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Worldwide Nickel Ore Trade, Its Stability and the Characteristics:

A Fresh Policy Analysis

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Abstract

Purpose: The study is conceptualized to examine structural characteristics and the strength of nickel ore network trading from 2011 to 2025, and focuses on studying major nations' involvement and their risk potential for disruptions in supply.

Design/methodology/approach: Network analysis is utilized to examine the topology of the nickel ore trade network and recognize influential players. Robustness simulations are directed to evaluate the influence of targeted and random disruptions on network stability, with emphasis on vulnerabilities associated with critical nodes.

Findings: The findings reveal that the nickel ore trade network shows a scale-free structure, where a few dominant states exercise disproportionate influence on the trade flows. Simulation findings confirm that disruptions among these key players abruptly decrease network stability, escalate systemic risks, and endanger international supply chains.

Research limitations/implications: The analysis is constrained by data availability and doesn't encompass informal networks of trade or future policy changes that could transform network structure.

Practical implications: Findings provide actionable policy recommendations for governments and industry stakeholders to design strategies that enhance resilience, diversify trade routes, and ensure a sustainable nickel supply.

Originality/value: The originality of this study lies in the application of network robustness simulations to the global nickel ore trade, offering a novel, evidence-based assessment of systemic risks from targeted disruptions—a dimension underexplored in prior literature.

Relevance to Decision Sciences: This research contributes to the field of Decision Sciences by providing a quantitative framework that supports policymakers and corporate strategists in evaluating supply chain vulnerabilities, anticipating risks, and making informed decisions regarding resource security and international trade policy.

Keywords: Nickel ore trade, Network analysis, Supply disruption, Scale-free network, Trade stability

JEL Classifications: F14, Q37, L72, C63, O13

1. Introduction

Nickel plays a crucial role as a key raw element in the manufacturing of electroplating, ternary batteries, alloy steel, stainless steel, and various products. It also finds extensive use in the infrastructure and building industries. Modern civilization relies heavily on nickel materials, and products incorporating nickel exhibit enhanced energy efficiency, prolonged durability, and reduced maintenance requirements (Mistry et al., 2016). Numerous countries have extended significant governmental support to nickel mining and production in response to the soaring demand for nickel in industrial development. Consequently, since 1950, nickel output has witnessed exponential growth (Mudd, 2010). Advancements in prospecting, smelting, and purification technologies have facilitated this progress. However, the quality of nickel ore has been declining due to the continuous extraction of high-grade ore. As a result, future mining costs are expected to rise, posing serious threats to nickel's global supply and trade (Olafsdottir & Sverdrup, 2021).

The supply–demand imbalance in nickel ore has become increasingly visible, with extraction concentrated in a few geographic regions that account for more than 60 percent of global supply. Such heavy concentration exposes the entire supply chain to systemic risks, as disruptions in a small number of producing countries can trigger widespread instability in global markets. In recognition of these vulnerabilities, major economies such as the United States, China, and members of the European Union have classified nickel ore as a critical and strategic resource. This classification allows governments to prioritize extraction and trade security, reflecting nickel's central role in technological innovation, energy transition, and industrial competitiveness.

These developments highlight a pressing challenge: the global nickel ore trade is not only vital for sustaining industrial growth but also increasingly fragile due to its dependence on a few key players. The rising importance of nickel in the renewable energy sector, especially in electric vehicle batteries and clean energy technologies, further intensifies these vulnerabilities. As nations race to secure supplies, the international trade network faces greater risks of volatility, bottlenecks, and supply chain shocks. For instance, export restrictions, geopolitical conflicts, or sudden natural disasters in key supplier countries could disrupt the stability of global nickel trade, amplifying uncertainty for both producers and consumers.

Despite the growing strategic importance of nickel, research into the stability and resilience of its trade network remains underdeveloped. Most previous studies have concentrated on other mineral or energy commodities, such as oil, iron, cobalt, or rare earths, leaving nickel comparatively neglected. As a result, there is limited understanding of how nickel trade networks evolve, how vulnerable they are to shocks, and which nations act as critical nodes within the system. Without such insights, policymakers and industries lack a quantitative foundation for designing effective strategies to secure supply chains and mitigate systemic risks.

This study addresses this gap by applying complex network theory to evaluate the structure and resilience of the global nickel ore trade between 2011 and 2025. Using robustness simulations, we model both targeted disruptions—such as trade restrictions on key nations—and random shocks—such as natural disasters or unforeseen global crises. This approach provides empirical evidence on how shocks in specific nodes or trade routes propagate through the network, destabilizing supply chains and exposing systemic vulnerabilities.

The contributions of this paper are threefold. First, it identifies the structural properties of the nickel ore trade network, revealing the role of dominant exporters and importers in shaping global flows. Second, it quantifies the resilience of the network by simulating the effects of targeted and random disruptions, thereby offering new insights into its capacity to absorb shocks. Third, it translates these findings into policy-relevant recommendations that inform governments, industries, and international organizations on strengthening supply chain resilience, diversifying trade dependencies, and mitigating systemic risks.

This research is original because it combines complex network theory with robustness simulations to analyze the stability of the global nickel ore trade, offering a novel methodological approach that has rarely been applied to mineral resources. Unlike prior studies that focus on broader commodities such as oil, iron, or rare earth elements, this study provides a dedicated and systematic examination of nickel — a resource of growing strategic importance in renewable energy and battery technologies. By modeling both targeted disruptions (such as policy restrictions or geopolitical conflicts) and random shocks (such as natural disasters or global crises), the study captures dimensions of systemic vulnerability that have been overlooked in existing literature. This originality ensures that the findings not only enrich academic understanding but also extend practical insights into how fragile yet critical trade networks function under stress. Furthermore, the study is directly relevant to the field of Decision Sciences, as it introduces a quantitative framework that equips policymakers, industries, and corporate strategists with the ability to evaluate global supply chain vulnerabilities, anticipate risks, and design evidence-based policies for resource security, trade diversification, and international cooperation. Through this dual contribution, the paper bridges theoretical innovation with real-world decision-making, thereby advancing both scholarship and practice in the area of global trade resilience.

2. Literature Review

The supply and demand dynamics for nickel ore were examined to look into potential future nickel extraction. According to the data, nickel supply is anticipated to peak around 2050 and might run out entirely by 2190. Expanding the exploitation of new nickel resources is therefore viewed as a necessary strategy to partially satisfy national demand and reduce supply-related challenges (Elshkaki et al., 2017; Nakajima et al., 2018a; Zeng et al., 2018). To understand the dynamic flow of nickel materials across different life stages, researchers have employed Life Cycle Assessment (LCA) and Material Flow Analysis (MFA). These methods make estimating nickel's supply, demand, and inventory easier. Investigators can spot patterns in the transfer of nickel ore between various nations by looking at how international nickel resources are used and mined in both the industrial and consuming sectors. This plan offers insightful information and possible routes to guarantee a steady supply of nickel resources. The investigations carried out by Wei et al. (2020), Nakajima et al. (2018b), Takeyama et al. (2016), and Reck et al. (2008) have all made contributions to this area of investigation. These studies primarily emphasize supply-demand projections and environmental implications, whereas they do not address the network-level stability of global commerce, leaving a gap that this research aims to plug.

The demand and supply of vital natural resources, like nickel ore, show a clear mismatch, with around 62 percent of nickel ore extraction operations concentrated in several distinct geographic regions. Recognizing its significance, numerous countries, including the US, Europe, and China, have classified nickel ore as an essential resource. This classification allows these nations to prioritize their nickel mining activities and gain a competitive advantage in the global supply chain. In order to ensure a consistent supply of nickel ore, these countries often establish international trade agreements or invest in multinational mining initiatives. As a result of the trade of nickel-related products between nations, intricate global networks have been formed. These networks can be represented through complex network theory, which uses nodes to depict the various components of the structure and edges to represent the interactions between them. Analyzing the trade movements of products through the construction of International Trade Networks (ITNs) is a common approach in complex network theory. ITNs are similar to real-world networks, displaying small-world characteristics and adhering to scale-free network principles (Barigozzi et al., 2010; Fagiolo et al., 2009). Complex network topology has been broadly utilized to investigate trade relationships and global trade trends among mineral-producing and demand nations. Studies focusing on the oil trade network have provided comprehensive insights into the stability of international trade connections, examining the impact of changes in export and import tendencies over short and long timeframes (Sun et al., 2017). Researchers employ multifaceted systems to assess and understand drivers and obstacles in national metal and mineral trade, investigating the trends and mechanisms of interregional supply and demand that shape this trade. Nevertheless, the direct application of complicated network assessment to the nickel trade is still infrequent, despite its confirmed usefulness in various products.

By examining the demand and supply association growth among trading partners, researchers can forecast a nation's capability to manage its market and resources (Dong et al., 2020; Ji et al., 2014). They explore the crucial factors influencing the trade network integrity and the general pattern of trade stability among leading nations. Complex network measures investigate the network's fundamental features, the trading economies' status, and their influence on the international market (Liu et al., 2020). Various trade network structures for mineral and metal properties have been examined, including iron (Zhong et al., 2018), cobalt (Zhao et al., 2020), aluminum ore (Shi et al., 2018), rare earth (Hou et al., 2018), copper concentrate and scrap (Dong et al., 2018), and others. These investigations primarily utilized parameters such as average clustering coefficient, modularity, network density, average route length, and degree distribution of complex networks. By employing these parameters, researchers examined trade transmission effectiveness, trade connectedness, the intermediary role of trading nations, the status of trade center economies, and other relevant factors. By analyzing these parameters, investigators identified the small-world characteristics present in the global mineral trade. They tracked the evolution of network characteristics and the roles played by key trading nations. Some researchers took a broader perspective by considering the entire upward supply chain like a system and examining the business system of natural resources based on nations. For instance, the cobalt trade network was constructed by considering connections between nations, miners, smelters, and metal-producing businesses (Van den Brink et al., 2020). Furthermore, complex network theory has been used by multiple researchers to develop trade networks for twenty-four important minerals. This research helps identify the "leading companies" in global commerce and determines the natural resources' relative value for participating nations (Zhu et al., 2020). These examples offer a foundation for assessing the nickel trade networks, but the specific case of nickel remains largely unexplored in terms of network resilience and stability.

