A Network Perspective on the Global Meat Trade: Examining Trade Flows, Resilience, and Dependency

COMP0047 – Data Science

Tomás Barbosa Romeiro
University College London
Student ID: 24022849
tomas.romeiro.24@ucl.ac.uk

March 2025

1 Introduction

Global meat trading represents a critical component of the international food supply chain, involving complex interactions among numerous countries. In recent years, shifts in consumer demand, trade policies, and economic dynamics have made it increasingly important to understand how meat products (specifically frozen beef, prepared or preserved meat, and frozen pork) move across borders. This report leverages network analysis to unravel the intricate structure of global meat trade. By representing countries as nodes and their trade relationships as directed edges weighted by trade volume, we aim to identify key trading players, reveal significant dependency relationships, and uncover hidden community structures within the market. Through this multifaceted approach, our study provides valuable insights into which nations dominate the trade, how intermediary roles influence overall connectivity, and the resilience of the trade network to potential disruptions.

2 Methodology

2.1 Dataset Description, Cleaning and Preparation

We use the Global Trade Atlas dataset, which provides time-series data on global trade flows for various commodities from 2005 to 2040. Our focus is on three meat-related commodities, Pork frozen, Beef, frozen, and Meat, prepared or preserved, treated collectively at the annual level to capture long-term trends. Prior to constructing our network, we perform a rigorous data cleansing process:

1. We remove any entries where trade value or trade volume (or both) is null or zero, ensuring only meaningful trade flows remain.
2. We exclude any entries representing trade flows between a specific country and "World Total," except for the "World Total" to "World Total" entries, which we retain to provide an overall view of volume, price, and value evolution.
3. We split the dataset into actual (historical) and forecast subsets, facilitating separate or combined analyses as needed.

2.2 Initial Market Analysis

After cleaning the data, we begin with an overview of the global meat market. Specifically, we aggregate the retained "World Total" to "World Total" entries to observe the historical and forecasted trade value (in billions USD), trade volume (in millions of tons), and price level (USD per ton). This step establishes a high-level understanding of how meat trade has evolved historically (e.g., from 2005 to the most recent actual year) and how it is forecasted to evolve up to 2040. By plotting these trends, we gain insight into the general growth of the market and any significant shifts in price or volume over time.

Following this, we examine the concentration of trade value among importers and exporters in the last actual year (2022). We rank countries by their total trade value (for imports and exports separately) and compute the cumulative proportion of trade. The analysis reveals that around 80% of import trade value is accounted for by 28 countries, whereas the same 80% threshold for exports is reached with only 17 countries. Additionally, we show how these 17 major exporters (as of 2022) have historically contributed to the overall market and how their combined share is forecasted to change in the coming years.

2.3 Overview of Analysis Workflow

Building on the insight that the market is more concentrated on the supply side, we proceed with a comprehensive workflow that analyses the entire trade history in the dataset (2005-2022):

1. Network Construction & Pruning: We represent each country as a node, each directed edge as an export flow (from exporter to importer) with a weight equal to the aggregated trade value. We then prune the network by retaining only edges cumulatively accounting for 90% of the total trade value, ensuring we focus on significant trade relationships.

2. Visualization: We scale node sizes by their node strength (the sum of incoming and outgoing trade flows) and distinguish between the 17 major exporters and remaining countries. Edge widths are proportional to the trade flow between countries.

3. Advanced Analyses:

- Centrality Measures (degree, closeness, betweenness, eigenvector, PageRank) help identify influential nodes.

- Dependency Analysis highlights cases where an importer relies on a single exporter for over 50% of its trade.

- Backbone Extraction using a Maximum Spanning Tree (MST) to reveal the network's most critical trade links.

- Community Detection applies a greedy modularity algorithm to find clusters.

- Robustness and Spectral Analyses assess network stability by simulating node removals and examining Laplacian eigenvalues.

2.4 Detailed Descriptions of Methods Applied

In this section we provide the technical descriptions of the methods used as the foundation of our analysis

2.4.1 Network Construction and Pruning

Each edge in the directed network represents trade from exporter u to importer v with weight:

$$w(u,v) = \sum_{years} TradeValue(u,v) \tag{1}$$

where $TradeValue(u,v)$ is the total trade value from u to v for each year in the dataset.

