

MAPPING INDIA'S COMMODITY EXPORT NETWORK: SECTORAL INTERCONNECTEDNESS AND BEHAVIOR AT TAIL DISTRIBUTION WITH LEADING GLOBAL ECONOMIES

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ABSTRACT

This study investigates the interconnectedness of India's commodity exports with thirteen major global economies from 2000 to 2023, employing the quantile-quantile connectedness approach. The analysis, illustrated through an extensive network graph, highlights significant variations and dependencies across three economic indicators, particularly in extreme distribution scenarios across various export categories. Our findings reveal convoluted non-linear and multiscale interdependencies that elucidate global economic behavior, especially in India's bilateral trade relationships. Economic Policy Uncertainty (EPU), Consumer Price Index (CPI), and Producer Price Index (PPI) of destination countries have a decisive role in the export network, alongside key export categories such as Petroleum, Agriculture, Ores, and Manufacturing, underscoring India's pivotal role within the global commodity export network. Furthermore, Principal Component Analysis

(PCA) is utilized to consolidate economic variable outcomes into a singular, interpretable metric for each commodity category. These results underscore the significance of extreme economic conditions and tail dependencies in shaping policy, with critical implications for international trade and economic strategy. This study's methodological and sector-specific insights offer valuable guidance to policymakers and economists in understanding global economic interdependence and crafting more resilient trade and economic policies.

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INTRODUCTION

Understanding India's economic interdependencies and connectedness to

major global economies is essential to making informed international trade policy decisions and strategic choices. Especially in extreme market conditions, correlation and cointegration analyses often fail to capture the full scope of these relationships. This study employs a quantile-quantile connectedness approach to analyze India's economic ties with major global economies, such as the US, China, Germany, Japan, and ten others, addressing a gap in the literature. The research reveals non-linear interconnections that conventional methods often overlook. Studying India's economic relationships with other major economies is essential, especially considering its growing influence on the global stage. These relationships influence international trade, financial stability, and economic policies in India and globally.

Objectives of the Study

1. To examine India's relationships with major global economies across three key economic indicators and export sectors by conducting an Economic Interdependency Analysis using a quantile-quantile connectedness approach.

To emphasize non-linear and tail dependencies in these economic relationships to better understand extreme market conditions.

Derive policy-relevant empirical evidence.

Need for the Study

Global economies' trade and export networks are increasingly interconnected in today's highly integrated world. Understanding these complex relationships, especially in extreme economic conditions, is essential for sound economic

and trade policies. This study examines India's commodity export network, a key economic factor, and its non-linear and multiscale interdependencies with thirteen major global economies.

Traditional correlation and cointegration analyses often overlook relationships, particularly under extreme market conditions. This study addresses this gap by employing a quantile-quantile connectedness approach to assess India's role in the global economy. India's growing prominence and the significance of its export sectors, from agriculture to manufacturing, highlight the need to examine how external economic indicators such as Economic Policy Uncertainty (EPU), Consumer Price Index (CPI), and Producer Price Index (PPI) influence these sectors. The study identifies tail dependencies and market behaviors critical for policymakers and economists to formulate trade policies that can endure global economic shocks. Furthermore, these findings provide valuable insights into India's negotiation power during challenging economic scenarios and escalated diplomatic tensions, making this research relevant for stakeholders in trade, business, and economic management.

This study is organized to provide a coherent and systematic analysis of India's commodity export network and its economic interdependencies. The subsequent sections proceed as follows. The literature review synthesizes prior research on economic interconnectedness and highlights key methodological advancements, establishing the gaps that this study aims to address. Next, the data description outlines the key economic indicators and export categories used in the

analysis, detailing their sources, temporal scope, and relevance to the study objectives.

The methodology section describes the analytical framework, beginning with procedures for ensuring stationarity in the data and moving to the application of quantile-quantile connectedness analysis, which captures the relationships across different distributional quantiles. The study further employs network graph construction to visualize trade interdependencies, incorporating measures of path-based connectivity, node centrality, and layout algorithms. Principal Component Analysis (PCA) is introduced to consolidate multidimensional data into interpretable metrics, facilitating an integrated understanding of sectoral dynamics.

The results and discussion section presents the findings, emphasizing sectoral interdependencies and the critical influence of tail dependencies under varying economic conditions. This is followed by an exploration of the broader implications, offering insights into strategies to strengthen India's position within global trade networks. Finally, the conclusion synthesizes the contributions of this research, reaffirming its relevance to policymakers and scholars, and identifies directions for future inquiry in the domain of economic interconnectedness.

To ground this study within the existing body of knowledge, we commence with a discussion of the relevant literature in the next section.

LITERATURE REVIEW

The literature review shows several ways to study economic connectedness. Traditional correlation and cointegration analyses may

not fully capture the complexity of quantile relationships, but they are informative. Quantile regression and connectedness measures now capture tail dependencies and non-linear relationships better. The quantile coherency method captures general dependence structures in economic time series that traditional methods miss. This method effectively evaluates joint distribution in the frequency domain, revealing tail risks in financial markets (Baruník & Křehlík, 2018). High-quantile regression for time series data with tail dependence allows for the study of the asymptotic theory of high-quantile regression estimators under serial dependence, improving insights into economic variable tail behavior (Xu et al., 2020). The Multiscale Quantile Correlation Coefficient (MQCC) measures tail dependence in financial time series by integrating multiscale analysis with quantile correlation to assess correlation strength across quantiles, revealing tail behavior asymmetries across financial markets (Xu et al., 2020). Quantile-based connectedness measures have also been used in volatile markets like cryptocurrency. Bouri et al. (2021) show that these measures are more connected than mean-based measures during extreme events, emphasizing the importance of tail dependencies for dependency assessment in such markets.

Building on these methodological advancements, recent studies have applied quantile-based measures to specific domains, such as financial markets and extreme event analysis. Studies have stressed interconnectedness in trade and financial markets. Bekhet (2009) found that mean intermediate coefficient totals per sector and intermediate transaction percentages help measure economic connectedness in Malaysia.

Raddant and Kenett (2021) analyzed stock dependencies from 15 countries, showing the importance of the US and Germany and the rising importance of the energy and materials sectors, providing a global economic dependency view.

While these methods have proven valuable in financial contexts, their application to trade networks further enhances our understanding of global economic interdependencies. The Global Industrial Value Chain Network (GIVCN) model simulates and measures economic competitive advantages and weaknesses using input-output (IO) tables and network theory. This model accurately depicts intermediate goods flows between industrial sectors, showing global value chain resource competition.

The GIVCN model framework is represented as a directed and weighted graph:

$$G = (V, E, W)$$

V denotes the set of nodes, each representing an industrial sector within a country.

E represents the set of directed edges, indicating the trade flows between sectors.

W is the set of weights assigned to each edge, corresponding to the trade volumes of intermediate goods.

In this context, the nodes V can be defined as $V = \{v_1, v_2, \dots, v_n\}$, where each node v_i represents an industrial sector. The directed edges E are defined as $E = \{(v_i, v_j) \mid v_i, v_j \in V\}$, representing the trade flows from sector v_i to sector v_j . The weights W are given by $W = \{w_{ij} \mid (v_i, v_j) \in E\}$, where w_{ij} denotes the trade volume from sector v_i to sector v_j .

The competitive strength of an industrial sector i against another sector j is quantified through the following formula:

w_{ij} is the competitive strength of sector i relative to sector j .

w_j is the total trade volume associated with sector j .

w_{li} represents the trade volume from sector l to sector i .

w_{lj} represents the trade volume from sector l to sector j .

w_l denotes the total trade volume associated with sector l .

In empirical applications, the GIVCN model simulates trade scenarios and their effects on national competitive advantages and weaknesses. The model can assess how economic shocks and policy changes propagate through the global value chain, affecting the competitiveness of economies.

Some of the interesting characteristics of GIVCN models are:

1. Degree Centrality: The degree centrality for each node v_i is calculated as: where $\text{deg}(v_i)$ represents the total number of connections (both incoming and outgoing) for sector i .