Ore trade systems typically exhibit a scale-free architecture and abide by a power-law distribution, categorized by numerous bumps with limited connectivity and specific nodes with many interconnections. Due to their heterogeneous nature, Schneider et al. (2011) stated that scale-free networks are susceptible to disruptions, including strikes. The sustainability investigation in complex trade networks finds extensive applications in various industries such as transportation, smart grids, and engineering systems management. This study primarily employs ruggedness investigation techniques. Robust control theory originated in the 1970s and assesses the system's ability to continue functioning as intended in the presence of errors or disruptions (Nacher & Akutsu, 2015). This proposes that the resilience-oriented approaches are extremely pertinent to minerals trade networks, where unanticipated shocks may disrupt international flows.

For instance, the simulated stochastic strikes and node degree strikes examine the stability patterns of a complex bus network, aiming to identify potential sites where the network may fragment into clusters (Tran et al., 2019). Sole and Montoya (2001) investigated the responses of ecological food webs to random and planned disturbances, focusing on the role of essential organisms. In a study by Sun et al. (2020), the supply chain networks' dynamic resilience was assessed by employing the node-cascade failure approach. Ding et al. (2020) examined the Chinese natural gas import network's robustness by subjecting it to arbitrary and deliberate attacks on edges and nodes. Furthermore, they proposed three alternative strategies to enhance the robustness of the network. Node-degree attack tactics have been extensively utilized by researchers in various investigations. In addition to the maximum degree of attack, closeness centrality and betweenness centrality attack tactics were additionally considered (Rungta et al., 2018). These techniques exhibit the adaptability of robustness assessment across domains, but their application to the nickel ore trade remains inadequate, exhibiting a clear investigation gap.

The results indicate that relatively little investigation has been done on analyzing developments in the nickel ore trade network and comprehending the present situation of the main trading partners. Only a few scholars have investigated the stability of the nickel ore trade networks by considering the variety of the global trade network and doing thorough assessments utilizing target and random attack approaches. Given the growing rivalry among important nations for vital natural resources, this research seeks to fill this gap using complex network theory to build an extensive international trading network for nickel ore. The study examines the evolving structure of global nickel ore trade patterns and the shifting relationships between trading countries. The paper develops this strategy by modeling the effects of targeted and random assaults on the stability of the network using resilience evaluation. Significant insights are obtained by looking at the consequences and harms caused to the nickel ore trade network due to supply uncertainty impacting particular nations or channels. Therefore, the research builds upon previous studies while advancing the literature by emphasizing precisely the nickel ore, a product of surging tactical importance, through the lens of systematic risk analysis and network stability.

3. Methodology and Data

3.1 Data

According to Ni et al. (2015), China has been the largest consumer of refined nickel globally since 2009. The worldwide supply chain for nickel ore experienced significant disruptions due to the COVID-19 pandemic in 2021. This impact is reflected in the data for "Nickel ores and concentrates" (HS code 260400), collected from the United Nations Comtrade database, covering the period from 2011 to 2025. The dataset includes approximately 80-150 annual trade links (edges) and 60 trading states (nodes). Missing data and reporting delays were addressed by utilizing importer-side declarations, which are commonly considered more reliable in commerce statistics. It is worth noting that various factors, including economic and political considerations, have led some countries to report their annual product statistics to the United Nations Comtrade on a delayed calendar. This article thoroughly analyzes each engaged nation's trade capacity and quantity in the annual nickel ore trade. Every nation is considered a node in the research, trade connections are represented as edges, and the net weight of the trade is used to measure these connections. Although different methodologies may be employed, leading to variations in trade quantities reported by importing and exporting nations, this study consistently utilizes the annual import amounts of each nation as the basis for calculations.

This study aligns with recent advancements in econometric and financial modeling that emphasize nonlinear, asymmetric, and time-varying relationships across macroeconomic and environmental contexts. Several works—such as Ali et al. (2022), Bagadeem et al. (2024), and Chang et al. (2023)—apply advanced panel and time-series models to explore globalization, energy use, and climate risk. Similarly, Chang (2020) and Chang et al. (2022) incorporated nonlinear ARDL approaches to analyze asymmetric effects of oil prices, terrorism, and innovation on financial and environmental systems. Studies by Gohar et al. (2022a, 2022b, 2022c), Hashmi and Chang (2021), and Hashmi et al. (2021a, 2021b, 2022) further advanced this framework by employing quantile and threshold models to detect heterogeneous responses in energy, stock, and trade markets, while Imane et al. (2023) and Peng et al. (2022) demonstrated the importance of nonlinear modeling in examining exchange rate volatility and energy demand.

Building on these methodological innovations, Gohar et al. (2023a, 2023b), Lu et al. (2023), Maydybura et al. (2023), Mei et al. (2024), Jin et al. (2024), and Wang et al. (2024) extended the analysis to time-varying connectedness, quantile regression, and nonlinear bounds testing to evaluate market interactions and energy–finance dynamics. Likewise, Salman et al. (2023a, 2023b), Noman et al. (2023), Uche et al. (2022a, 2022b), and Gong et al. (2023) employed asymmetric and quantile ARDL models to uncover structural asymmetries in trade, investment, and consumption behavior, while Syed et al. (2019) revealed volatility spillovers between financial and goods markets. Collectively, these studies demonstrate the effectiveness of nonlinear and ARDL-based econometric approaches in capturing asymmetric, heterogeneous, and time-varying effects—providing strong justification for adopting similar techniques in the present analysis of global trade network dynamics.

To ensure that the estimated relationships are free from spurious regression problems, the study follows the methodological cautions raised by Cheng et al. (2021, 2022), Wong, Cheng, and Yue (2024), Wong, Pham, and Yue (2024), Wong and Yue (2024), and Wong and Pham (2022a, 2022b, 2023a, 2023b, 2025a, 2025b), who demonstrate that significant results may become unreliable when the underlying data are nearly non-stationary or contain autoregressive components. In response, this research employs the ARDL framework, which accommodates mixed integration orders and mitigates the risk of spurious regression by jointly modeling short- and long-run dynamics. Additionally, following the diagnostic guidelines of Hui et al. (2017), residual-based tests were performed to verify model validity and ensure that the estimated models satisfy the required econometric assumptions, thereby confirming the robustness and reliability of the empirical results.

3.2 Methodology

3.2.1 Network Characteristic Indicators

This investigation implements a weighted nickel ore complex network approach denoted as $\mathrm{A} = (\mathrm{V}, \mathrm{E})$ where V represents the set of nodes (countries) and E represents the set of directed edges (trade relationships) under the theory of complex networks. Formally, $V = \{v_i | i = 1,2,3, \dots n\}$, where n is the total number of countries participating in the global nickel ore trade. Each node v_i corresponds to a country that may act as an exporter, importer, or both, while $\mathrm{E} = \{\mathrm{e}_{\mathrm{ij}} | \mathrm{i}, \mathrm{j} \in \mathrm{V}\}$ denotes the set of directed trade flows from country i (exporter) to country j (importer). Each edge e_{ij} carries a weight w_{ij}, representing the volume of nickel ore traded between the two countries. Accordingly, the weighted adjacency matrix $\mathrm{W} = [\mathrm{w}_{\mathrm{ij}}]$ captures the magnitude and direction of all trade relationships, reflecting the structure and intensity of the global nickel ore trade network as expressed in Equation (1).

This investigation implements a weighted nickel ore complex network approach $A = (B, C)$ that includes node B and edge C under the theory of complex network . $B = \{B_i, i = 1,2,3, \dots n\}$, where the aggregate number of nodes is indicated by n. To illustrate, all first-exporting nations utilize the vector $B = [B_i]$, and all ultimate importing nations, utilize $B = [B_j]$. $C = \{C_i, i = 1,2,3, \dots m\}$, in which the number of the edges is indicated by m. The edges of a weighted trade network show the movement of goods between trading partners and countries and indicate the transaction's magnitude. The weight given to the associated edge is the amount of nickel ore traded between countries i and j, denoted as X_{ij}. The matrix that reflects the nickel ore trade progress worldwide is depicted in Equation 1.

$$X = \begin{pmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{pmatrix}. \tag{1}$$

A. Degree

The degree of a node in a complex network denotes how many edges are linked to that node in aggregate. A higher degree means more nodes or edges connecting the particular node. The out-degree in a directed network represents a nation's export interactions with different nations in a given year p. In contrast, the in-degree represents the overall import interactions. Equations 2 to 4 serve as a representation of these interactions. Nickel ore exports from nation i to nation j are represented by the $S_{ij}(p)$, whereas nickel ore imports from state j into state i are represented by $S_{ij}(p)$. It is split into two categories, out-degree and in-degree, depending on the position of the edge connecting the linked nodes. $T_i^{out}(p)$ stands for the out-degree, representing all trade and export associations involving nickel ore for nation i. $T_i^{in}(p)$ stands for in-degree, signifying every connection involving trade and import of nickel ore for nation i.

$$T_i^{out}(p) = \sum_{j=1}^{n} S_{ij}(p)\,; \tag{2}$$

$$T_i^{in}(p) = \sum_{j=1}^{n} S_{ij}(p)\,; \tag{3}$$

$$T_i^{degree}(p) = T_i^{out}(p) + T_i^{in}(p). \tag{4}$$

B. Distribution of Degree

The node degree possible distribution throughout the whole network is referred to as the degree distribution, as shown in Equation 5. A power-law distribution in the degree distribution of multiple complex networks indicates that they belong to scale-free networks.

$$P(k) \approx k^{-\gamma}, \tag{5}$$

where γ is the exponent of the power-law distribution, k is the degree, and $P(k)$ is the possibility of degree.

C. Density

An intuitive measurement of the degree of the interaction between nodes in the trade network, network density is a gauge of the prosperity of complex trade networks. The degree of trade prosperity is shown by the density, represented as D and determined by Equation 6. Greater trade prosperity and deeper ties between trading countries are indicated by higher values of D. A lower value of D, on the other hand, denotes a smaller trade scale and less prosperous trade.

$$D = \frac{2m}{n(n-1)}, \tag{6}$$

where m is the total number of edges and the n is total number of nodes $(n \geq 2)$. For an undirected network, the density is $D = \frac{2m}{n(n-1)} \in (0,1)$.

D. Average Clustering Coefficient

In Equation (7), the average clustering coefficient is used to assess the interdependence degree between trading partners. It reveals the degree of clustering and the intensity of connections between nodes and the nodes next to them. Stronger ties between trade partners are indicated by a higher coefficient (L), which increases the possibility of sustaining long-term and stable trade partnerships. In contrast, smaller L-values show weaker ties between trade partners, leading to fewer stable alliances.

$$L = \frac{1}{n}\sum_{\mathrm{i}=1}^{n} \frac{n_j}{I_i(I_i - 1)}\ , \tag{7}$$

where L stands for the average clustering coefficient, i is the edge aggregate number among the node i's nearby nodes, and I_i is the node aggregate number immediately close to node i.

