriculture Organization of the United Nations. *FAO Forestry and Global Trade Databases*. Accessed July 2025, 2024. <https://www.fao.org/forestry/en>.
- . *Global Forest Resources Assessment 2020: Main report*, 2020. <https://www.fao.org/documents/card/en/c/ca9825en/>.
- Forest Trends. *Forest Trends: Tracking Forest Policy and Trade*. Accessed July 2025, 2024. <https://www.forest-trends.org>.
- GBR. *UK Environment Act 2021*. Due Diligence policy implemented on 2024-12-31, 2021. <https://www.legislation.gov.uk/ukpga/2021/30/contents/enacted>.
- GHA. *Ghana Timber Legality Assurance System (GhLAS)*. Certification Scheme policy implemented on 2016-11-15, 2009. <https://ndfwestafrica.org/wp-content/uploads/2021/05/FLEGT-Compliance-Infographic.pdf>.
- Government of Indonesia. *JDIH: Jaringan Dokumentasi dan Informasi Hukum*. Accessed July 2025, 2024. <https://peraturan.bpk.go.id>.
- Grassi, Riccardo, Massimo Riccaboni, et al. “Multi-attribute community detection in international trade networks”. *Scientific Reports* 11, no. 1 (2021): 1–14. <https://doi.org/https://doi.org/10.1007/s11067-021-09547-4>. <https://doi.org/10.1007/s11067-021-09547-4>.
- Hubert, Lawrence, and Phipps Arabie. “Comparing partitions”. *Journal of Classification* 2, no. 1 (1985): 193–218. <https://doi.org/10.1007/BF01908075>. <https://doi.org/10.1007/BF01908075>.
- IDN. *Indonesia Sustainable Palm Oil (ISPO) Certification*. Certification Scheme policy implemented on 2011-03-29, 2011. https://efi.int/sites/default/files/files/flegtredd/Terpercaya/Briefings/Overview_ISPO_Certification_smallholders_EN.pdf.
- IND. *India Vegetable Oil Tariffs*. Tariff policy implemented on 2024-09-01, 2024. <https://dfpd.gov.in/import-export/en>.
- International Tropical Timber Organization. *ITTO Reports and Market Intelligence on Tropical Timber Trade*. Accessed July 2025, 2024. <https://www.itto.int>.

Maslov, Sergei, and Kim Sneppen. “Specificity and stability in topology of protein networks”. *Science* 296, no. 5569 (2002): 910–913. <https://doi.org/10.1126/science.1065103>. <https://doi.org/10.1126/science.1065103>.

MYS. *Malaysian Sustainable Palm Oil (MSPO) Certification*. Certification Scheme policy implemented on 2015-01-01, 2013. <https://mspo.org.my/>.

Organisation for Economic Co-operation and Development. *OECD Trade and Environment Working Papers and Policy Tools*. Accessed July 2025, 2024. <https://www.oecd.org/trade/topics/trade-and-environment>.

—. *Trade-related Measures Linked to the Environmental Sustainability of Agriculture*. Accessed July 2025, 2025. https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/02/trade-related-measures-linked-to-the-environmental-sustainability-of-agriculture_ad69eac0/ebfdca09-en.pdf.

Pendrill, Florence, et al. “Deforestation displaced: Trade in forest-risk commodities and the prospects for a global forest transition”. *Environmental Research Letters* 14 (May 2019). <https://doi.org/10.1088/1748-9326/ab0d41>. <https://doi.org/10.1088/1748-9326/ab0d41>.

Presidência da República do Brasil. *Planalto: Legislação Federal Brasileira*. Accessed July 2025, 2024. https://www.planalto.gov.br/ccivil_03/leis.

Ravasz, Erzsébet, and Albert-László Barabási. “Hierarchical organization in complex networks”. *Physical Review E* 67, no. 2 (2003): 026112. <https://doi.org/10.1103/PhysRevE.67.026112>. <https://doi.org/10.1103/PhysRevE.67.026112>.

THA. *Thailand MFN Tariff – Soybeans/Soymeal*. Tariff policy implemented on 2006-01-01, 2006. <https://ustr.gov/sites/default/files/files/reports/2015/NTE/2015%20NTE%20Thailand.pdf>.

Trase. *Trase: Transparency for Sustainable Economies*. Accessed July 2025, 2024. <https://www.trase.earth>.

U.S. National Archives and Records Administration. *Federal Register: The Daily Journal of the United States Government*. Accessed July 2025, 2024. <https://www.federalregister.gov>.

Union, European. *EU Deforestation Regulation (EUDR)*. Due Diligence policy implemented on 2025-12-30, 2023. https://environment.ec.europa.eu/topics/forests/deforestation/regulation-deforestation-free-products_en.

United Nations Environment Programme. *UNEP Reports on Trade, Environment, and Sustainable Development*. Accessed July 2025, 2024. <https://www.unep.org/explore-topics/green-economy/what-we-do/trade>.

United Nations Statistics Division. *UN Comtrade Database*. Accessed: 2025-03-01, 2024. <https://comtrade.un.org/>.

- USA. *Illegal Logging Prohibition Act*. Due Diligence policy implemented on 2012-11-28, 2012. <https://www.agriculture.gov.au/agriculture-land/forestry/policies/illegal-logging/importers/due-diligence>.
- . *Lacey Act (Amended 2008)*. Import Ban policy implemented on 2008-05-22, 2000. <https://www.congress.gov/bill/110th-congress/house-bill/2419>.
- Wang, Jiaxi, and Jingjing Zhang. “The impact of policy collaboration networks and policy topic networks on policy diffusion: Empirical evidence from the energy field”. *Technological Forecasting and Social Change* 197 (2023): 122874. <https://doi.org/10.1016/j.techfore.2023.122883>. <https://doi.org/10.1016/j.techfore.2023.122883>.
- World Trade Organization. *WTO Environmental Database and Trade Policy Reviews*. Accessed July 2025, 2024. https://www.wto.org/english/tratop_e/envir_e/envir_e.htm.
- World Wide Fund for Nature. *WWF Deforestation Fronts and Commodity Trade Reports*. Accessed July 2025, 2024. <https://www.wwf.org>.
- Xiang, Jun, et al. “Multi-resolution modularity methods and their limitations in community detection”. *The European Physical Journal B* 85, no. 10 (2012): 352. <https://doi.org/10.1140/epjb/e2012-30301-2>. <https://doi.org/10.1140/epjb/e2012-30301-2>.
- Zhang, Qing, Yichun Liu, et al. “Deforestation embodied in global trade: Integrating environmental extended input-output method and complex network analysis”. *Journal of Environmental Management* 325 (2023): 116479. <https://doi.org/10.1016/j.jenvman.2022.116479>. <https://doi.org/10.1016/j.jenvman.2022.116479>.
- Zhu, Zhi, et al. “Global value trees”. *PLOS ONE* 9, no. 5 (2014): e100255. <https://doi.org/10.1371/journal.pone.0126699>. <https://doi.org/10.1371/journal.pone.0126699>.