2. Weighted Degree Centrality: The weighted degree centrality incorporates the trade volumes:

3. Betweenness Centrality: Betweenness centrality measures the extent to which a sector lies on the shortest paths between other sectors: st is the total number of shortest paths from sector s to sector t , and $st(v_i)$ is the number of those paths that pass through v_i .

1. Closeness Centrality: Closeness centrality measures the average length of the shortest path from a sector to all other sectors in the network:

2. where $d(v_i, v_j)$ is the shortest path distance between sectors i and j .

Understanding trade trends depends on knowing the relative relevance of sectors and nations in global value chains, which these measures offer vital insights into. By employing these detailed mathematical formulations and network metrics, the GIVCN model provides a comprehensive and technically rigorous approach to analyzing the competitive dynamics and interconnectedness within the global industrial landscape. Extending beyond network metrics, other approaches, such as confirmatory factor analysis, offer complementary perspectives on economic dependencies (Guan et al., 2018). Additionally, the dimensions of economic dependency through international trade, external debt, and foreign investment, tested using confirmatory factor analysis in developing countries, challenge established theoretical arguments and highlight the interconnected nature of economic dependency (Huang & Slomczynski, 2003). Developed a framework to rank jurisdictions based on trade size and interconnectedness using data from the IMF's Direction of Trade Statistics. This study highlighted the overlap between systemically important trade and financial jurisdictions, providing essential insights for policymakers. The conceptual exploration of economic connectedness further emphasizes the importance of network theory and the interconnected nature of economic systems (Moten, n.d.). Discuss the limitations of traditional macroeconomic models, advocating for network science to better predict and explain economic events.

To further enhance the analysis of economic and financial networks, computational network methods offer reliable instruments for capturing

structural complexity and characteristics. Emmert-Streib et al. (2017a) provide a computational analysis of economic and financial networks, offering methods to quantify structural properties and network complexity. The study introduces advanced methods for capturing the complexities of economic dependencies using quantile coherency and tail risk measures. Quantile coherency assesses the dependence structure in the frequency domain, providing critical insights into how economic variables behave under extreme conditions. This method goes beyond traditional correlation by focusing on tail dependencies, which are essential for understanding the impact of rare but significant economic events. Given the limitations of traditional models in capturing extreme behaviors, quantile regression offers a promising alternative for analyzing tail dependencies. Quantile regression models, particularly high-quantile regression, have been shown to effectively capture tail dependencies. The asymptotic theory of high-quantile regression estimators under serial dependence allows for a more accurate depiction of the extreme behavior of economic variables. This is mathematically represented as:

where is the check function for the τ th quantile.

The check function is defined as:

Where is the indicator function? This formulation is crucial for capturing the nuances of economic relationships that traditional methods often overlook.

The quantile function for a given quantile can be written as:

Thus, the high-quantile regression model is specified as:

where is the error term. Network analysis provides a robust framework for understanding economic interconnectedness. Emmert-Streib et al. (2017b) emphasize the use of centrality measures, such as degree centrality, betweenness centrality, and eigenvector centrality, to identify key nodes in economic networks. These measures help pinpoint which countries or sectors hold significant influence within the global economic landscape.

For instance, the eigenvector centrality of a node in an adjacency matrix is given by:

where is the largest eigenvalue of the matrix. This measure not only considers the number of connections a node has but also the quality of those connections, thus providing a deeper insight into the economic significance of each node.

The degree centrality of a node is given by:

Betweenness centrality measures the extent to which a node lies on paths between other nodes: where is the total number of shortest paths from node to node, and is the number of those paths that pass through node. Additionally, closeness centrality is given by:

where is the shortest path distance between nodes and. These measures collectively provide a comprehensive view of the centrality and importance of nodes in an economic network. The multiscale quantile correlation coefficient (MQCC) integrates quantile regression with multiscale analysis, allowing for a comprehensive assessment of tail dependencies across different time scales. Hynes et al. (2021) emphasize the necessity of adopting a new economic paradigm that focuses on resilience and interconnectedness. The COVID-19 pandemic highlighted the fragility of interconnected

systems and underscored the need for resilience in the face of systemic shocks.

Upon examining foundational econometric and computational methodologies relevant to this study, we justify our selection of variables, particularly the Producer Price Index (PPI) and Consumer Price Index (CPI). The PPI serves as a robust indicator of farm-level economics, capturing the prices farmers receive for their products as they exit the farm gate (Almadani et al., 2021). According to the IMF (2004), such farm gate prices accurately reflect the initial stages of the agricultural supply chain and offer a granular perspective on economic activity in the sector. Additionally, value-added producer price indices, which incorporate weighted averages of output and intermediate input prices, provide a more comprehensive view of the value added at each stage of production, making them essential for analyzing inflation dynamics and economic extremes.

The interrelationship between PPI and CPI has been well-documented in the literature. For example, Su et al. (2016) demonstrated through bootstrap panel Granger causality analysis that changes in the PPI significantly influence CPI movements, supporting the moderate inflation model. This causality highlights how producer-level price changes propagate through the supply chain to affect consumer prices. Similarly, studies on Hungarian data reveal that CPI fluctuations Granger-cause variations in PPI, emphasizing the bidirectional nature of these indicators. Such findings are critical for policymakers, as they underscore the importance of focusing on PPI when designing inflation-targeting strategies.

Moreover, targeting both PPI and CPI inflation simultaneously has been shown to generate larger welfare losses compared to strategies focused on a single indicator. This underscores the importance of understanding how the cost of production—determined by input prices and raw materials—affects final goods and services. The linkages between CPI and PPI, therefore, provide essential insights into how supply and demand dynamics shape inflationary trends, making these indicators central to our analysis of economic interconnectedness.

The Economic Policy Uncertainty (EPU) index serves as a key measure of fiscal and monetary policy uncertainty, derived from media coverage of topics that heighten economic ambiguity (Čižmešija & Škrinjarić, 2021). Research indicates that increased media attention to economic uncertainty correlates with heightened market volatility. In the U.S., the EPU significantly impacts financial market stability, particularly in government-dependent sectors such as healthcare, defense, and construction. Higher EPU levels have been shown to reduce industrial production, investment, and employment, and in probit models, the EPU effectively predicts U.S. recessions. Beyond the U.S., the EPU also exerts considerable influence on macroeconomic conditions in the euro area (Čižmešija & Škrinjarić, 2021).

Elevated EPU has pronounced effects on firm-level decision-making, often resulting in more conservative policies. During periods of heightened policy uncertainty, firms tend to scale back capital investments (Gulen & Ion, 2016), delay or cancel initial public offerings (Çolak et al., 2017), and curtail merger and acquisition activities (Bonaime et al., 2018;

Nguyen & Phan, 2017). Furthermore, they may adopt more cautious payout policies (Panousi & Papanikolaou, 2012; Walkup, 2016) and bolster cash reserves as a precautionary measure (Demir & Ersan, 2017; Phan et al., 2019; Zhao & Park, 2017). These responses are often asymmetric, varying significantly by market and sector (Gupta et al., 2019; Hassan et al., 2018; Istiak & Alam, 2019).

In the Indian context, EPU volatility poses additional challenges, particularly by discouraging investment activity. Analysis using the DCC-MGARCH model demonstrates that fluctuations in EPU over time can significantly influence macroeconomic variables (Bagchi et al., 2023). These findings underscore the critical role of policy uncertainty in shaping economic behavior and its far-reaching implications for financial markets and broader economic stability. While prior research has applied methodologies like quantile regression and network analysis to study economic interdependencies, there remain notable gaps, particularly in addressing trade networks of emerging economies like India. Most studies focus on financial markets or specific sectors, often relying on simplified models that fail to account for the unique characteristics of diverse trade relationships, especially under extreme conditions.

Here come the contributions of this study to the field. First, it introduces the quantile-quantile connectedness framework to analyze India's export interdependencies with global economies, incorporating sectoral and multiscale variations to capture relationships across different quantiles. Second, it refines network analysis methods by introducing trade-specific

centrality and connectivity measures, offering a clearer view of the roles and interactions within the global trade network. Finally, it integrates these methodologies with an empirical focus on India's export sectors and key economic indicators, including the EPU index, CPI, and PPI, to provide a detailed analysis of trade interdependencies under varying conditions.