E. Length of diameter and average path

These two measures how effectively and smoothly the nickel ore transaction operates. A greater threshold for the number of edges needed to execute a trade operation indicates lower trade transmission efficiency. Equation 8 puts this idea into numbers, which define the average path length.

$$W = \frac{1}{n(n-1)}\sum_{ij} d_{ij}\,, \tag{8}$$

in which the average path length is signified by W, while d_{ij} is the fastest route between nodes i and j.

F. Modularity

The degree of globalization and community heterogeneity in the nickel ore trade is measured by the degree of modularity. Equation 9 defines it. Greater modularity (M) suggests the emergence of more separate communities among trade organizations, which results in greater localization and less globalization. A smaller value of M, on the other hand, indicates a higher degree of international trade and fragile interactions among trading companies.

$$M = \frac{1}{2m}\sum_{ij}\left(v_{ij} - \frac{O_i O_j}{2m}\right)\mu(r_i, r_j)\,, \tag{9}$$

where v_{ij} demonstrates the edge's weight from node i to node j. The $O_i\ and\ O_j$ represent the overall edges' total weight linked to nodes i & j. The community sets of nodes i & j are represented by r_i and r_j.

$\mu(r_i, r_j)$ is set to 1 when the node i and node j are members of the identical community; if not, $\mu(r_i, r_j)$ is set to 0.

G. Development indicators for the position of the important nations

(1) Closeness Centrality

A closeness centrality metric shows how interconnected a trade nation is to other nations within a complex network. In general, it is stated as the reciprocal of the sum of the distances between each nation and each nation in the network. Closeness centrality of nation i is defined as the reciprocal of the sum of the shortest path distances between nation i and every other nation j in the network:

$$CC = \frac{1}{\sum_{j=1}^{n} d_{ij}}. \tag{10}$$

A trade nation with a greater closeness centrality (CC) rating interacts more directly and closely with other nations, making it more influential and less subject to their influence. On the other hand, if a nation has a low closeness centrality, other nations may impose trade restrictions on it. Equation 10 defines the computation of closeness centrality.

(2) Betweenness Centrality

According to Equation 11, betweenness centrality is the probability that nation i is situated along the shortest route between two other nations. It highlights the trading nation's major role as an intermediate in the larger network, demonstrating its ability to influence the complex network, including nickel ore. A higher value of BC indicates better regulatory powers and more influence on the trade network since it increases the likelihood that the trading organization will be integrated into the shortest route connecting the two nations. On the other hand, a lower value of I denotes a poorer capacity to govern as an intermediate, causing it to be harder to exercise influence on the trade network's edifice.

$$BC = \frac{2}{(n-1)(n-2)} \sum_{r=1}^{n} \sum_{s=1}^{n} \frac{u_{rs(i)}}{u_{rs}}, \tag{11}$$

where $u_{rs(j)}$ indicates that node j is the shortest route from node r to node s, and u_{rs} is the smallest route between r and s. $(j \neq r \neq s;\ r = 1, 2, 3, \ldots, n;\ s = 1, 2, 3, \ldots, n)$.

(3) Eigenvector Centrality

It describes the function of the nation's commerce in the complex network by highlighting the significance and sway of surrounding nations. Several nations' standing cannot be determined merely by whether they are significant importers or exporters; it is also important to consider how their partners' economies are faring. Countries like this exhibit the trait that "cooperation with powerful nations will become more robust," which indicates that they often have substantial trade links to other nations with high eigenvector centrality, demonstrating that they have indirect control of the trade framework. Equation 12 illustrates the eigenvector centrality.

$$A_x = \lambda_x. \tag{12}$$

Eigenvector centrality is described by the equation $A_x = \lambda_x$, where the adjacency matrix of the network is denoted by A, the eigenvector containing centrality scores for each node is indicated by x, and λ is the major eigenvalue of A. This formulation designates that a state's significance is calculated not only by its own trade acquaintances but also by the significance of its partners. Higher eigenvector centrality echoes stronger incorporation into the international nickel ore trade network.

3.3 Econometric Specification

While this network assessment offers valuable structural information, it does not describe the dynamic causal associations between trade variables. To address this, the research incorporates the ARDL (Autoregressive Distributed Lag) approach, following Pesaran et al. (2001), which permits assessing both short- and long-run associations among trade volume, clustering coefficient, average degree, and network density.

The general ARDL (p, q_1, q_2, q_3) approach is described as:

$$\begin{aligned}\Delta TV_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta TV_{t-i} + \sum_{i=0}^{q_1} \gamma_j \Delta CC_{t-i} + \sum_{i=0}^{q_2} \delta_k \Delta AD_{t-i} + \sum_{i=0}^{q_3} \emptyset_k \Delta ND_{t-i} + \\ \mu_1 TV_{t-1} + \mu_2 CC_{t-1} + \mu_3 AD_{t-1} + \mu_4 ND_{t-1} + \varepsilon_t,\end{aligned} \tag{13}$$

where $TV_t, CC_t, AD_t, ND_t, \Delta, and\ \varepsilon_t$ indicates the trade volume, clustering co-efficient, average degree, network density, first-difference operator and Error term, correspondingly. The parameters $\mu_1, \mu_2, \mu_3\ and\ \mu_4$ captures the long-run equilibrium, where the differenced terms assess the short-run dynamics. The ARDL approach is ideal for this research because it accommodates mixed integration orders (I(0)) and (I(1)) and generates robust findings even with small samples.

3.4 Network Stability and Robustness Analysis

The network of nickel ore trade is a complex structure comprising numerous national organizations. Given the intense competition for nickel ore supplies, supply issues could disrupt the network's normal functioning. These risks primarily arise from nations and trade routes. The transportation of nickel ore encounters significant challenges when a nation is subject to trade restrictions, regional threats, or when trade routes are disrupted. Fluctuations in the nickel ore trading network directly affect the risk of fragmentation in the global supply chain. This research utilizes a programming technique to model variations in the network stability when the nickel ore business faces hazards to assess the impact of these risks. Specifically, it simulates targeted and arbitrary strikes on network nodes and edges. Targeted strikes simulate potentially hazardous situations that nations may encounter, such as circumstances where nations cannot engage in commerce because of variations in natural resource policies or international relations with other nations.

Additionally, tactical restraint among nickel-trading nations is taken into consideration. The strike tactic incorporates several techniques, including EBCA (edge betweenness centrality attack), DA (degree attack), CCA (closeness centrality attack), and BCA (betweenness centrality attack). The nodes are attacked individually based on the node degree, betweenness centrality, and relevant parameters. Similarly, the attack focuses on edges based on their betweenness centrality. The RA (random attack) is utilized to emulate the influence of unpredictably high dangers on specific nations or conveyance routes in the nickel ore business network. These risks encompass a wide range of catastrophic natural calamities, like volcanic eruptions, earthquakes, tsunamis, public health crises like coronavirus outbreaks and Ebola, acts of political violence, terrorist attacks, and political unrest. The random attack approach targets one network node at a time, repeating this process ten times until all nodes and edges have been destroyed or no longer exist.

Network connectivity and efficiency are key factors in assessing stability indicators, which gauge the ability of the network to sustain its operations following risk-based attacks. Practical metrics utilized to evaluate the network's condition post-assault consist of network connectivity and efficiency coefficients. The stability modeling in this study focuses on 2023, as there has not been a significant increase in the number of nations and trade connectivity within the nickel ore trade network.

A. Network Connectivity

Equation 14 defines the connectivity of the network. According to this equation, if at least one route connects the two nodes slightly in the system, the nodes are considered linked. When they are all linked, the network is considered connected. The initial network exhibits a complete connection, with a connectivity coefficient of 1. However, in the event of targeted attacks on the linked network, some nations may decide to withdraw from the trade network, resulting in the network being divided into multiple disconnected sections. These disconnected portions are referred to as linked subgraphs during the network separation. The largest subgraph, which contains the maximum number of nodes, provides insight into the connectedness of the network following the strike.

$$NC = \frac{H'}{H} , \tag{14}$$

where H' is the linked subgraph nodes' greatest number after the supply disruption's possibility, which is the nations' number still present in the network. NC is the nickel ore trading network's connectivity coefficient.

B. Network Efficiency

The efficiency of the operation of the nickel ore trading network is measured using a statistic called network efficiency. It is calculated by applying Equation 15 to the intricate link index to get the average route length.

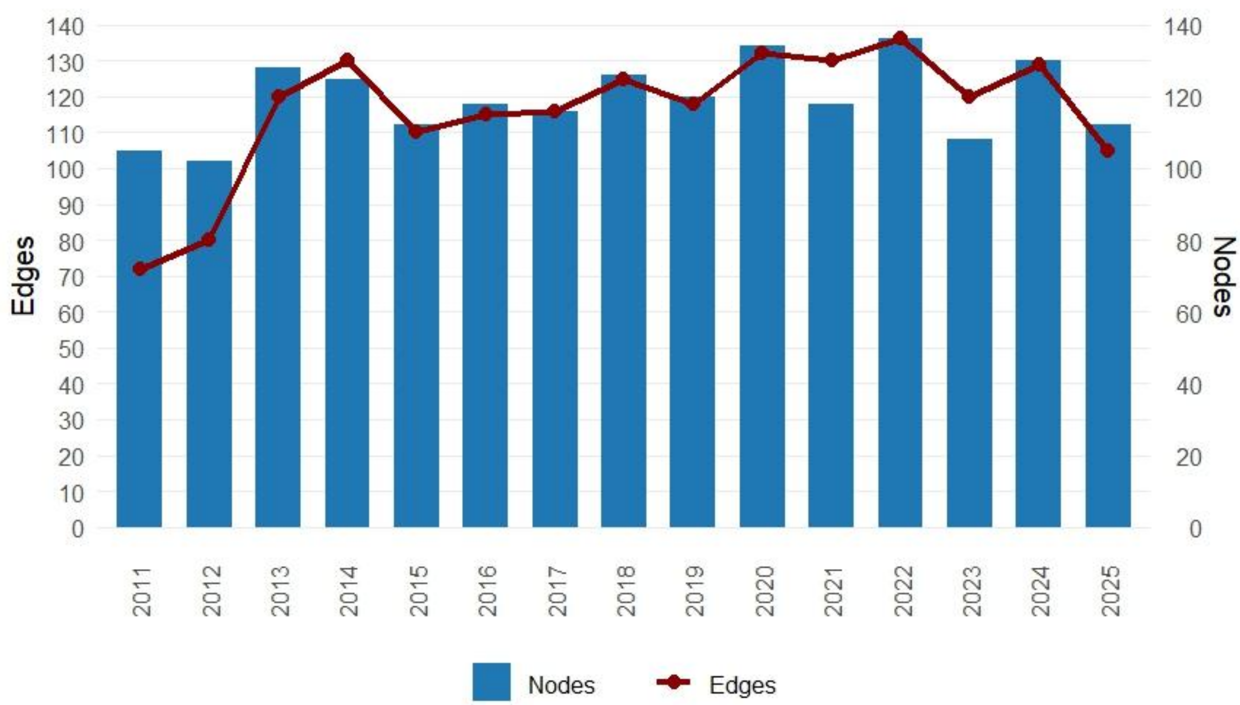
$$NE = \frac{1}{N(N-1)} \sum_{\mathrm{i} \neq j} \frac{1}{d_{ij}} , \tag{15}$$

where NE stands for the average value of the domestic risk effectiveness over each node, and it shows the influence of a network attack on the effectiveness of network distribution. N represents the network nodes' aggregate number, whereas d_{ij} is the smallest distance between nodes i and j. The node risk effectiveness is represented by the inverse of d_{ij}, written as $1/d_{ij}$. Lower network stability and efficiency are correlated with bigger d_{ij}. A larger d_{ij}, on the other hand, suggests a more effective and stable link.