2.4.2 Node Strength and Visualization

The strength of each node n is

$$NodeStrength(n) = \sum_{(u,n)\in E} w(u,n) + \sum_{(n,v)\in E} w(n,v). \tag{2}$$

We scale node sizes by node strength. Edge widths are proportional to the trade flow between nodes.

After determining each node's strength, we scale node sizes by dividing each node's strength by the maximum node strength in the network and then multiplying by a constant (plus a small offset for base size). This ensures that nodes with larger trade involvement appear proportionately larger. Likewise, each edge's width is determined by dividing its weight by the maximum edge weight and then multiplying by a chosen scaling factor. By following this method we effectively rescale raw trade values to a visually manageable range, thereby making the network diagram clearer and more comparable across different nodes and edges.

2.4.3 Centrality Measures

We compute the following centrality metrics to assess node influence:

Degree Centrality: this metric simply counts the number of connections a node has. In a directed network, it can be split into in-degree (number of incoming connections) and out-degree (number of outgoing connections). A high degree indicates that a node is well-connected within the network.

Closeness Centrality [3]: measures how near a node is to all other nodes by taking the reciprocal of the average shortest path distance from the node to every other node. Nodes with high closeness centrality can quickly interact with all other parts of the network.

$$C(n) = \frac{N-1}{\sum\limits_{v\neq n} d(n,v)} \tag{3}$$

where $d(n,v)$ is the shortest path distance and N is the total node count.

Betweenness Centrality [2]: quantifies the frequency with which a node appears on the shortest paths between other nodes. A node with high betweenness centrality acts as a bridge, indicating it may have a significant role in controlling the flow of information or goods within the network.

$$B(n) = \sum_{s\neq n\neq t} \frac{\sigma_{st}(n)}{\sigma_{st}} \tag{4}$$

where σ_{st} is the total number of shortest paths from s to t, and $\sigma_{st}(n)$ the subset passing through n.

Eigenvector Centrality [4]: unlike degree centrality, eigenvector centrality not only considers the number of connections a node has but also the importance of its neighbours. Nodes connected to highly influential nodes will receive a higher eigenvector score, highlighting their role in a network of influential partners.

$$\mathbf{x} = \lambda\,\mathbf{A}\,\mathbf{x}, \tag{5}$$

where $\mathbf{A}$ is the adjacency matrix.

PageRank [1]: originally proposed by Larry Page and Sergey Brin, the founders of Google, it is similar to eigenvector centrality but incorporates a damping factor, which models the idea of random jumps within the network. It assigns a score to each node based on both the quantity and quality of its links, making it particularly useful in directed networks where the direction of trade flow matters.

$$x_i \;=\; \alpha \sum_{j=1}^{p} \frac{A_{ij}}{k_j^{+}}\, x_j \;+\; \beta, \quad \textit{where} \quad \beta \;=\; \frac{1-\alpha}{p}. \tag{6}$$

where:

- x_i is the PageRank (or centrality) of node i.
- α is the damping factor (e.g., 0.85).

- A_{ij} is the adjacency matrix entry from j to i.
- k_j^+ is the out-degree of node j.
- p is the total number of nodes.
- β is the teleportation term, often written as $\frac{1-\alpha}{p}$.

2.4.4 Dependency Analysis

We detect importers relying on a single exporter for more than 50% of their trade. If, for importer v and exporter u,

$$\frac{w(u,v)}{\sum_{(x,v)\in E} w(x,v)} > 0.5. \tag{7}$$

we retain (u,v) in a simplified dependency graph.

2.4.5 Maximum Spanning Tree (MST)

We build a maximum spanning tree [6] from an undirected version of the network, selecting edges with the highest total weight without forming cycles. This reveals the network's backbone of critical trade links.

2.4.6 Community Detection

A greedy modularity algorithm [5] partitions the network into communities. The modularity Q is:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{8}$$

where:

- A_{ij} is the element of the adjacency matrix between nodes i and j.
- k_i and k_j are the degrees of nodes i and j respectively.
- m is the total number of edges.
- $\delta(c_i, c_j)$ equals 1 if nodes i and j are in the same community, and 0 otherwise.