By addressing these gaps, the study advances both the methodological and empirical literature on global trade interdependencies. It positions India's export network as a case to illustrate broader patterns in international trade. Having reviewed the methodological and conceptual advancements in studying economic interconnectedness, the next section focuses on the data and indicators central to this analysis.

DATA DESCRIPTION

The data used in this study consists of three economic indicators, namely Economic Policy Uncertainty (EPU), Consumer Price Index (CPI), and Producer Price Index (PPI). The countries considered include the USA, China, Germany, Japan, the UK, France, Italy, Canada, Russia, Brazil, Korea, Australia, and Mexico. The export categories include Petroleum (PET), Agriculture (AG), Ores (ORE), Manufacturing (MAN), and Others (OTH). The selection of variables and data for this study is grounded in both theoretical and practical considerations, ensuring their relevance to the research objectives. While the literature review provides a detailed justification for the inclusion of the EPU index, CPI, and PPI, we now turn to the rationale for focusing on 13 major global

economies and five export categories within India's commodity trade.

The decision to focus on commodities rather than services or other sectors stems from the unique characteristics of commodity markets. Unlike services, commodities often serve as inventory, with price fluctuations directly influencing storage costs, long-term production planning, and supply chain management. Commodities are also highly price-sensitive, with their consumption either targeted to end-users or serving as critical raw materials for further production. These attributes make commodity exports particularly significant in shaping trade dynamics and economic policies. By analyzing these categories, the study captures the critical role of commodities in global trade and their sensitivity to economic and policy-driven disruptions. The inclusion of 13 major global economies is based on their substantial trade volumes with India, which can be visualized in the further discussion sections' Sankey diagram. These economies not only represent a significant proportion of India's export destinations but also wield considerable negotiation power in the global arena. Understanding India's trade interdependencies with these nations becomes crucial in scenarios involving diplomatic tensions or trade disputes. By examining these relationships, this study seeks to provide insights into India's negotiation leverage and strategies for mitigating risks during periods of economic or political conflict. Furthermore, the five export categories—agriculture, ores, petroleum, manufacturing, and others—were selected to reflect India's diverse export portfolio while maintaining a focus on sectors with significant global

demand. These categories capture the breadth of India's commodity trade, encompassing primary goods and value-added products. This targeted selection allows the study to explore sector-specific interdependencies and the broader implications for India's trade network without diluting the analysis with less impactful categories. By narrowing the focus to these variables and data, the study achieves a balance between depth and scope.

3.1 Export Categories

Petroleum: This sector includes crude oil and petroleum products. It consists of crude oil, refined petroleum products, lubricants, and other petroleum gases. These commodities form the backbone of India's energy-related exports, catering to the global demand for fuel and related products.

Agriculture: A broad sector, it contains various products. Key subcategories include cashew, cashew nut shell liquid, castor oil, cereal preparations, coffee, cocoa products, cotton raw including waste, floriculture products, fresh fruits and vegetables, fruits/vegetable seeds, groundnuts, and guar gum meal. Each of these subcategories highlights India's rich agricultural diversity and its capacity to supply a wide range of raw and processed food products to international markets.

Ore: This sector contains various types of mineral ores essential for industrial purposes, including iron ores, copper ores, and aluminum ores. These minerals are critical for the manufacturing and construction industries, making them significant export commodities for India.

Manufacturing: This sector includes a diverse range of manufactured goods. Notable

subcategories are machinery, vehicles, electronics, textiles and apparel, chemicals, and pharmaceuticals. These products showcase India's growing industrial base and its ability to produce complex and high-value items that meet global standards.

Others: This sector captures all other export categories not specifically listed in the aforementioned sectors. It includes leather products, handicrafts, gems and jewelry, furniture, toys, and games.

The structured categorization of export data ensures that the study provides a balanced view of India's trade relationships, capturing both strategic and diversified trade flows.

3.2 Data Sources and Collection

Data for the EPU index was sourced from policyuncertainty.com, while CPI and PPI data were obtained from the Federal Reserve Economic Data (FRED). Export data for each category were extracted from the CMIE Economic Outlook database. To ensure consistency and accuracy, missing data points were supplemented using national and international databases, including central banking repositories of the selected countries.

3.3 Data Span and Frequency

The study spans data from 2000 to 2023, providing a robust temporal framework for analyzing trade interdependencies. Data are recorded at a monthly frequency, capturing seasonal variations and trends. For earlier years with incomplete monthly data, interpolation was performed using later-year monthly shares of yearly data. This approach ensures that the dataset reflects seasonal characteristics while maintaining analytical

reliability. The comprehensive dataset forms a strong foundation for the quantile-quantile connectedness and network analysis employed in this study.

METHODOLOGY

This section outlines the methodological framework adopted to analyze the economic connectedness between India and 13 major global economies. The analysis follows a systematic process involving data preparation, quantile-quantile connectedness analysis, network graph construction to visualize the results, and the consolidation of individual indicator connectedness measures into a single metric using principal component analysis for interpretation.

4.1 Stationarity and Differencing

Ensuring that the time series data is stationary is crucial for conducting accurate time series analysis. To test stationarity, we use the Augmented Dickey-Fuller (ADF) test.

The ADF test is used to check for the presence of a unit root in the time series. The null hypothesis of the ADF test states that the time series has a unit root (is non-stationary), while the alternative hypothesis is that the series is stationary. The ADF test regression model is given by: where Δ is the first difference of, α is a constant term, β is a time trend, γ is the coefficient of, and $\delta_1, \delta_2, \dots, \delta_p$ are the coefficients of the lagged differences, and ϵ_t is the white noise error term.

If the p-value obtained from the ADF test is greater than 0.05, indicating non-stationarity, we difference the series until stationarity

is achieved. The differenced series after differencing operations is given by:

where Δ is the lag operator.

4.2 Quantile-Quantile Connectedness Analysis

To analyze the connectedness between economic indicators and export categories across countries, we employ quantile-quantile connectedness. This involves comparing specific quantiles of the time series data for different countries and indicators.

Given two time series and a set of quantiles, the quantile-quantile connectedness is calculated as:

where q_1 and q_2 are the q_1 -th and q_2 -th quantiles of the series and, respectively.

For each pair of quantiles, the connectedness is determined by the differences in their values. The average connectedness between two series is computed as the mean of the absolute differences across all quantiles.

This provides a summary measure of connectedness by averaging the absolute differences in quantile values. By focusing on specific quantiles, we can identify how extreme values in one series relate to extreme values in another. The choice of quantile-quantile analysis is justified by its ability to reveal dependencies that are not apparent in traditional mean-based analyses. This method allows for the detection of asymmetries in the relationships between variables, highlighting the tail behaviors that are crucial for understanding risks and co-movements during periods of economic stress or market turbulence.

Firstly, we identify the relevant quantiles for the time series data. Commonly used quantiles

include the 0.05, 0.25, 0.50, 0.75, and 0.95 levels, which correspond to the lower tail, lower quartile, median, upper quartile, and upper tail of the distribution, respectively. These quantiles are selected to capture a range of behaviors from extreme low values to extreme high values. Next, we compute the quantile values for each time series at these specified quantiles. This involves sorting the data and identifying the values that correspond to each quantile. Once the quantile values are determined, we calculate the connectedness at each quantile level using the absolute differences between the corresponding quantile values of the two series. Finally, we aggregate these connectedness measures to obtain the average connectedness, which provides a single summary measure of the overall degree of connectedness between the series. This aggregated measure is useful for comparing the connectedness across different pairs of series and for identifying general patterns of interdependence in the data. By employing this quantile-quantile connectedness approach, we can gain deeper insights into the economic relationships between indicators and export categories across countries. This method not only highlights the central tendencies but also illuminates the tail dependencies.

4.3 Network Graph Construction

To visualize the economic connectedness between India and other major economies, we employ a range of graph-theoretic measures and algorithms. These measures are crucial for understanding the connectivity, centrality, and overall efficiency of the network. Below are the detailed steps and mathematical formulations used in this construction.

4.3.1 Path-Based Measures

where (n) is the number of nodes in the graph. This metric provides insights into the overall efficiency of the network in terms of information or economic shock propagation.