4. Findings and Discussions

4.1 The international nickel ore trade network characteristics

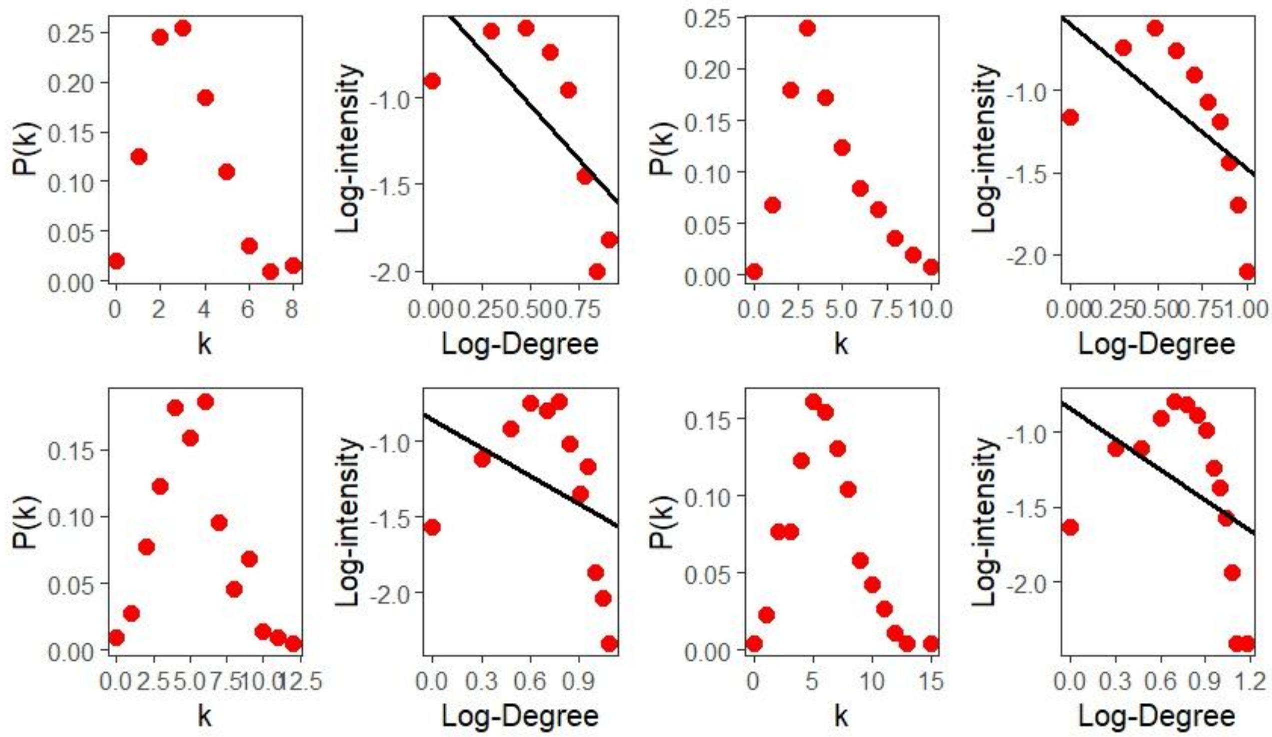
Figure 1. The number of edges and nodes in the nickel trade networks



Note: This figure demonstrates the trade acquaintances number (right axis, nodes) and the participating states number (left axis, edges).

Figure 1 depicts the trade interactions and the number of nations involved in the nickel ore trade. Around sixty nations participated in nickel ore trading between 2011 and 2025. There were no significant global shifts in the nations' involvement. The highest number of participating nations was sixty-five, recorded in 2015 and 2018. The lowest number of trade nations was fifty-two in 2006, while in 2011 and 2025, it was fifty-three. There was a slight trend in the trading interactions within the nickel ore trade. In 2011, eighty-five trade partnerships steadily increased to a peak of 154 in 2018 before decreasing to 116 by 2025. Overall, there is a growing diversity in the interactions between nickel ore exporters and importers.

Figure 2. The international nickel ore trade network's degree distribution. Right: log-log scale; Left: Original scale.

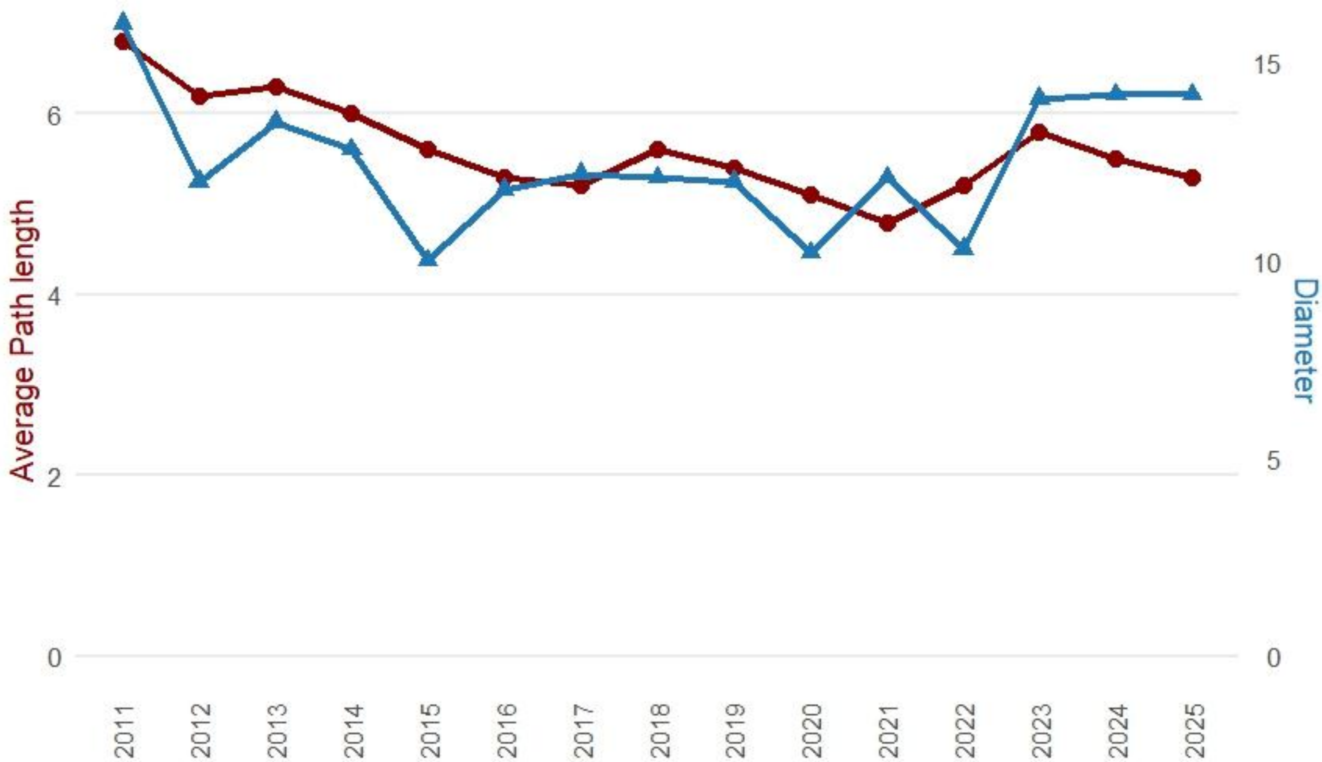


Note: The y-axis demonstrates the probability of degree, and the x-axis shows the degree (both in log scale on the right panel). The scale-free property is verified by the straight line fit.

In Figure 2, logarithmic coordinates depict the probability distribution and degree distribution (comprising out-degree and in-degree) for 2025, 2017, 2012, and 2011. The nickel ore trading network's degree distribution exhibits characteristics of a scale-free link, as it displays a power-law shape. Mostly, the nodes have truncated degrees and restricted connections. In contrast, some nodes have high degrees and multiple interactions, as observed in the degree possibility distribution plot on the left.

The interconnectedness of these high-degree nodes is crucial for the overall functioning of the network. The entire network could rapidly halt if destructive attacks or face risks target these nodes. When the degree and degree probability values are transformed into logarithmic values, the linear regression approach comes close to a continuous mark in the logarithmic coordinate structure on the graph's right side. It demonstrates that the degree distribution of the trade network obeys a power-law distribution. The degree probability distribution graph exhibits a clear linear declining trend. A goodness-of-fit analysis is conducted on the power-law distribution to demonstrate the scale-free nature of the network. This analysis estimates a p-value to assess the degree of fit between the data and various distributions. By comparing the p-values of the power-law distribution with those of alternative distributions (such as truncated power law and stretched exponential), it is determined that the data sets for the years 2011, 2012, 2017, and 2025 conform to the power-law distribution. The fact that all the p-values are greater than 0.1 supports the finding that the network follows the scale-free topology (Clauset et al., 2009).