2.4.7 Robustness and Spectral Analysis

We simulate the removal of high-eigenvector-centrality nodes [8] to see how the largest connected component changes, indicating the network's resilience. Additionally, we compute the Laplacian matrix:

$$L = D - A \tag{9}$$

where:

- A is the adjacency matrix. It is a square matrix where each element A_{ij} represents the weight of the edge between node i and node j (or 1 if an edge exists in an unweighted graph).
- D is the degree matrix. This is a diagonal matrix where each diagonal element D_{ii} is the sum of the weights of all edges incident to node i. In unweighted graphs, D_{ii} equals the number of edges connected to node i.
- L is the Laplacian matrix and encapsulates the connectivity structure of the graph. It is widely used in spectral graph theory and various network analyses to study properties such as connectivity and clustering.

  We then examine its eigenvalues to glean structural insights about connectivity and clustering [7].

2.5 Software and Libraries

The analysis is implemented in Python using libraries such as:

- Pandas**:** for data manipulation and aggregation.
- NetworkX**:** for building and analysing the trade network.
- Matplotlib and Seaborn**:** for visualizing graphs and statistical distributions.

3 Results and Discussion

In this section, we present and interpret the outcomes of our network-based investigation of the global meat trade. We begin by examining high-level trends in trade value, volume, and price, followed by an exploration of how imports and exports are distributed among different countries. Building on these initial observations, we then delve deeper into the structure of the meat trade network, identifying the most influential exporters, quantifying dependencies, detecting community patterns, and assessing the system's overall resilience. This multi-faceted approach allows us to construct a holistic picture of the market's dynamics and vulnerabilities.

3.1 Initial Market Overview

3.1.1 Historical and Forecasted Trade Value, Volume, and Price Level

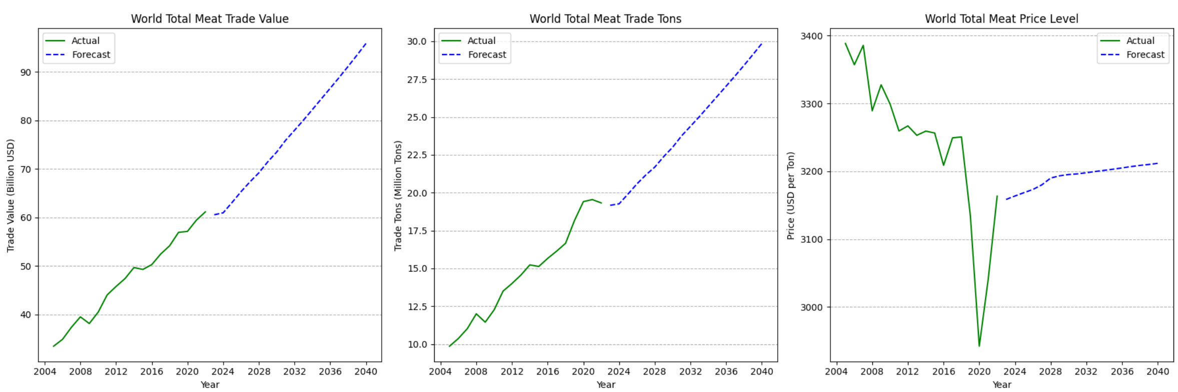

Figure 1: Trade Value, Volume and Price Level of International Meat Trading, 2005-2040

Figure 1 displays the annual world total meat trade value (in billions of USD), trade volume (in millions of tonnes), and price level (USD per tonne) from 2005 to 2040, with actual data up to 2022 and forecasts thereafter. Over the historical period, the trade value exhibits a steady upward trend, reflecting growing global demand for meat products. This growth is mirrored in the increasing trade volume, suggesting that consumption patterns for meat have expanded significantly over the past two decades. By contrast, the price level (USD per tonne) had been decreasing steadily between 2004 and 2020 (by approximately 15%). However, the average price per tonne experienced a sudden increase in from 2020 to 2022, coinciding with the COVID-19 pandemic, which disrupted global supply chains, significantly increasing the prices of many commodities.