4.3.2 Node and Edge Definition

V represents the set of countries.
 E represents the set of edges, indicating the connectedness between India and other countries.

The weight of each edge is determined by the average connectedness value between India and another country, defined as:

Here, is the mean of the absolute values of the quantile connectedness results, capturing the degree of connectedness between the economic indicators and export categories of India and other countries.

4.3.3 Spring Layout Algorithm

The spring layout algorithm is employed to position the nodes in the network graph. This algorithm minimizes the overall energy of the system, where nodes repel each other and connected nodes attract each other proportionally to their edge weights. The positions of the

Represents the spring constant (or weight of the edge).

Denotes the rest length of the spring (the desired distance between nodes).

Is a constant repulsion factor.

4.4 Principal Component Analysis (PCA)

where $\lambda_1, \lambda_2, \dots$ and v_1, v_2, \dots are the coefficients determined by the PCA, representing the loadings of each

variable on the first principal component, and x_{ij} and y_{ij} are the normalized values for country i and country j .

To ensure that all PCA scores are non-negative, we shift the PCA scores by subtracting the minimum score:

where x_{min} is the minimum PCA score across all countries.

By integrating stationarity testing, quantile-quantile connectedness analysis, network graph construction, and principal component analysis, this study establishes a rigorous framework for examining the interconnectedness between economic indicators and export categories across countries. This methodological approach ensures that both individual and aggregated measures of connectedness are captured, providing a structured foundation for the results and their interpretation in the subsequent sections.

the influence of specific economic indicators on various export sectors. For example, changes in Economic Policy Uncertainty (EPU) in oil-producing nations could strongly impact India's petroleum exports. Similarly, shifts in the Producer Price Index (PPI) in ore-importing countries, such as China, may influence India's manufacturing and heavy industry exports. In addition, fluctuations in the Consumer Price Index (CPI) of importing countries can affect India's exports of consumption-driven goods.

RESULT AND DISCUSSION

Building on the methodological framework outlined earlier, this section examines the interconnectedness of India's export network with major global economies, focusing on sector-specific and quantile-specific insights. The heatmaps and network diagrams reveal important patterns that highlight the trade relationships between India and its partners. A key aspect of this analysis is understanding how trade volumes with specific countries align with India's role as a significant exporter in their import portfolios. It is equally important to assess the extent to which India's economic and financial systems are synchronized with those of its trading partners. This involves identifying

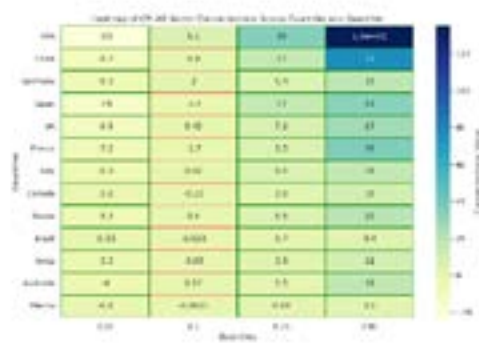


Figure 0-1

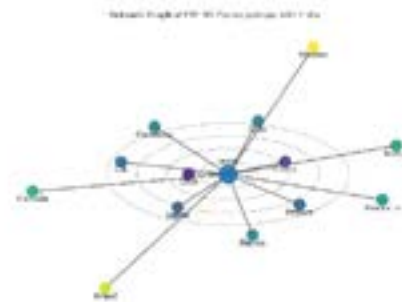


Figure 1-1

The heatmap (Figure 0-1) shows that at the 0.25 quantile, connectedness values are usually negative or low, indicating that declining CPI

increases agricultural exports. The USA has a significant negative value of -23. In the lower tail of the distribution, a lower CPI is associated with an increase in exports, possibly due to price competitiveness. At the 0.50 quantile, the USA and China have positive connectedness (6.1 and 0.8, respectively). Connectivity increases significantly at the 0.75 quantile for the USA (35), China (17), and Japan (17). The USA has a remarkable value of 140 at the 0.95 quantile, followed by China at 77, suggesting stronger interconnectedness under extreme conditions, likely caused by synchronized economic cycles or global market shocks.

Country-specific variations show that the US has large negative values at lower quantiles and large positive values at the highest quantile. This indicates extreme connectedness fluctuations. China, Germany, and Japan are more connected at higher quantiles, reflecting stronger agricultural sector CPI influences. China and the US have significant results at higher quantiles, demonstrating their robust connectedness values. The network graph shows strong agricultural sector CPI interdependencies with the US, China, and Germany. Mexico and Brazil, farther from India in the graph, have weaker connections. Higher quantiles of agricultural sector CPI interconnectedness indicate that extreme economic conditions, like inflationary pressures or global market shocks, significantly affect it. With large agricultural exports and imports, the US and China show their economic and trade ties to India. This interconnectedness suggests that inflationary pressures and price competitiveness in one country can affect others, especially through trade and economic policies.

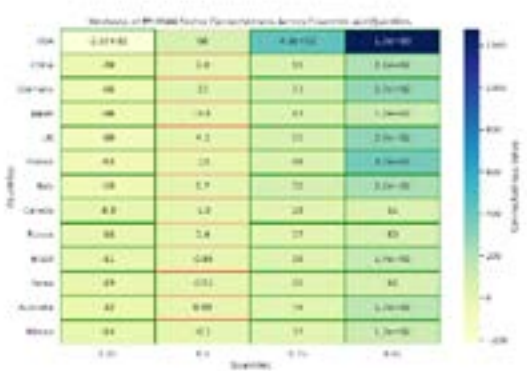


Figure 0-2



Figure 1-2

The heatmap (Figure 0-2) illustrates the connectedness between India's manufacturing sector exports and the Producer Price Index (PPI) fluctuations in various countries across different quantiles. The USA and France show particularly strong connectedness with India's manufacturing exports, with values peaking at 1300 and 370, respectively. This suggests that significant PPI fluctuations in these countries have a notable impact on India's manufacturing

exports. When manufacturing costs and prices rise or fall in the USA and France, it directly influences the demand for Indian manufacturing exports, reflecting the close economic ties and dependency on these major markets.

In contrast, countries like Germany, Japan, and Canada show moderate connectedness, with values ranging from -66 to 270, indicating that while their PPI fluctuations affect India's manufacturing exports, the impact is less pronounced compared to the USA and France. Meanwhile, countries such as Brazil, Mexico, and Australia exhibit relatively low connectedness, suggesting that their PPI fluctuations have minimal influence on India's manufacturing exports. These insights are crucial for Indian policymakers, exporters, and trade strategists, as they highlight the importance of monitoring PPI trends in key global markets. Understanding these connections allows for better forecasting, risk management, and strategic decision-making to enhance the competitiveness and stability of India's manufacturing exports in a globally interconnected economy.

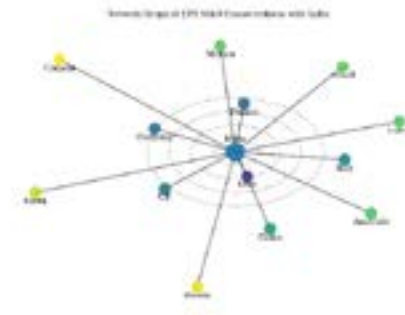


Figure 1-3

From the heatmap (Figure 0-3), the USA shows a highly positive connectedness value of 430 in the 0.75 quantile, indicating a strong positive relationship between EPU in the USA and India's manufacturing exports at this quantile. Conversely, negative values, like -220 in the 0.25 quantile for the USA, indicate a strong negative relationship. Similarly, countries like Germany and Japan also show significant variation across different quantiles, reflecting varying degrees of impact on India's manufacturing sector depending on the level of EPU. Overall, this heatmap demonstrates how changes in economic policy uncertainty in different countries are interconnected with fluctuations in India's manufacturing exports. By identifying how changes in policy uncertainty across different nations impact India's export performance, stakeholders can better anticipate risks and opportunities in the global market. This understanding enables more informed decision-making, allowing for the strategic adjustment of export strategies, diversification of markets, and risk management practices. Additionally, it helps in tailoring diplomatic

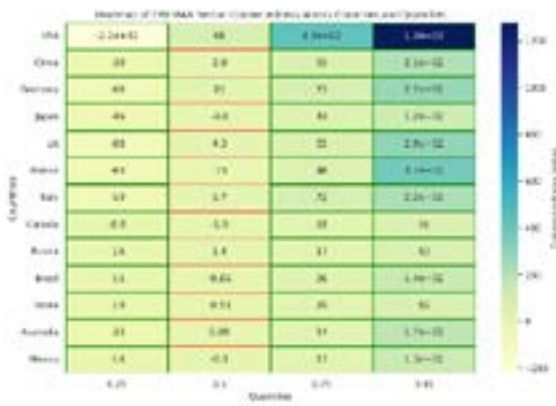


Figure 0-3

and economic policies to mitigate adverse effects from countries with high policy uncertainty, thereby strengthening India's overall export resilience and economic stability.