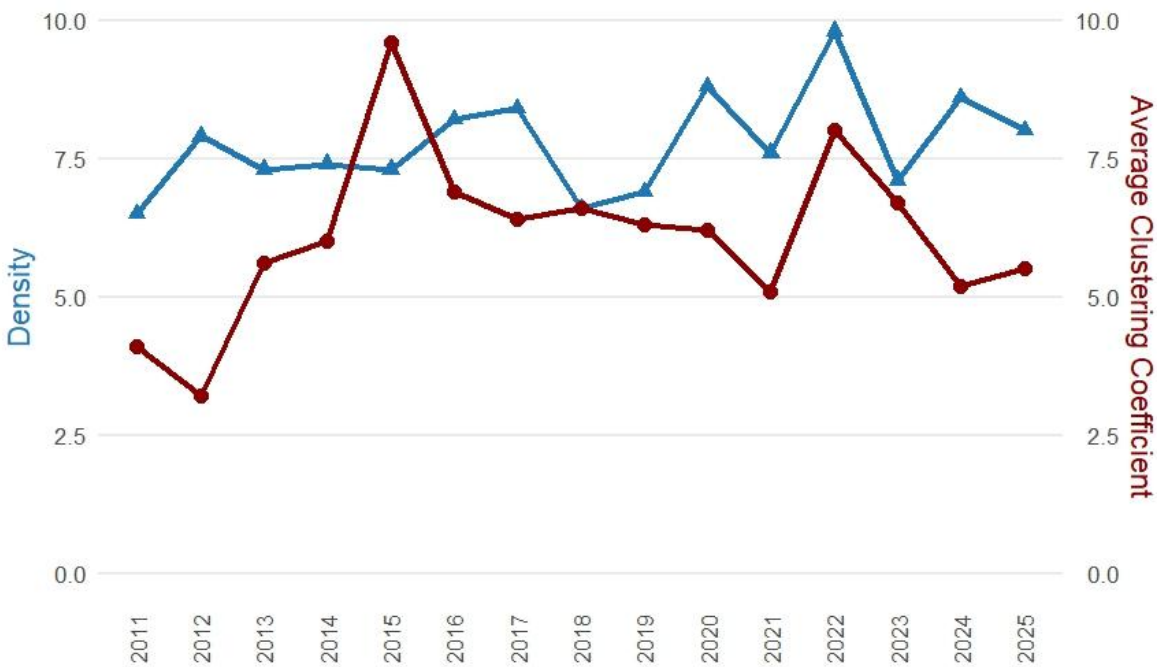
Figure 3. The international nickel trade network's diameter and average channel length, 2011 to 2025.



Note: Diameter (right y-axis, dashed line) and Average Path Length (left y-axis, solid line) of the international nickel trade network, 2011–2025.

The internationally connected nickel ore intricate network’s average route length reduced from 3.298 to 2.792 between 2011 and 2025 (Figure 3). It indicates higher efficiency and interconnectivity in trade operations involving nickel ore between exporting and importing nations. The network average route length remained constant at 3, suggesting that, on average, three intermediate nations facilitate trade between nations and their trade allies. In 2011, when trade efficiency was at its lowest, the mean route length reached its highest point. The network's transmission efficiency and trade smoothness remained relatively stable from 2012 to 2016, with minor variations observed between 2021 and 2025. In contrast, the network width exhibited more frequent fluctuations than the average route length, ranging from a low value of 5 to a high value of 8. The network diameter normally ranged between 5 and 6.

Figure 4. The international nickel trade network's density and average clustering coefficient, 2011 to 2025.



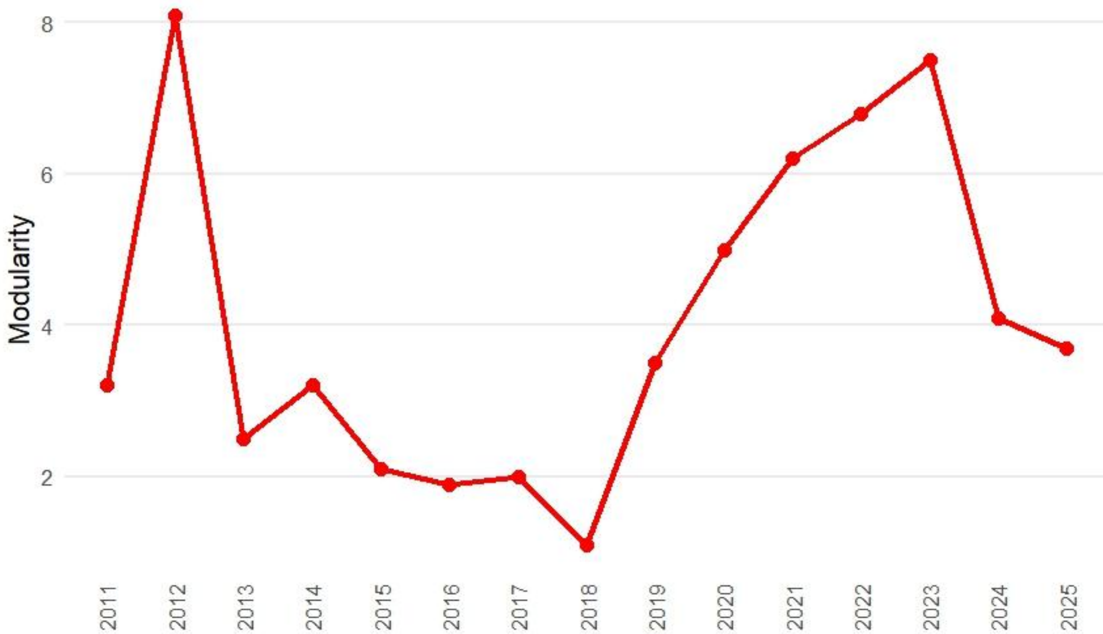
Note: This figure demonstrates the Density (right axis) and the average coefficient of clustering (left axis). The coefficient of clustering shows the localized trade cluster intensity, whereas the density imitates the aggregate proportion of realized trade association. These measures indicated how strongly the network was linked throughout the time.

Figure 4 illustrates the fluctuating trend of the average clustering coefficient in the nickel ore trade network. Starting at 0.212 in 2011 and increasing to 0.482 in 2015, the clustering coefficient did not exhibit consistent annual growth. Clear clustering between trade nations and their partners indicates a sustained level of strong interactions. The highest intimacy among trade partners was observed in 2011, which can be attributed to the international economic disaster of 2008. This catastrophe substantially influenced the world economy and resulted in substantial losses in the stainless-steel sector.

Consequently, the demand for nickel decreased, potentially leading to closer ties between trade partners. After the economic downturn of 2012, trade nations began seeking alternative trade partners that offered greater adaptability. It allowed them to mitigate supply risks and adjust to changing market conditions, leading to a more relaxed state among trade nations. Consequently, from 2012 to 2016, the average clustering coefficient exhibited a relatively consistent development pattern. Between 2021 and 2025, the clustering coefficient showed less fluctuation, with a peak of 0.401 reported in 2017 over the five years. It indicates that there is still room for enhancement in trade associations and the potential for further strengthening connections between nations engaged in the nickel ore trade.

The trade network density exhibited variations between 2011 and 2021, ranging from 0.059 to 0.087. These fluctuations suggest the nickel ore trade's scale remained generally lucrative and stable. Prior to 2013, the density of the network persisted at 0.069. However, after 2015, it showed increased fluctuations. It can be attributed to the global transformation of the nickel sector from excess to scarcity. In 2019, the shortage of nickel ore reached its highest level, indicating the influence of fluctuations in the world nickel ore market on the network density. The changing market conditions and availability of nickel ore directly influence the trade network density.

Figure 5. The international nickel trade network's modularity, 2011 to 2025.



Note: This figure demonstrates the modularity values over time. The values that are below 0.2 denote high globalization, whereas the values that are higher than 0.2 propose stronger regional clustering. Crests in modularity link to shocks in supply and trade problems, which supported the trade associations' localization.

Figure 5 demonstrates significant changes in the nickel ore trade modularity between 2011 and 2025, signifying globalization's fluctuating level. The modularity remains below 0.2, except for 2006 and 2017 to 2020, when it exceeds this threshold. It suggests that before 2015, the nickel ore trade exhibited a high degree of globalization without clear geographical peculiarities. In 2018, the first-ever nickel supply deficit occurred, followed by a trade dispute in 2020. These events influenced the growth of modularity in the trade network. Trading nations sought to mitigate the adverse effects by improving their trade interactions with other regional economies. Consequently, localization increased, and the degree of international trade interdependence decreased.

4.2 Diagnostic Assessment

To evaluate the statistical properties of the key variables in the nickel ore trade network, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were conducted for trade volume, clustering coefficient, average degree, and network density. The results, presented in Table 1, reveal that trade volume and average degree are stationary at level I(0), while clustering coefficient and network density become stationary only after first differencing, I(1). This mixed order of integration (a combination of I(0) and I(1) variables) makes it inappropriate to rely on standard correlation or trend analysis, as these approaches risk producing spurious results. To address this issue, we employ the Autoregressive

Distributed Lag (ARDL) framework (Pesaran et al., 2001). The ARDL methodology is specifically designed to accommodate variables integrated at different orders, provided none are integrated at I(2) or higher. This approach ensures that both short-run dynamics and long-run equilibrium relationships among trade indicators are estimated in a statistically valid and robust manner. Succeeding the ARDL approach specification described in Section 3.3, the research further conducts the bounds assessment for cointegration to ensure the availability of a long-run association among the variables. The estimated F-statistic of 5.91 exceeds the upper critical bound value of 4.37 at the significance level 5%, verifying the existence of cointegration among trade volume, clustering coefficient, average degree, and network density. Ultimately, the Autoregressive Distributive Lag (2,1,1,0) approach is selected as optimal lag structure on the basis of AIC (Akaike Information Criteria).

Table 1. The findings of the Unit Root Assessment

Variable	ADF Stat	PP Stat	Integration Order
Trade Volume (TV)	-3.2100**	-3.1500**	**I(0)**
Clustering Coefficient (CC)	-2.0500	-2.1000	**I(1)**
Average Degree (AD)	-4.0200***	-3.9500***	**I(0)**
Network Density (ND)	-1.8800	-1.9200	**I(1)**

Note: Significance indicators: ***p < 0.01; **p < 0.05; *p < 0.10.

After confirming the mixed integration orders among the variables, the Autoregressive Distributive Lag (2,1,1,0) approach was utilized to assess both short- and long-run link among the trade volume, clustering coefficient, average degree, and network density. The approach selected based on the AIC captures how structural changes within the trade network affect overall trade performance. The long-run estimates expose that AD and CC have a positive and significant effect on the trade volume, denoting that greater clustering and stronger trade connectivity augment nickel-ore trade flows, while ND displays a weaker yet favorable contribution. In the short run, volatility in CC substantially influences the trade volume, whereas the influences of ND and AD remain statistically insignificant. The error-correction term (ECM_{t-1}) is negative and highly significant (–0.61; t = –4.25), verifying a stable long-run equilibrium. This implies that approximately 61 percent of any disequilibrium in trade volume is corrected within one period. These findings show that short-term shocks in the network gradually converge towards a steady long-run association, highlighting the dynamic and persistent interdependence among the structural features of the international nickel-ore trade.