The forecast portion of the series (dotted blue lines) indicates a continued rise in both trade value and volume, suggesting that, given the inclination of the curves, international meat markets are expected to keep growing at the same rate as in the past two decades. Meanwhile, the projected price level shows either stabilisation or modest growth, implying that despite the anticipated increase in volume, producers and consumers may experience relatively steady prices if global production capacity and logistical infrastructure continue to match demand. It is important to note that the dataset does not provide the underlying assumptions used to generate these long-horizon price forecasts. As a result, we are unable to evaluate the reliability or robustness of the projected stability in meat prices. However, the relatively steady trajectory of the forecast implies that it does not account for major external shocks to the global meat trade system. In light of the current geopolitical environment, particularly the recent initiation of new tariffs by the United States Administration, which may escalate into broader trade barriers worldwide, it will be instructive to revisit and compare actual market data in the near future to these projections, especially if meat products become entangled in escalating tariff disputes.

3.2 Concentration of Trade Value Among Importers and Exporters

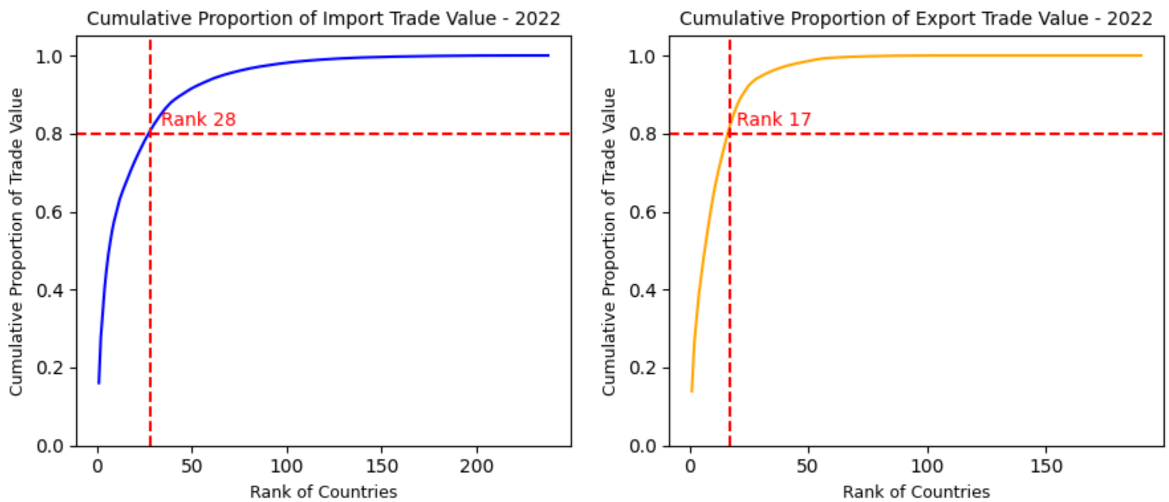

Figure 2: Cumulative Proportion of Import and Export Trade Value in the International Meat Market (2022)

Figure 2 illustrates the cumulative proportion of import and export trade value in 2022, plotted against the rank of countries (from highest to lowest trade value). The import side (left panel) shows that 80 per cent of the total import value is accounted for by 28 countries, while the export side (right panel) reaches the same 80 per cent threshold with only 17 countries. This discrepancy points to a more concentrated supply side, in which a smaller group of key exporters accounts for the majority of global meat exports. By contrast, import demand is spread across a somewhat broader range of countries.

From a policy or market perspective, this asymmetry implies that disruptions among the leading exporters (for instance, due to environmental shocks or trade barriers) could have a disproportionately large impact on global meat availability and prices. Conversely, although also exhibiting a high degree of concentration, demand is comparatively diversified, meaning it may be more resilient to localised disturbances.