Here, we've demonstrated a select few examples from the fifteen possible network graphs and heatmaps to illustrate our methodology. These examples show the steps we followed to arrive at the final result, which involved calculating the average connectedness of various countries with India and aggregating the connectedness magnitudes across different quantiles.

Before proceeding with the further interpretation and aggregation of the result, let us revisit the data preprocessing ADF test result. The stationarity of the time series data is a crucial prerequisite for reliable econometric analysis, as it ensures that statistical properties such as mean and variance remain constant over time,

avoiding spurious relationships. Table 1 outlines the number of differencing steps required for each economic indicator and export category to achieve stationarity, as determined by the Augmented Dickey-Fuller (ADF) test.

While certain series required first-level differencing and others second-level, this adjustment does not compromise the validity of the analysis. Differencing is a standard practice to stabilize time series data, ensuring robustness in subsequent model applications. Importantly, the quantile-quantile connectedness methodology is inherently designed to work with stationary data and focuses on the relationships across quantiles rather than linear trends. Thus, the preprocessing ensures the methodological framework remains appropriate and effective for uncovering the complex, non-linear interdependencies central to this study.

Table 1 - Differentiation Required for making series stationary

Country	EPU	CPI	PPI	PET	AG	ORE	MAN	OTH
USA	0	2	1	1	1	1	1	1
China	1	0	0	1	1	1	1	1
Germany	1	1	1	0	1	1	1	1
Japan	0	1	1	1	1	1	1	1
UK	1	1	1	1	1	1	1	1
France	1	1	0	1	1	0	1	1
Italy	0	0	0	1	1	1	1	1
Canada	1	1	1	0	1	1	1	1
Russia	1	0	0	1	1	2	1	0
Brazil	0	0	1	0	1	0	1	1
Korea	0	2	0	1	1	1	1	1
Australia	0	1	0	1	1	0	1	1
Mexico	1	2	1	0	1	1	1	0

As outlined in the methodology section, our subsequent focus will be determining the average connectedness values for each export category corresponding to the economic indicators of the 13 economies. We will commence our discussion with Economic Policy Uncertainty (EPU), which exerts varying influences on India's export sectors across different trading partners, as summarized in Table 2. This table underscores sector-specific reliance on policy uncertainty in major economies, offering insights into critical risks.

The values in Table 2 reveal that sectors such as manufacturing and petroleum are more sensitive to EPU, particularly in countries like Brazil. The USA, being the most connected

country across the export category, leaves it to the readers to make similar interpretations.

Table 3 shifts focus to CPI, illustrating how consumer price levels in partner economies impact India's export sectors. This analysis is key to understanding demand-side drivers of trade. Table 3 presents the average connectedness of India's export sectors with the Consumer Price Index (CPI) of trading partners, highlighting sector-specific influences. Agricultural exports are notably affected by CPI fluctuations in Brazil (131.24) and the United States (33.5), while the 'others' category shows high sensitivity, particularly with the United States (499.48) and France (123.01). Manufacturing exhibits moderate connectedness, led by China (25.72)

Table 2 - EPU – Average Connectedness Value of Each Sector

Country	EPU -AG	EPU -MAN	EPU - ORE	EPU - OTH	EPU -PET
Australia	111.28	127.32	128.79	92.37	130.63
Brazil	58.33	189.05	185.6	152.07	189.72
Canada	46.01	43.66	47.12	28.11	46.96
China	25.98	12.52	7.07	37.79	37.28
France	15.98	32.64	42.89	80.62	41.26
Germany	40.14	37.27	43.56	63.47	42.15
Italy	124.17	123.7	127.22	84.92	127.46
Japan	99.94	109.62	114.16	89.86	116.42
Korea	165.22	173.07	174.72	160.29	175.42
Mexico	23.17	22.13	23.14	20.37	22.55
Russia	67.59	60.08	66.95	44.0	67.07
UK	27.85	27.34	37.1	70.79	36.07
USA	131.04	122.25	158.25	416.02	153.13

Table 3 - CPI - Average Connectedness Value of Each Sector

Country	CPI-AG	CPI-MAN	CPI- ORE	CPI- OTH	CPI-PET
Australia	20.26	5.94	2.45	54.72	0.94
Brazil	131.24	1.05	4.0	43.82	0.49
Canada	1.24	3.36	0.1	19.41	0.12
China	12.29	25.72	42.65	76.03	0.97
France	28.48	12.35	1.62	123.01	3.13
Germany	3.99	7.43	0.4	107.44	1.85
Italy	4.42	7.34	1.38	88.9	1.32
Japan	24.2	16.39	6.83	52.84	2.13
Korea	15.18	4.16	1.43	25.05	0.37
Mexico	0.16	0.88	0.14	40.17	1.54
Russia	0.95	7.07	0.56	23.53	0.29
UK	10.34	10.85	1.11	108.92	2.11
USA	33.5	49.28	2.59	499.48	9.33

and Japan (16.39). These results underscore the varied impact of consumer price changes across sectors, emphasizing the need to account for demand-side factors in trade strategies.

Moving to production-side dynamics, Table 4 presents the influence of Producer Price Index (PPI) variations in trading economies on India's export sectors. This perspective is crucial for understanding the cost-driven factors affecting India's trade. Table 4 highlights the strong impact of PPI on manufacturing and ore exports, especially in countries like China and the United States. This reflects the importance of production cost variations in driving demand for these sectors.

Aggregation Result

The sectoral aggregation of PCA-based connectedness scores by combining quantile connectedness to each economic indicator

reveals how India's global economic partners influence its trade network. Each sector highlights distinct dynamics, reflecting the varying roles of key trading partners.

Agriculture Sector

The PCA-based connectedness scores for the agriculture sector reveal a distinct hierarchy among India's global economic partners. The United States emerges as the most connected country, with a PCA score significantly higher than that of other nations. This result underscores the critical role of the USA in India's agricultural trade network, driven by substantial bilateral trade agreements and a high volume of agricultural exports and imports. Following the USA, China and Japan hold the second and third positions, respectively, but their scores are notably lower, indicating a secondary level of economic engagement compared to the USA.