4.3 Development of the status of key trading economies

The international networks associated with the nickel ore trade are graphically shown using Gephi. The width of interactions and the size of nodes are strongly connected with the trading volume of nickel ore. The illustration's font size and node size represent the degrees of interaction. The evolution of the intricate network of trade in nickel ore from 2011 to 2025 is visually depicted in Figure 6, moving from left to right. This section examines the changing trade relations of specific nations. China has consistently maintained a key position within the network by participating in several trade alliances and substantial trade volume. The trading locations of Belgium, Australia, and Canada have significantly transformed over time, progressively shifting away from the trade network midpoint.

Table 2. Findings of the ARDL Bound Assessment of Cointegration.

Variables	**F-Statistics**	**Conclusion**
Trade Volume (TV)	5.910***	Long-run cointegration
Clustering Coefficient (CC)	4.780**	Long-run cointegration
Average Degree (AD)	4.950**	Long-run cointegration
Network Density (ND)	3.640*	Long-run cointegration
Significance Level	**Lower Bound**	**Upper Bound**
10%	2.63	3.35
5%	3.12	4.37
1%	4.13	5.00

Note: *,**, and *** indicate at the 10%, 5%, and 1% significance level, respectively.

Conversely, the trade position of South Korea, Japan, the United States, and Germany has been mostly stable, maintaining an influential position at the trade network's midpoint for a considerable period. The arrows' magnitude indicates that New Caledonia, the Philippines, and Indonesia have continuously distributed a significant amount of nickel ore to their reliable trade associates. These nations play a vital role in the complete characteristics of the international nickel trade network, serving as major participants. Several nations on the network's periphery are characterized by their small economies. Due to limitations in long-distance shipping capabilities, low market demand, and restricted mining supply ability, their trading positions have largely remained stable. As a result, they primarily engage in commerce with a small number of specific nations, experiencing minimal growth or diversity.

Table 3. Estimated Long- and Short-Run Results of the ARDL(2,1,1,0) Model

	Dependent Variables for each model (Panel A and B)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Panel A: Long-Run estimates				
Independent Variables	**Trade Volume (TV)**	**Clustering Coefficient (CC)**	**Average Degree (AD)**	**Network Density (ND)**
CC	0.427 (3.14) ***	—	—	—
AD	0.362 (3.55) ***	—	—	—
ND	–0.298 (–2.38) **	0.155 (2.17) **	—	—
TV	—	0.271 (2.82) **	0.347 (3.05) ***	0.193 (2.06) **
Panel B Short-Run estimates				
Variables	**ΔTV**	**ΔCC**	**ΔAD**	**ΔND**
ΔCC (–1)	0.211 (2.40) **	—	—	—
ΔAD (–1)	0.157 (2.49) **	0.118 (2.05) **	—	—
ΔND (–1)	–0.095 (–1.82) *	–0.076 (–1.66) *	–0.043 (–1.57)	—
ΔTV (–1)	—	0.189 (2.41) **	0.217 (2.87) ***	0.146 (2.03) **
ECM(–1)	–0.612 (–4.25) ***	–0.524 (–3.97) ***	–0.487 (–3.62) ***	–0.453 (–3.45) ***

Note: This table presents the long- and short-run estimates of the Autoregressive Distributed Lag (ARDL) model specified in Equation (13), which examines the relationship among trade volume (TV), clustering coefficient (CC), average degree (AD), and network density (ND) in the global nickel ore trade network. The optimal lag structure (2,1,1,0) was selected based on the Akaike Information Criterion (AIC). All variables are expressed in first differences for short-run dynamics, while the lagged level terms capture long-run equilibrium relationships. The coefficient of ECM(–1) denotes the error-correction term, which measures the speed of adjustment toward long-run equilibrium after a short-run shock. The t-statistics are shown in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The negative and statistically significant ECM coefficient confirms a stable long-run relationship among the variables.

Table 4. The Diagnostic assessment of the ARDL approach

Variables	Adj. R^2	ECM(–1)	LM	RESET	CUS(CUS²)
Trade Volume (TV)	0.793	–0.612***	1.521	0.824	S(S)
Clustering Coefficient (CC)	0.768	–0.524***	1.684	0.715	S(S)
Average Degree (AD)	0.742	–0.487***	1.932	0.629	S(S)
Network Density (ND)	0.711	–0.453**	1.845	0.947	S(S)

Note: This table reports the diagnostic and stability tests corresponding to the ARDL model presented in Table 3. Adj. R^2 denotes the adjusted coefficient of determination, indicating model fit. ECM(–1) represents the lagged error-correction term derived from the long-run equilibrium relationship. LM refers to the Breusch–Godfrey Lagrange Multiplier test for serial correlation in the residuals, and RESET refers to the Ramsey Reset test for model specification. CUSUM and CUSUM² represent the cumulative sum and cumulative sum of squares stability tests. The notation S(S) indicates that both the CUSUM and CUSUM² tests confirm model stability within the 95% confidence bounds. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The leading five nations in terms of out-degree and in-degree are presented in Tables 5 and 6.

Table 5. The leading five nations in Leading Five Nations in Three Centrality Measures (Closeness, Eigenvector, Betweenness.

	Closeness Centrality	Eigenvector Centrality	Betweenness Centrality
2011	1.China 2.Philippines 3.Netherlands 4.USA 5.Japan	1. China 2. Italy 3. Spain 4.Philippines 5.Belgium	1.USA 2.Australia 3.China 4.Finland 5.Belgium
2012	1.Algeria 2.Indonesia 3.Japan 4.Australia 5.New Caledonia	1.China 2.Belgium 3.USA 4.Canada 5.Finland	1.China 2.USA 3.Australia 4.Indonesia 5.Belgium
2013	1.USA 2.Germany 3.Australia 4.South Africa 5.Indonesia	1.Belgium 2.China 3.France 4.Netherlands 5.Germany	1.China 2.Germany 3.South Africa 4.Belgium 5.Netherlands
2014	1.Australia 2.Indonesia 3.Netherlands 4.USA 5.Canada	1.China 2.Singapore 3.France 4.India 5.South Korea	1.China 2.Netherlands 3.Canada 4.India 5.Germany
2015	1.USA 2.Indonesia 3.Canada 4.Australia 5.Germany	1.China 2.Singapore 3.South 4.Korea Belgium 5.United Kingdom	1.China 2.Germany 3.Canada 4.South Africa 5.United Kingdom
2016	1.Uganda 2.USA 3.Australia 4.Indonesia 5.Brazil	1.China 2.Singapore 3.France 4.Belgium 5.United Kingdom	1.China 2.United Kingdom 3.Germany 4.South Africa 5.USA
2017	1.USA 2.Canada 3.Indonesia 4.Italy 5.Finland	1.China 2.South Korea 3.India 4.Germany 5.Singapore	1.China 2.Singapore 3.Belgium 4.Indonesia 5.Canada
2018	1.Indonesia 2.USA 3.Australia 4.Brazil 5.Japan	1.China 2.South Korea 3.India 4.Germany 5.USA	1.China 2.Germany 3.USA 4.South Africa 5.Canada
2019	1.Poland 2.Kenya 3.Finland 4.Australia 5.Germany	1.China 2.Spain 3.South Africa 4.Singapore 5.Canada	1.China 2.Netherlands 3.France 4.South Africa 5.United Kingdom
2020	1.Canada 2.USA 3.Finland 4.United Kingdom 5.Netherlands	1.China 2.Germany 3.USA 4.South Korea 5.India	1.China 2.USA 3.France 4.Germany 5.United Kingdom
2021	1.USA 2.Brazil 3.Australia 4.Canada 5.United Kingdom	1.China 2.Germany 3.Canada 4.USA 5.France	1.China 2.USA 3.Canada 4.Germany 5.United Kingdom
2022	1.USA 2.Japan 3.Thailand 4.China 5.Canada	1.China 2.Germany 3.Malaysia 4.Singapore 5.USA	1.USA 2.China 3.Germany 4.South Africa 5.Finland
2023	1.USA 2.China 3.Japan 4.Canada 5.New Caledonia	1.Germany 2.China 3.Singapore 4.Vietnam 5.Canada	1.China 2.Germany 3.Canada 4. United Kingdom 5. USA
2024	1.Luxemburg 2.USA 3.Japan 4.China 5.Indonesia	1.South Korea 2.Germany 3.China 4.Vietnam 5.Philippines	1.China 2.USA 3.Germany 4.Vietnam 5.Philippines
2025	1.USA 2.Indonesia 3.China 4.Philippines 5.New Caledonia	1.Germany 2.China 3.Vietnam 4.United Kingdom 5.Italy	1.China 2.USA 3.Germany 4.South Korea 5.Philippines

Note: This table presents the top five countries ranked by Closeness, Eigenvector, and Betweenness Centrality for each year from 2011 to 2025. Data are derived from the UN Comtrade database.

Table 5 reveals that China consistently held the top annual imports throughout the research period. Germany consistently ranked second behind China for nine years. Belgium was among the leading five nations before 2012, but lost its position afterward. On the other hand, South Korea began appearing in the top five positions in 2012 and has been steadily improving. From 2016 to 2019, the United States was the only nation consistently ranked among the top five, while other nations' rankings fluctuated.

Regarding these nations' nickel usage, South Korea, Germany, and China were comparatively nickel ore-consistent importers throughout the research period. The data demonstrates that China maintained the top import spot from 2011 to 2025. With its progressive production technologies and R&D techniques, Germany is the top stainless-steel manufacturer in Western Europe. Driven by its thriving battery sector, South Korea significantly relies on nickel ore, particularly with companies like SK Innovation, SAMSUNG SDI Co., Ltd., and LG Energy Solution supplying batteries to global electric car manufacturers. It is important to note that Japan, despite having a relatively lower ranking in terms of degree, still engages in significant commerce with specific trading partners.

The United States maintained the top position throughout the 10-year research period when considering the leading five exporting nations. South Africa held a significant position due to its long-standing history of nickel exports, while Indonesia consistently ranked second in nickel exports. The exports of China entered the leading five ranks after 2014, but their position experienced significant fluctuations. Despite not having substantial nickel deposits or bulky nickel mines, the US has retained a considerable influence through its ownership of shares in the foremost nickel supply and mining firms worldwide.