3.3 Share of Major Exporters in the Global Market

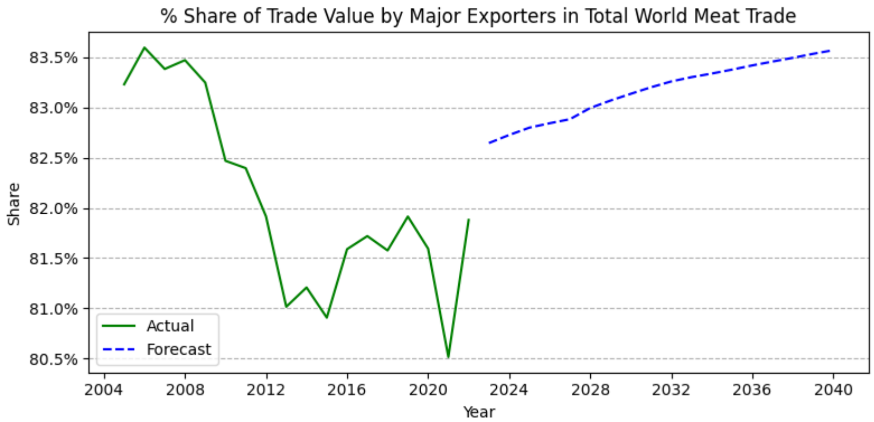

Figure 3: Percentage Share of Trade Value by the 17 Countries Accounting for 80% of Total World Meat Trade Value (2022)

Figure 3 tracks the historical and forecasted percentage share of trade value held by the major exporters (the 17 countries that collectively account for 80% of exports in 2022). Historically, this group's combined share has fluctuated around the 80-83.5% , with occasional dips or surges likely driven by short-term economic and political factors. The forecast data (dotted blue line) suggests a modest yet persistent upward trend in these exporters' share, rising to nearly 84 per cent by 2040. This indicates a potential further consolidation of the global meat export market, where a handful of large suppliers could wield greater influence over trade patterns and price formation.

Such a trend may offer economies of scale to these exporters but also heightens the risk of supply disruptions if one or more of these countries experiences a significant production shortfall. For importers, depending heavily on a narrow pool of suppliers might prompt considerations of diversification or strategic reserves, especially if climate change or geopolitical events increase volatility in production regions.

Overall, the initial market analysis underscores three key points: (1) a steady, long-term rise in global meat trade value and volume, with relatively stable (though sometimes fluctuating) price levels; (2) a more pronounced concentration among exporters compared to importers; and (3) a forecast that the major exporters' share of the total market will likely continue to expand over the coming decades. These observations motivate further network-based analyses to better understand the roles of individual countries, dependencies, and vulnerabilities in the global meat trade system.

3.4 Overall Network Structure

The initial aggregation of bilateral trade flows yielded a network with 2,907 edges connecting 246 countries. However, after applying our pruning method, which retains only those edges that cumulatively account for 90% of the total trade value, the network becomes much sparser, comprising only 256 edges among 73 nodes. This substantial reduction indicates that while the full dataset records trade among a wide array of 246 countries, the dominant trade flows are concentrated among a relatively small subset of 73 countries. In practical terms, this suggests that the vast majority of global meat trade value is routed through a limited number of key players, with many bilateral connections being relatively minor. The concentration of trade in this pruned network underscores the critical role of these 73 countries, particularly on the export side, in driving the global market, and highlights potential vulnerabilities if disruptions were to occur among these major nodes.

The pruned network in Figure 4 shows a clear distinction between **major exporters** (in red) and all other countries (in blue). Major exporters generally occupy more central positions in the diagram, suggesting they have larger node strength (the sum of their incoming and outgoing trade) and hence bigger node sizes. This aligns with the earlier observation that meat exports are highly concentrated among a small group of countries.