Table 4 - PPI - Average Connectedness Value of Each Sector

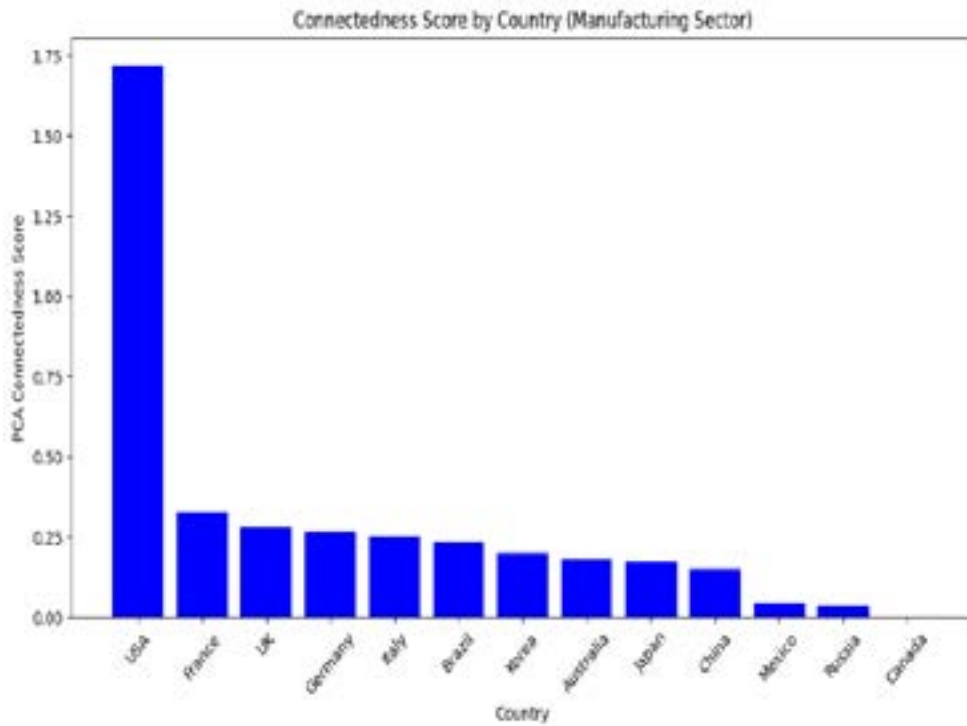
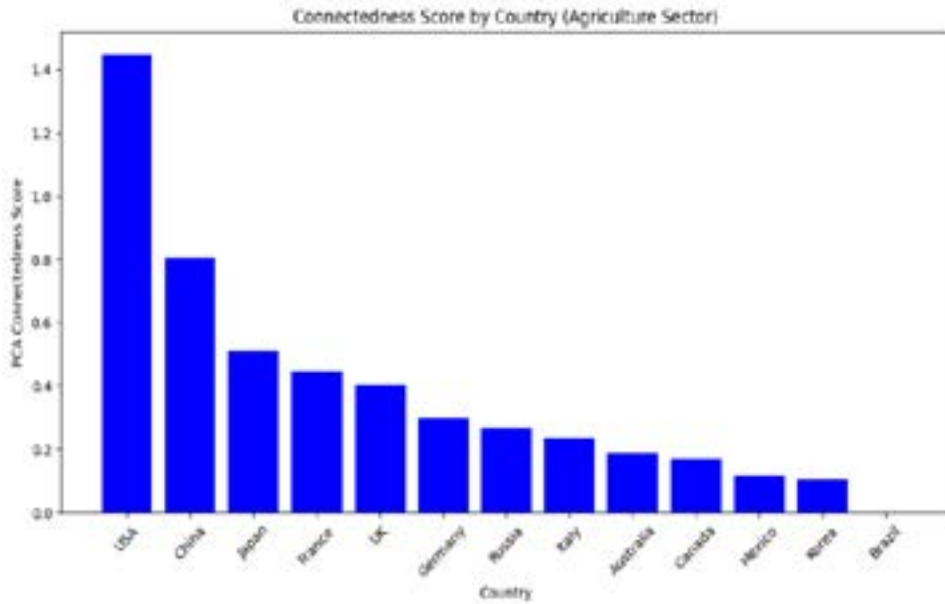
Country	PPI-AG	PPI-MAN	PPI- ORE	PPI- OTH	PPI-PET
Australia	19.9	5.5	2.01	54.26	0.76
Brazil	131.16	0.68	3.89	43.2	0.45
Canada	1.13	3.07	0.44	19.11	0.29
China	9.43	22.5	38.99	72.36	2.71
France	28.45	12.32	1.43	122.98	3.1
Germany	3.86	7.39	0.38	107.41	1.82
Italy	4.22	7.17	1.18	88.73	1.12
Japan	24.08	16.26	6.7	52.72	1.99
Korea	14.86	3.84	1.11	24.73	0.07
Mexico	0.57	0.64	0.56	39.92	1.03
Russia	1.31	6.65	0.73	23.02	0.35
UK	10.11	10.64	0.93	108.71	1.88
USA	32.15	47.94	1.27	498.13	7.99

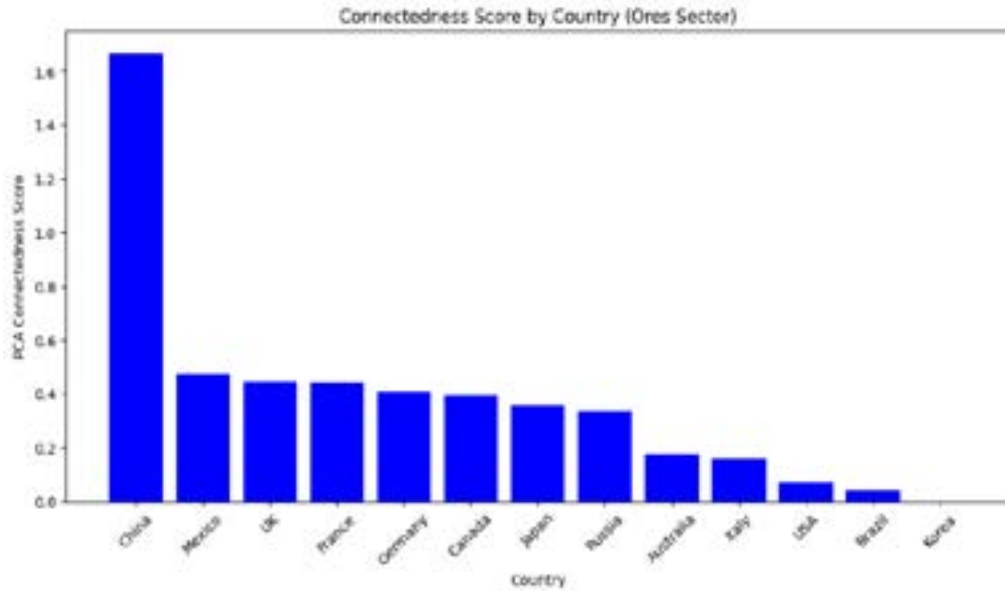
Manufacturing Sector

In the manufacturing sector, the PCA scores again highlight the United States as the top economic partner for India, reinforcing its central role in the global manufacturing supply chain. France, the United Kingdom, and Germany also show considerable connectedness, reflecting the strong economic ties between India and these European economies. The significant presence of these countries in the manufacturing sector indicates India's integration into global manufacturing networks, particularly with advanced economies known for their technological advancements and industrial outputs.