The United States has maintained a strong and stable trading position over a significant period due to the extensive commercial connections it has established globally. Regarding nickel ore production, Indonesia has consistently held the top position, solidifying its status as a major nickel exporter on the international stage. Despite having abundant nickel ore deposits, New Caledonia and the Philippines are less often seen in the leading ten due to having fewer trade associates. Major nickel mining players like the United States, Australia, and Russia are involved in South African mining, production, and exploration activities. As a result, South Africa maintains business relationships with numerous nations in exporting goods, further strengthening its position within the network of nations involved in the nickel trade.

The concept of betweenness centrality is utilized in the complex network approach to statistically evaluate a nation's management capacity and mediating function within the trade network. This metric focuses on a nation's potential impact on trade networks, emphasizing it more than simply highlighting trade density. Table 5 presents the top five nations with the highest betweenness centrality scores. Over ten years, China consistently held the first position, while the United States ranked second for two years and first for five years. Germany also remained within the top five for the entire decade. These three nations exhibit significant influence and strength within the trade network, as evidenced by their substantial immediate impact. In general, the main nickel ore exporters insignificantly affect the trade networks, with a capability to manage trade networks and a nation's standing primarily dependent on the purchasing market.

Table 6. The leading five nations Leading Five Nations by Node Degrees (Out-degree and In-degree).

	Out-degree	Indegree
2011	1.Germany 2.South Africa 3.Australia 4.USA 5.Indonesia	1.China 2.Belgium 3.Finland 4. Japan 5. Australia
2012	1.USA 2.Indonesia 3. Australia 4. South Africa 5.Japan	1.China 2.Belgium 3.North Macedon 4.Finland 5.Germany
2013	1.USA 2.Indonesia 3. Australia 4. South Africa 5.Germany	1.China 2.Germany 3.Belgium 4.France 5.Canada
2014	1.Indonesia 2.USA 3.Netherlands 4.United Kingdom 5. Belgium	1.China 2.Germany 3.Canada 4.India 5.France
2015	1.USA 2.Indonesia 3.Canada 4.China 5.Germany	1.China 2.Canada 3.Belgium 4.Germany 5.France
2016	1.USA 2.Indonesia 3.South Africa 4.United Kingdom 5.Germany	1.China 2.France 3.Germany 4. Belgium 5.Finland
2017	1.USA 2.Indonesia 3.Canada 4.Finland 5.South Africa	1.China 2.Germany 3.Canada 4.South Korea 5.Finland
2018	1.Indonesia 2.USA 3.Australia 4.South Africa 5.Germany	1.China 2.Germany 3.South Africa 4.South Korea 5. Canada
2019	1.China 2.South Africa 3.Netherlands 4.Indonesia 5.Germany	1.China 2.South Africa 3.Canada 4.Spain 5.South Korea
2020	1.USA 2.Finland 3.Australia 4.China 5.France	1.China 2.Germany 3.South Korea 4.India 5.South Africa
2021	1.USA 2.China 3.Germany 4. United Kingdom 5.South Africa	1.China 2.Germany 3.USA 4.Canada 5.South Africa
2022	1.USA 2.Germany 3.United Kingdom 4.China 5.Finland	1.China 2.USA 3.Germany 4. South Korea 5. Canada
2023	1.China 2.USA 3.Canada 4.Germany 5.Japan	1.China 2.Germany 3.Canada 4. South Korea 5. USA
2024	1.USA 2.Japan 3.Indonesia 4.China 5.Canada	1.China 2.Germany 3.Canada 4.South Korea 5.North Macedon
2025	1.USA 2.China 3.Japan 4. South Korea 5. Indonesia	1.China 2.Germany 3.South Korea 4.South Africa 5.North Macedon

Note: This table presents the top five countries ranked by out-degree (number of export partners) and in-degree (number of import partners) for each year from 2011 to 2025. Data is sourced from UN Comtrade.

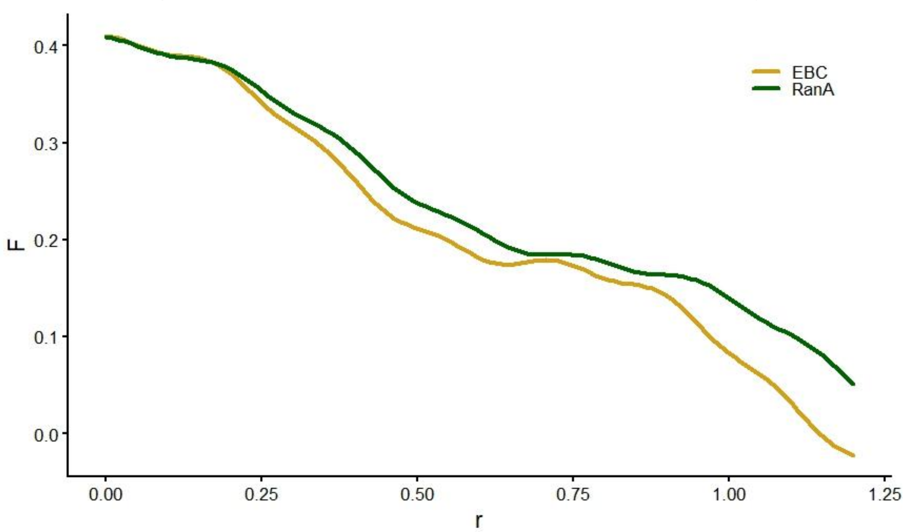
Closeness centrality measures a nation's capacity to resist domination within a complex network based on the distance between nodes. In the trade network from 2011 to 2025, the United States held the top position for seven years and the second position for four years, demonstrating its strong anti-control capabilities. Australia also obtained a high score, indicating fewer restrictions on trading connections with other countries. In the past, Indonesia ranked second, while China has consistently been among the top five nations since 2018. Overall, China, Indonesia, the US, and Australia have relatively short trade distances with other economies, placing them in advantageous positions within the international nickel ore trade. The US, in particular, has consistently maintained a high closeness centrality, indicating its stability in trade relationships. It can be attributed to its extensive geopolitical connections and the high level of trade independence it enjoys. Main nickel ore exporters like South Africa and Indonesia also hold valuable positions within the trade network, underscoring the significance and value of export-oriented countries in international trade.

Eigenvector centrality is a relevant indicator of a trading nation's indirect influence on the network structure. This measure considers the characteristics and properties of the other nodes connected to the target node. A nation's eigenvector centrality score is higher if linked to more significant nodes. China has maintained a relatively consistent position in terms of eigenvector centrality over the past 15 years, starting from 2011, with no significant changes in its trade partners. Most of China's trade partners are highly developed nations that engage in both exports and imports. In terms of eigenvector centrality, Germany has consistently ranked well. It is attributed to Germany's extensive bilateral trade relationships with various countries in Western Europe and its strong ties to key trading partners worldwide. Other countries such as South Korea, Singapore, Belgium, France, and the United States have also demonstrated substantial eigenvector centrality rankings throughout the study period, indicating their significant influence on the indirect patterns within trade links.

4.4 International nickel ore trade network stability

Figure 6 depicts how the node connection patterns of the network change under various attack methods. The connections between trading nations are exclusive in the nickel ore trade network, meaning there are no additional trade interactions. The initial network connectivity in 2021 resulted in a rating of 0.961. In 2017, the connectivity rating was 1, while it was 0.931 in 2012 and 0.962 in 2011. Throughout this period, the initial association coefficient remained relatively stable.

Figure 6. The attack nodes' proportion and the connectivity variation under various attack tactics.



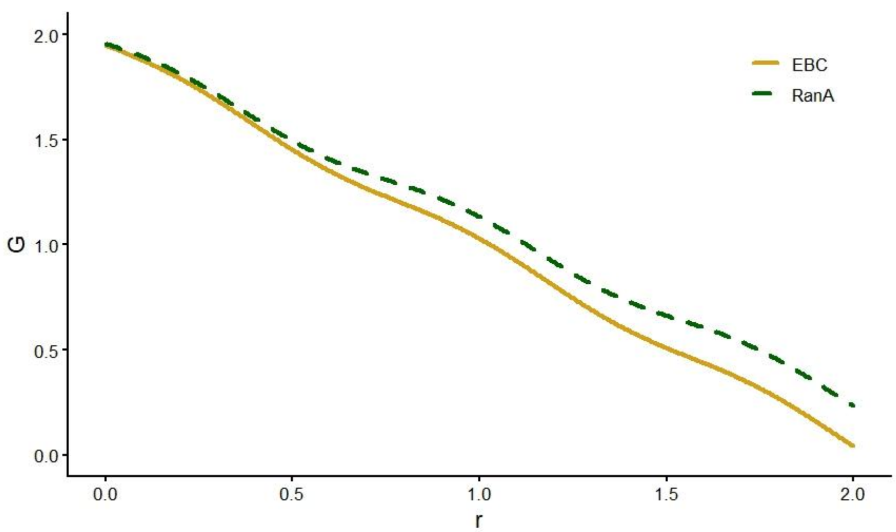
Note: This figure demonstrates the connectivity of the network (y-axis) as nodes are removed (x-axis). The r indicates the damage to the network degree, that is, the proportion of attacked nodes to the total number of nodes in the network. The results of random attacks are in a gradual decrease, whereas the targeted attacks on the high-degree nodes cause swift disintegration. This shows the scale-free susceptibility.

The network's connectivity gradually declines consistently under random assaults (RanA). However, the nickel ore trading network experiences a faster decline in connectivity when subjected to targeted assaults, particularly when employing the highest degree of attack method (DA). When the percentage of eliminated nodes (P) reaches a specific level, such as 20 percent, the connectivity under DA and the shared neighbor attack (CCA) becomes equal. In contrast to DA and CCA, the connectedness under the betweenness centrality attack (BCA) is higher, indicating a more connected subgraph. The trading link under BCA and DA becomes separated when the P grasps 40 percent.

Furthermore, under CCA, the trade network is mostly severed when P exceeds 50 percent. As of 2021, there were 53 trading nations included in the network. The network's structure is significantly affected, leading to the emergence of additional segments when failures occur in approximately 10-15 nations. South Korea, Japan, Germany, the United States, and China are the top five nations with the highest degrees in 2021. The connected subgraph size rapidly decreases when these five nations are selected based on their centrality degree. The interaction value quickly drops to 0.490 due to an attack on Indonesia, and attacks on nations such as the Netherlands, Belgium, and Brazil cause a sudden decline in connection to 0.235. It demonstrates that these nations are also significant players with a strong network connectivity influence.