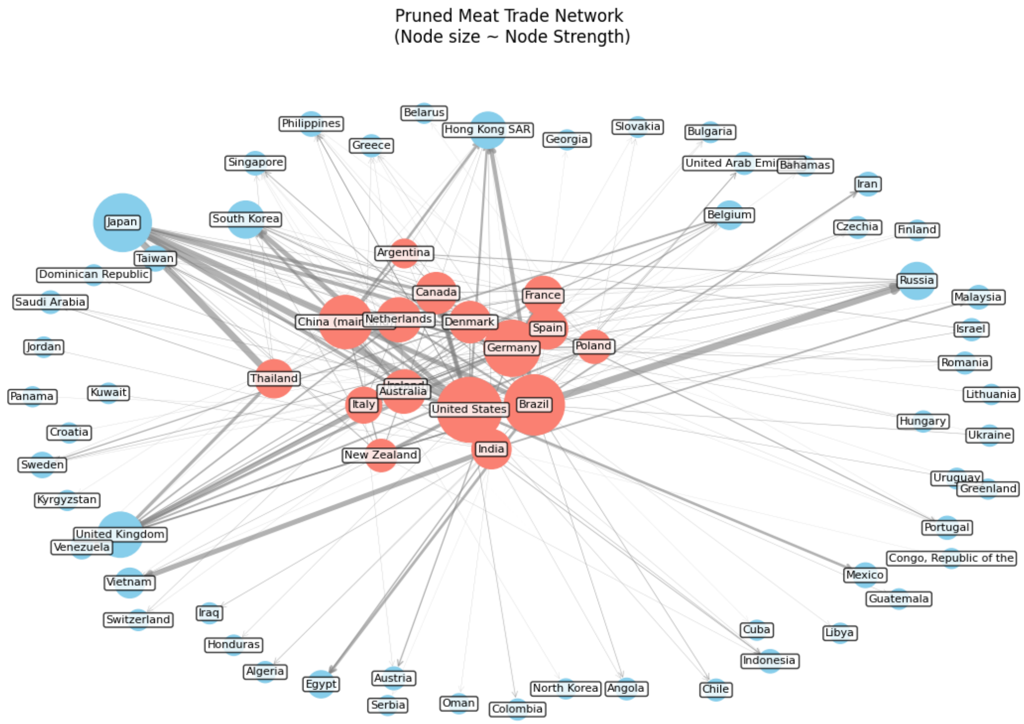

Figure 4: Pruned Meat Trade Network

Table 1 reveals that Brazil, Germany, Spain, and the United States top the list with out-degree values ranging from 20 to 30. This indicates they export to a wide variety of destinations in the pruned network. Meanwhile, countries such as Canada, New Zealand, and Argentina still appear in the major exporters group but have a lower out-degree (under 10), implying they ship to fewer destinations in this 90% pruned subset.A high out-degree in a pruned network often signifies that the country's exports reach many different regions at relatively high trade volumes. Some exporters (like Brazil) seem to have a broader global reach, whereas others are more regionally specialised or simply do not export in as many large flows that pass the pruning threshold.

Exporter	Out-Degree	Importer	In-Degree
Brazil	30	Japan	15
Germany	27	China (mainland)	12
Spain	20	South Korea	11
United States	20	United Kingdom	11
Netherlands	19	United States	10
Denmark	17	Hong Kong SAR	10
Poland	17	Germany	10
India	16	Netherlands	10
Australia	14	Russia	9
Italy	14	France	8

Table 1: Out-Degree and In-Degree for major Exporters and Imports

Regarding top in-degree countries, Japan tops the list with an in-degree of 15, followed by China (mainland) with 12. This indicates that both countries import significant volumes from a broad set of exporters (in the pruned, 90% subset). The appearance of South Korea (11) and the United Kingdom (10) near the top similarly suggests these nations are sourcing from multiple large flows, reflecting diverse supply chains and possibly strong demand for various meat products.

Some entries in the table, such as the United States (in-degree 10) and Germany (in-degree 10) also feature among the top exporters in the out-degree table. This demonstrates that certain countries are both large importers and exporters of meat, possibly due to reprocessing, redistribution, or specialisation in specific product categories. The presence of countries from different continents within the top exporters and importers underscores the global nature of meat trade. It also aligns with the earlier observation that meat trade encompasses a broader range of countries.

Higher in-degree values in a pruned network suggest that these countries maintain multiple significant supply channels. While this diversification can mitigate risks if one exporter experiences a shock, it also highlights the importance of stable international relationships for sustaining consistent meat supplies. Shifts in tariff policy or health regulations could disrupt multiple import pathways at once, especially for countries reliant on a handful of key exporters.

3.5 Centrality Measures and Key Players

3.5.1 Correlation of Centrality Metrics

The correlation heat-map in Figure 5 shows a very strong relationship between Eigenvector Centrality and PageRank (0.93), meaning nodes deemed influential by one measure tend to rank highly on the other. Closeness also exhibits a moderate to strong correlation (0.82) with these measures, indicating that nodes well-connected to other influential nodes (Eigenvector/PageRank) often have relatively short average path distances (Closeness) to the rest of the network. By contrast, Betweenness has relatively low correlation (0.36–0.53) with the other metrics, highlighting that the role of "bridge" or "broker" in the network is distinct from simply being well-connected or close to others.