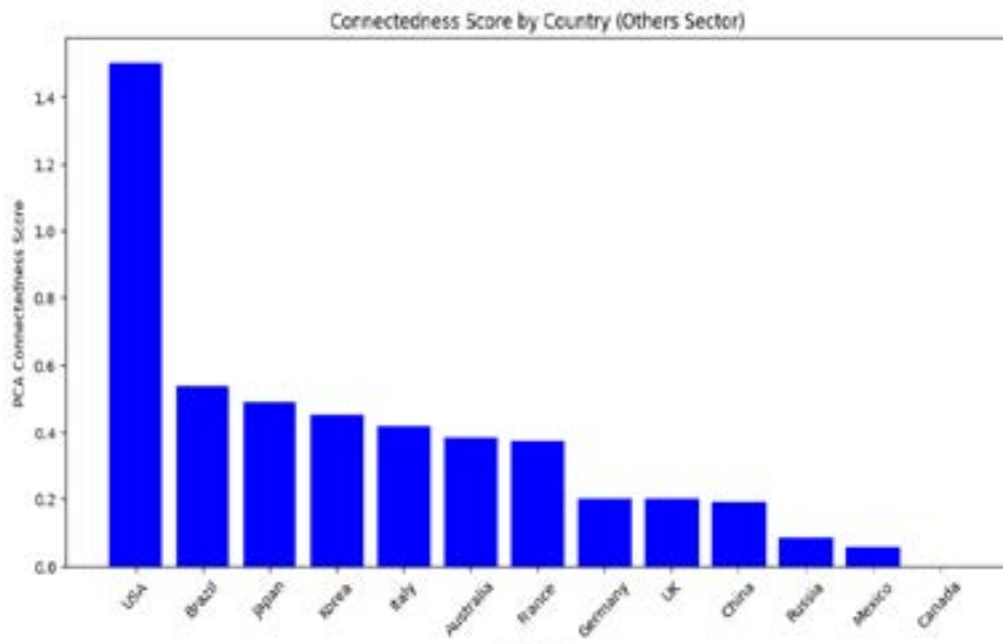
Ores Sector

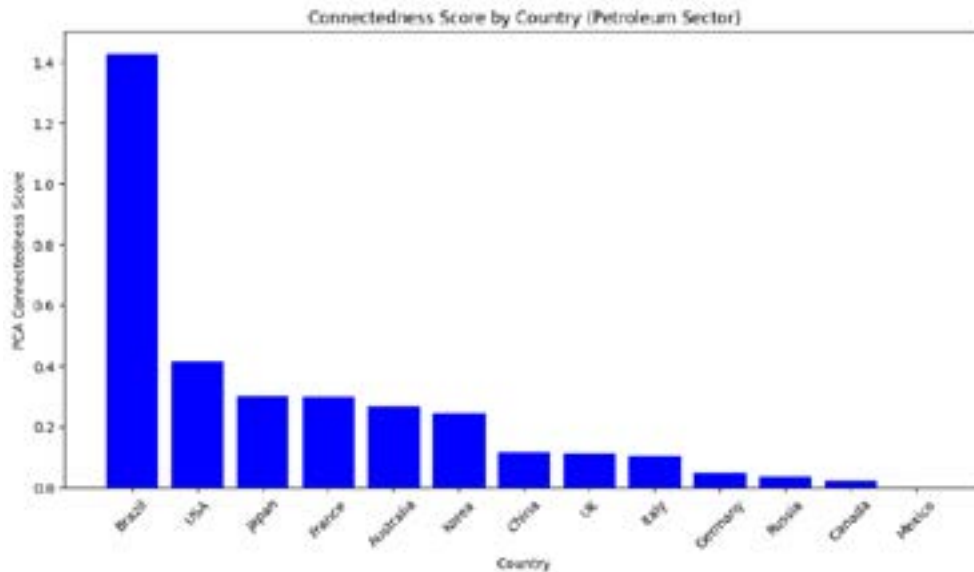
The ores sector presents a different dynamic, with China leading the list of connected countries. China's high PCA score is indicative of its substantial demand for raw materials and ores, essential for its expansive industrial sector. Mexico and the United Kingdom follow China, suggesting their significant roles in global trade networks for ores and minerals. These results highlight the strategic importance of mineral resources in China's economic relationship with India and underscore the critical supply chain linkages with Mexico and the UK.





Others Sector





In the 'Others' sector, which includes a variety of miscellaneous goods and services, the United States once again stands out with the highest connectedness score. This consistent top ranking across multiple sectors underscores the broad-based economic engagement between India and the USA. Brazil and Japan are the next most connected countries, reflecting their diversified economic interactions with India. These results highlight the multifaceted nature of economic relationships in the 'Others' sector, encompassing a wide range of industries and services.

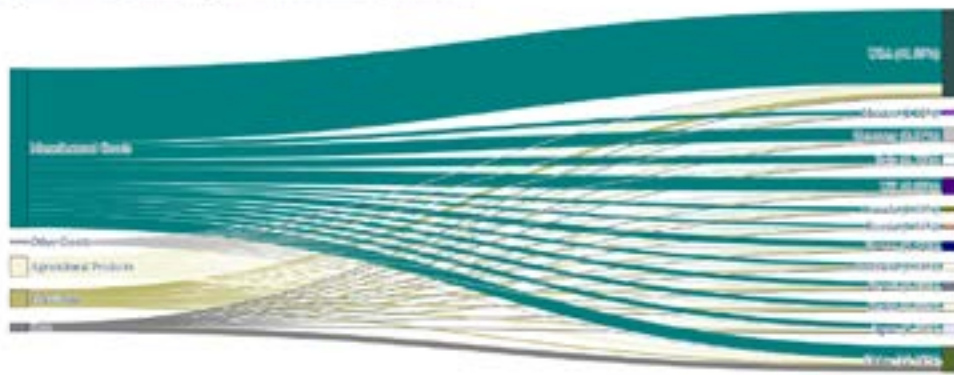
Petroleum Sector

The petroleum sector exhibits a unique pattern, with Brazil achieving the highest PCA score, followed by the United States and Japan. Brazil's leading position can be attributed to its significant exports of oil and gas, as well as technological exchanges in biofuels. The prominence of the USA and Japan in this sector

is supported by their advanced technology and substantial trade volumes in petroleum products. These findings highlight specific commodity-based interactions that shape India's economic relationships in the petroleum sector. The PCA-based connectedness scores across different sectors give a full picture of how India's economy is linked to the world's biggest economies. The United States' consistent top spot in a number of areas shows how important it is to India's trade and economic networks. China's leadership in the ores sector shows how its economy is based on resources, while Brazil's prominence in the petroleum sector shows how important it is in trade based on commodities. Overall, these results show how important it is to keep a variety of business relationships. India should keep working to strengthen these ties through its trade and economic policies, which will help both countries grow and be more resilient to changes in the world economy. This analysis gives policymakers sector-specific

Sankey Diagram of India's Exports to Top 13 Global Economies

Sankey Diagram: India's Exports to Top 13 Global Economies by Sector Share



information that can help them find strategic partners and set priorities for economic engagements based on the strengths and needs of each sector. These complex viewpoints are necessary to promote long-term economic growth and strengthen India's position in the global economy.

Overall, these sector-specific PCA scores depict a comprehensive picture of India's interconnectedness with global economies. They underscore the importance of maintaining diversified trade relationships and tailoring strategies to sectoral strengths, ensuring resilience and growth amid global economic shifts. Building on the insights from our analysis, we encourage readers to explore the trade volumes between India and the top 13 global economies. This examination highlights the critical importance of this study, the risks inherent in India's trade network, and the potential areas for improvement. Additionally, it provides valuable context for strategic decision-making. An informative Sankey diagram is

presented in the subsequent section to illustrate these trade volumes visually.

Further Discussion

It is imperative to comprehend the flow of India's exports to its most significant trading partners in order to evaluate the strengths, risks, and opportunities of its global trade network. To achieve this objective, a Sankey diagram has been incorporated to offer a concise and clear representation of the distribution of India's export volumes among its top 13 trading economies. This tool not only emphasizes the relative significance of each partner in terms of trade share but also highlights sectoral contributions, providing helpful perspectives into the interconnectedness of India's export relationships and the strategic implications for enhancing trade resilience and growth.

The Sankey diagram visualizes India's total exports to its top 13 global trading partners, with percentages representing each country's

share of India's overall exports. The United States, accounting for 41.99% of India's exports, is the largest importer, driven primarily by manufactured goods, reflecting strong industrial and consumer demand. China, with 12.48%, significantly imports ores, aligning with its vast manufacturing needs. Germany (6.87%) and the United Kingdom (8.03%) are notable European importers, indicating strong trade ties and demand for diverse Indian goods. Japan (5.20%), Brazil (3.80%), and South Korea (3.50%) feature prominently, showcasing substantial imports driven by both industrial and consumer demands. Brazil's imports include a notable share of petroleum products. Australia (2.91%), France (4.11%), Italy (1.78%), and Canada (2.09%) illustrate India's broad reach across developed economies, reflecting diversified trade relationships. Russia (1.95%) and Mexico (2.22%) highlight India's penetration into emerging markets, indicating a range of exported goods meeting specific market needs.

In traditional regression models, metrics such as R^2 and Bayesian Information Criterion (BIC) are used to assess model fit and explainability. However, the quantile-connectedness analysis adopted in this study operates on a fundamentally different framework, focusing on quantile-based interdependencies rather than point predictions or parametric relationships. Given this methodological distinction, metrics that capture distributional consistency and explainability of principal components are more appropriate. Specifically:

Quantile Variance:

This metric evaluates the variability of connectedness across different quantiles (e.g., 0.25, 0.50, 0.75, 0.95).

A low variance indicates robustness and consistency in the connectedness measures across the distribution, which are essential for capturing dependencies in extreme quantiles (tails).

PCA Explained Variance Ratio:

This measures the proportion of total variance captured by the first principal component.