In 2021, despite deliberate and accidental attacks on the network, Figure 7 illustrates the changing structure of network efficiency. The network efficiency started at 0.4234 in 2021. It was slightly higher in 2017 at 0.447 compared to 0.38 and 0.339 in 2014 and 2011, respectively. The collaboration efficiency of the nickel ore trading network remained consistently low over this period, with no significant changes observed. Minor fluctuations in the curve represent the decreasing pattern of random attacks. Network efficiency steadily decreases as nodes are eliminated, following a clear decreasing pattern until P reaches 0.5.

Figure 7. The proportion of attacked nodes and the network efficiency variation under various attack tactics.



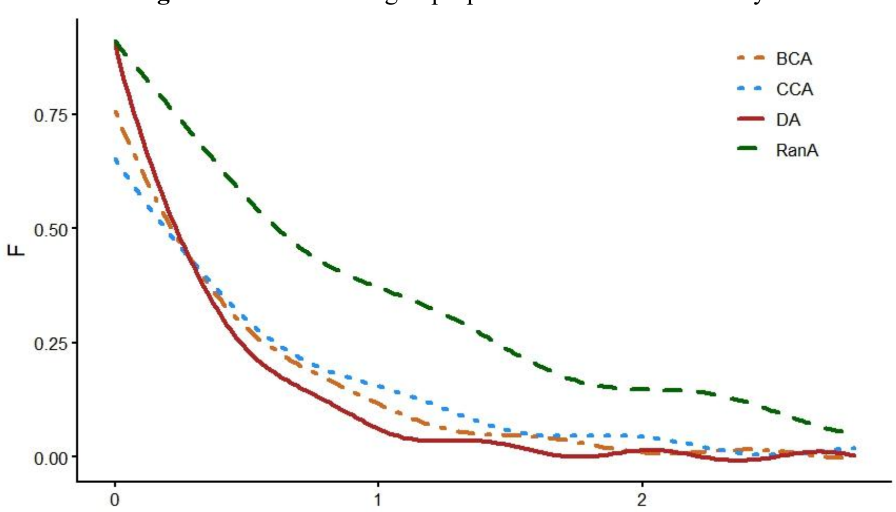
Note: This figure shows the efficiency of the network (y-axis) as a result of the node removal (x-axis). This random removal directly leads to a moderate decrease, whereas targeted attacks (betweenness, closeness, degree) abruptly decrease efficiency, showing the systemic brittleness.

On the other hand, under targeted assaults, network efficiency rapidly declines for all three attack types, with virtually identical effects on the network. The coefficient G reaches 0.05 at a P value of 20 percent and drops to around 0.02 at a P value of 0.4. The normal flow of information and minerals throughout the network is disrupted, leading to a collapse of the network when approximately ten member nations encounter difficulties. Targeting only the top five nations results in a noticeable decrease in network effectiveness of around 0.3. Furthermore, successive attacks on nations such as South Africa and Indonesia lead to a continuous decrease in network efficiency, albeit gradually slowing.

The trade network is significantly more vulnerable to targeted attacks, as their consequences are considerably more devastating than random attacks. Targeting large trading partners or powerful nations has a detrimental impact on the sustainability of the global trade network. Additionally, several nations that export nickel ore significantly influence the network's stability. However, developing countries with limited economic partners have minimal impact on shifts in stability. The trade network demonstrates exceptional resilience against random attacks, showcasing its ability to withstand such disruptions. Among the sustainability parameters, the degree of assortativity (DA) influences the network's integrity the most. Closeness centrality assortativity (CCA) and betweenness centrality assortativity (BCA) also have notable impacts on the network. Targeting the top five nations with high CC and BC has similar effects to targeting DA. When Indonesia was removed from the nickel ore trading network in 2025, the stability measures began approaching a critical state. This study emphasizes the significance of Indonesia as a crucial node that profoundly affects the stability of the global trading system.

Figure 8 depicts that no immediate isolated nodes appear when the network connection is subjected to the maximal edge betweenness centrality attack (EBC). Other important maritime channels within the network used for selling nickel ore may continue to provide continuous transit and connectivity. In contrast, under random attacks, the connectedness exhibits a pattern of initial decline followed by an increase. However, the connecting subgraph becomes divided after the "South Africa-China" edge is targeted. The connection curve demonstrates multiple phases of the targeted assault.

Figure 8. The attack edges' proportion and the connectivity variation under various attack tactics.

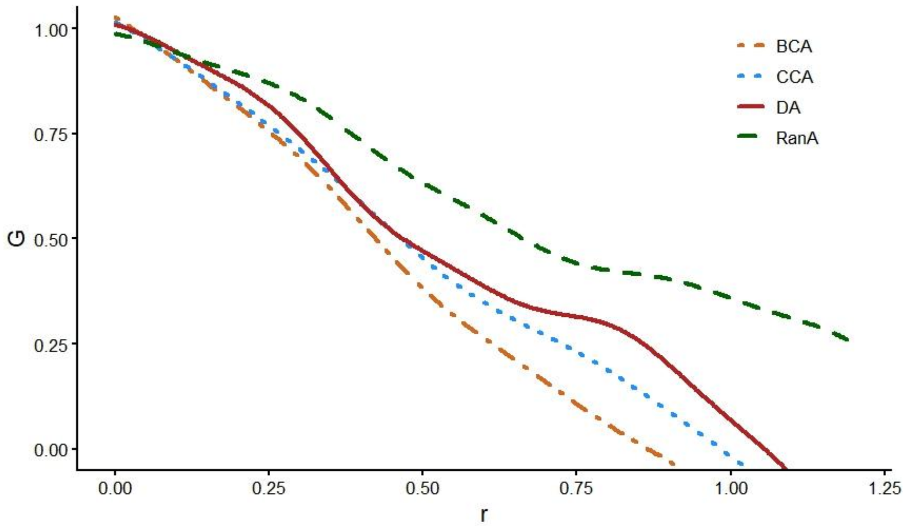


Note: This figure demonstrates the connectivity of the network during the removal of an edge. Failures of random edges primarily cause modest losses; however, the targeted removals (such as the South Africa-China association) substantially weaken the network, demonstrating the significance of the specific commerce corridors.

The network connection remains mostly stable, with little variation within the 20 percent to 40 percent range for P. During this period, the coefficient fluctuates between 0.81 and 0.79. As P approaches 50 percent, the network interaction declines in a zigzag pattern. When 90 percent of edges fail, the network is on the Brink of collapse.

Figure 9 also demonstrates the network efficiency pattern under both the maximal edge betweenness attack and the random attack scenarios. The network efficiency decreases as the number of failed channels or trade paths increases. The most significant loss in network efficiency occurs when P is below 20 percent, with a calculated efficiency of 0.26 at that point. Beyond this threshold, the network's transmission efficiency steadily declines, exhibiting minor variations. When the edge collapse proportion surpasses 80 percent, the network efficiency drops to 0.06, indicating a network breakdown where trading operations cannot be effectively conducted.

Figure 9. The attack edges' proportion and the network efficiency variation under various attack tactics.



Note: This figure demonstrates that as the trade edges are removed, the efficiency of the network decreases. The losses are high at the initial phase (<20% of edges), after which the efficiency continues to decline slowly. This shows that several primary trade paths sustain much of the efficiency of the network.

Compared to node attacks, targeted edge attacks generally result in less network stability than random attacks. However, regarding the impact on network stability resulting from node failures, the connectivity coefficient and network efficiency decline under the two-edge attack tactics are relatively slower. It indicates that the harm to network stability is less severe when edges are subjected to threats. It is because even when the trade relationship between two specific nations is severed, those nations may still engage in business with alternative trading partners. It is unlikely that any nation will become completely isolated from the network in a short period. Thus, the trade network exhibits some stability against hazards, even if the shipment of nickel ore is restricted. Interestingly, nine of the top 20 failed trade channels involve the export or import of nickel ore from China, two involve the shipment of nickel ore from Indonesia, and four involve the export of nickel ore.

5. Conclusion

The stability of the world trade network in nickel ore was tested in this study through the use of complex network science to determine its structural characteristics, dynamic trade flows, and perturbation robustness. In robustness simulations, the paper investigated how the network responds to targeted and stochastic attack processes. Through position analysis of influential trading nations, and the role played by investments, interregional links, and world market forces, the paper gives a comprehensive description of nickel ore trade stability.

The findings validate that the nickel ore trade presents a scale-free network structure in accordance with a power-law distribution. Despite the fact that the overall trade network has expanded in the period since the turn of the 21st century, inter-country connections are lopsided, and risks are tenacious. Despite greater reliability and efficacy in trade, stability drops significantly when dominant nodes are attacked, producing systematic susceptibilities. Central countries such as China, America, and Germany remain in central positions in sustaining trade flows, and South Africa, Indonesia, and the Philippines are seminal exporters whose removal causes systemic risks. Furthermore, states with vast financial associations, including Brazil and the Netherlands, contribute significantly to instability as targets. Half of the import routes by China are among the most disrupted trade flows, emphasizing the vulnerability to localized risks.

The study has a number of important implications. First, there is a need for international cooperation, diversification of trade partnerships, and encouraging openness in order to mitigate systemic risks. Large countries ought to advance international resource allocation approaches, guard foreign interests, and ensure sustainable and fair development of mineral supply chains. Second, a systematic assessment of nickel ore trade routes is required, considering supply concentration, geopolitical security, and logistical channels such as shipping routes and ports. These assessments will allow policymakers to allocate resources in a more effective way across diverse trade routes. Third, consumer nations ought to support supplier nations through technical, financial, and infrastructural support, thereby ensuring long-term stability in nickel ore flows. These initiatives can reduce the "Matthew effect," in which advantages are centralized in a small number of states, and encourage more participation in the world nickel ore trade.

The novelty in this research is in its use of network robustness simulations in the case of the nickel ore trade, providing evidence-based perspectives on how targeted interferences diffuse through trade networks globally. Unlike previous work, which mainly explored other minerals, the study points out the specific exposures of nickel ore supply chains and shows how they contribute to economic security globally.

This investigation has limitations. The assessment depends on the official data of trade, which might exclude the unreported or informal flows, and does not fully capture the sudden policy changes that could change the network. This context can be enhanced by future investigations by including additional variables such as trade dynamic modeling under climate policy scenarios, technological change in the steel and battery industries, and environmental regulations. Assessing multi-product interdependencies could also enhance the insights into common risks in the trade of resources. Ultimately, this research contributes to the literature on the international resource trade by offering a strong framework for assessing the stability of the nickel ore trade network. It delivers timely information for stakeholders of the industry and policymakers seeking to increase the resilience of the supply chain by ensuring sustainable trade flows and predicting vulnerabilities in a swiftly developing global market.

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