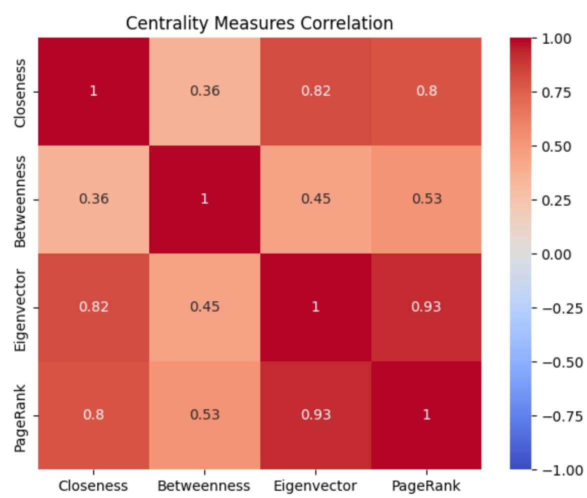

Figure 5: Centrality Measures Correlation Heat-map

3.5.2 Overall Patterns

Figure 10 (included in the Appendix due to size) shows each individual country's score per Centrality measure. The following is a short overview of some patterns present in the dataset:

- **Betweenness**: the majority of nodes show very low or zero Betweenness, reflecting that only a few countries appear on many shortest paths between other pairs of nodes. Notably, Germany (0.035) and the United States (0.033) rank among the highest in Betweenness, suggesting they serve as potential "bridges" in the pruned meat trade network.

- **Closeness**: a few nodes, such as Japan (0.209), China (mainland) (0.174), and the United Kingdom (0.169), have relatively high Closeness scores. This implies that they can reach other nodes with fewer intermediate steps, likely due to diverse or well-connected import/export links.

- **Eigenvector Centrality and PageRank**: countries like Japan, China, South Korea, and the United Kingdom stand out with high Eigenvector and PageRank values. This indicates that they are not only well-connected themselves but also connected to other influential nodes. Japan, for instance, scores particularly high (0.345 in Eigenvector and 0.026 in PageRank), placing it among the network's top hubs.

3.6 Dependency Analysis

As described in our methodology, we conducted this step to identify instances where an importer relies heavily on a single exporter. Specifically, we applied a 50% threshold, meaning that if one exporter accounts for over half of an importer's total incoming trade, we retain that edge in a simplified, directed graph. The goal is to highlight potential vulnerabilities: should a major exporter experience production shortfalls or impose export restrictions, dependent importers may struggle to find alternative suppliers quickly.

3.6.1 Simplified Dependency Graph

In the simplified graph (Figure 6) edges are drawn only when an exporter contributes more than 50% of an importer's trade, and the resulting network is considerably sparser than the full pruned network. Some exporters, such as Brazil and the United States, stand out with multiple thick edges, indicating numerous countries that rely on them for the majority of their meat imports. Others, like Denmark or Argentina, exhibit fewer connections but still appear as sole suppliers for one or two destinations. This visual structure underlines how trade dependencies cluster around certain key exporters, reinforcing earlier observations of high concentration among a small group of suppliers.