It quantifies the extent to which the aggregated connectedness metrics (derived from multiple indicators such as EPU, CPI, and PPI) can be effectively summarized. A higher value reflects a strong ability of the PCA metric to represent the underlying data structure.

These metrics are reported in Table 5 (Appendix Section) to substantiate the fitness of the quantile-connectedness model. Unlike R^2 , which evaluates linear relationships, or BIC, which penalizes model complexity in a parametric regression setting, the chosen metrics reflect the distributional and dimensional properties unique to this study's methodology. By reporting **Quantile Variance** and **PCA Explained Variance Ratio**, this study provides robust evidence of the model's ability to capture meaningful and consistent interdependencies across multiple economic indicators and export categories, validating the reliability of the presented findings.

Policy Recommendations

Diversify Trade Networks: Reduce over-reliance on major partners (e.g., the USA, China) by deepening trade ties with underleveraged regions like Southeast Asia, Africa, and Latin America to enhance resilience.

Sector-Specific Strategies:

Petroleum: Collaborate with Brazil on renewable energy exports to align with global decarbonization efforts.

Manufacturing: Foster exports to technologically advanced markets (e.g., the USA, Germany) through incentives for high-value industries.

Agriculture: Exploit price competitiveness in CPI and PPI-sensitive markets (e.g., the USA, Brazil) to maximize exports.

Price Stability and Risk Management: Establish long-term contracts and hedging mechanisms for PPI and CPI-driven sectors to mitigate price volatility and ensure steady trade flows.

Resilience Against Policy Uncertainty: Create dynamic trade safeguards and export risk funds for EPU-sensitive sectors like manufacturing and petroleum to manage volatility in critical markets.

Sustainable Trade Development: Transition exports toward greener technologies and practices, particularly in ores and petroleum, to enhance competitiveness and meet global sustainability standards and commitments.

Export Infrastructure Enhancement: Enhance supply chain efficiency by adopting AI-driven trade analytics and computational tools developed in this study. These tools serve as a foundational framework for dynamic trade optimization, enabling real-time decision-making to address price volatility and Economic Policy Uncertainty (EPU).

Strategic Multilateral Engagement: Strengthen participation in regional agreements like RCEP to diversify markets and reduce vulnerability to geopolitical tensions with dominant partners.

Leverage Quantile Insights: Use quantile-driven strategies to exploit extreme market conditions, targeting high connectedness during economic upswings and price advantages during low CPI periods.

Policy Alignment with Trade Interdependencies: Integrate sectoral interdependency insights (e.g., CPI's impact on agriculture, PPI on manufacturing) into trade policies to preempt risks and capitalize on opportunities.

Leverage India's Negotiation Power: High quantile connectedness with specific countries indicates stronger leverage during diplomatic tensions, allowing India to negotiate from a position of strength. Conversely, lower connectedness signals reduced negotiation power and the potential risk of losing stable markets in times of heightened diplomatic strain.

The succeeding conclusion section will explore the study's implications, emphasize its distinctive contributions, and identify potential areas for improvement. Furthermore, it will investigate methodological advancements that may be implemented in future research.

CONCLUSION

This study presents a detailed analysis of the interconnectedness between India's commodity export network and thirteen major global economies, highlighting the critical influence of EPU, CPI, and PPI on export relationships. By applying the quantile-quantile connectedness approach and Principal Component Analysis (PCA), the study captures non-linear and extreme dependency patterns that are often

missed by conventional linear methods. These insights are particularly significant during periods of economic instability, where tail dependencies can disrupt trade performance and impact global economic stability. The findings underscore the pivotal roles of key trading partners, such as the USA, China, and Brazil, in shaping India's export dynamics. The USA's influence spans multiple sectors, including manufacturing and agriculture, emphasizing its importance as a critical trading partner. China's reliance on ores highlights India's role as a supplier to its industrial supply chain, while Brazil's position in the petroleum trade reflects the importance of commodity-driven bilateral relations.

These results point to the need for strategic policy interventions to address risks associated with over-dependence on specific economies. Diversifying trade partnerships and export portfolios can help reduce vulnerability to economic shocks and geopolitical tensions. The study also highlights the importance of stable trade policies to manage the impact of external uncertainties, particularly on sectors like manufacturing, which are highly sensitive to global EPU fluctuations.

In addition to mitigating risks, there is an opportunity to strengthen India's global trade

position by leveraging its interconnectedness in emerging sectors and exploring new markets. The findings emphasize the need for targeted measures to stabilize price-related risks, such as those arising from CPI and PPI fluctuations, through bilateral agreements and supply chain optimizations. The study also calls attention to the importance of aligning trade strategies with global sustainability trends, particularly in sectors like petroleum and ores. Transitioning to greener technologies and practices can improve resilience and competitiveness while meeting evolving international standards.

In conclusion, this research highlights the multifaceted nature of India's trade interdependencies and the critical role of evidence-based policies in strengthening its export network. By adopting proactive strategies to manage risks and harness opportunities, India can enhance its resilience to global economic challenges and maintain its growth trajectory in an increasingly interconnected trade environment. Future research should explore innovative methods and tools to deepen the understanding of these interconnections and support policy development that benefits India's long-term economic stability and global trade standing.

Appendix

Table 5 - Consolidated Results: Quantile Variance and PCA Explained Variance

Country	Export Category	Quantile Variance	Explained Variance Ratio
Australia	PET	0.050009	0.377626
Australia	AG	0.060382	0.361867
Australia	ORE	0.048471	0.343347
Australia	MAN	0.053730	0.356515

Australia	OTH	0.048836	0.389327
Brazil	PET	0.046524	0.537589
Brazil	AG	0.032217	0.497058
Brazil	ORE	0.039680	0.524604
Brazil	MAN	0.034251	0.453085
Brazil	OTH	0.037895	0.523838
Canada	PET	0.083597	0.525522
Canada	AG	0.144855	0.744980
Canada	ORE	0.094323	0.551902
Canada	MAN	0.123621	0.735780
Canada	OTH	0.083169	0.521684
China	PET	0.081875	0.491867
China	AG	0.075641	0.477697
China	ORE	0.052440	0.402799
China	MAN	0.077514	0.499992
China	OTH	0.067350	0.376225
France	PET	0.032722	0.478698
France	AG	0.040489	0.488303
France	ORE	0.031571	0.469910
France	MAN	0.038871	0.504600
France	OTH	0.031164	0.433185
Germany	PET	0.129194	0.589296
Germany	AG	0.125523	0.662301
Germany	ORE	0.132058	0.606730
Germany	MAN	0.136602	0.696170
Germany	OTH	0.127613	0.613917
Italy	PET	0.025267	0.514768
Italy	AG	0.064488	0.636650
Italy	ORE	0.036629	0.545429
Italy	MAN	0.034723	0.514437
Italy	OTH	0.053724	0.532021
Japan	PET	0.121168	0.543097
Japan	AG	0.126349	0.557212
Japan	ORE	0.133849	0.602149

Japan	MAN	0.143762	0.640641
Japan	OTH	0.124977	0.552221
Korea	PET	0.079101	0.661963
Korea	AG	0.074470	0.679666
Korea	ORE	0.071641	0.488161
Korea	MAN	0.121289	0.790096
Korea	OTH	0.074078	0.574209
Mexico	PET	0.168065	0.863783
Mexico	AG	0.170531	0.862533
Mexico	ORE	0.174602	0.679825
Mexico	MAN	0.246265	0.899455
Mexico	OTH	0.164907	0.766262
Russia	PET	0.048245	0.528239
Russia	AG	0.068364	0.652049
Russia	ORE	0.051475	0.489977
Russia	MAN	0.070987	0.669205
Russia	OTH	0.037290	0.456339
UK	PET	0.174662	0.836045
UK	AG	0.178216	0.863994
UK	ORE	0.172700	0.779322
UK	MAN	0.198712	0.885136
UK	OTH	0.183174	0.675274
USA	PET	0.171901	0.836620
USA	AG	0.156475	0.827377
USA	ORE	0.149463	0.663876
USA	MAN	0.163802	0.857181
USA	OTH	0.124324	0.767263

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