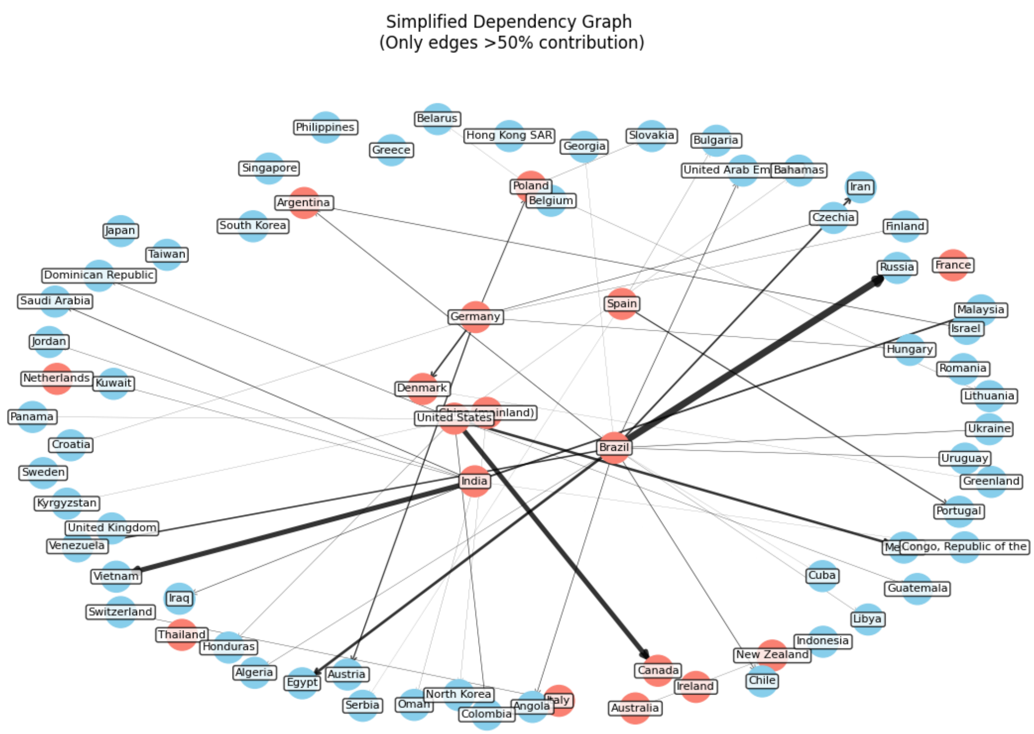

Figure 6: Simplified Meat Network (50% Dependency Threshold)

The dependency table (2) lists each major exporter followed by the set of countries that depend on it for over half of their total imports. Some immediate observations include:

- **Brazil** has a particularly large group of dependent importers (e.g., Algeria, Angola, Argentina, Egypt, Russia, and others). This wide reach suggests that disruptions in Brazil's supply chain could ripple through many importers.
- **United States** likewise appears as a dominant exporter for numerous countries, reflecting its status as both a top global meat producer and a major trade partner.

- **Some exporters** (e.g., Denmark) have only one or two dependent importers (e.g., Greenland), suggesting a geographically proximate or otherwise specialised trade relationship.
- **Smaller or regionally focused exporters** (like Argentina) may supply a small set of neighbouring or closely linked markets, but those markets can still be heavily reliant on them.

Exporter	**Dependent Importers**
Argentina	Brazil, Israel
Australia	New Zealand
Brazil	Algeria, Angola, Argentina, Chile, Cuba, Egypt, Georgia, Iran, Libya, Russia, Ukraine, United Arab Emirates, Uruguay, Venezuela
China (mainland)	Kyrgyzstan, North Korea
Denmark	Greenland
Germany	Austria, Croatia, Czechia, Denmark, Finland, Hungary, Poland
India	Congo, Republic of the, Iraq, Jordan, Kuwait, Malaysia, Oman, Saudi Arabia, Vietnam
Italy	Switzerland
Poland	Belarus, Lithuania, Slovakia
Spain	Bulgaria, Portugal, Serbia
United States	Bahamas, Canada, Colombia, Dominican Republic, Guatemala, Honduras, Mexico, Panama

Table 2: Dependency Table (above 50% threshold)

The above 50% threshold highlights the degree to which certain importers lack diversification. Should a major exporter face internal challenges (such as disease outbreaks, logistical bottlenecks, or policy changes), countries that rely on it for more than half of their imports may face immediate shortages or price shocks. Consequently, these findings provide useful signals for importers to consider diversifying their supply chains or establishing contingency plans.

By focusing on these dominant flows, the dependency analysis complements our other network insights. While overall trade is concentrated among a small set of exporters, this step makes explicit the one-to-one relationships where importers are especially exposed to a single supplier, thus underscoring potential weaknesses in the global meat trade system.

3.7 Backbone Extraction (Maximum Spanning Tree)

The Maximum Spanning Tree (MST) is constructed from the undirected version of the pruned network by selecting edges with the highest weights that connect all nodes without forming cycles. This "backbone" helps us see the most critical bilateral trade links that tie the entire network together.

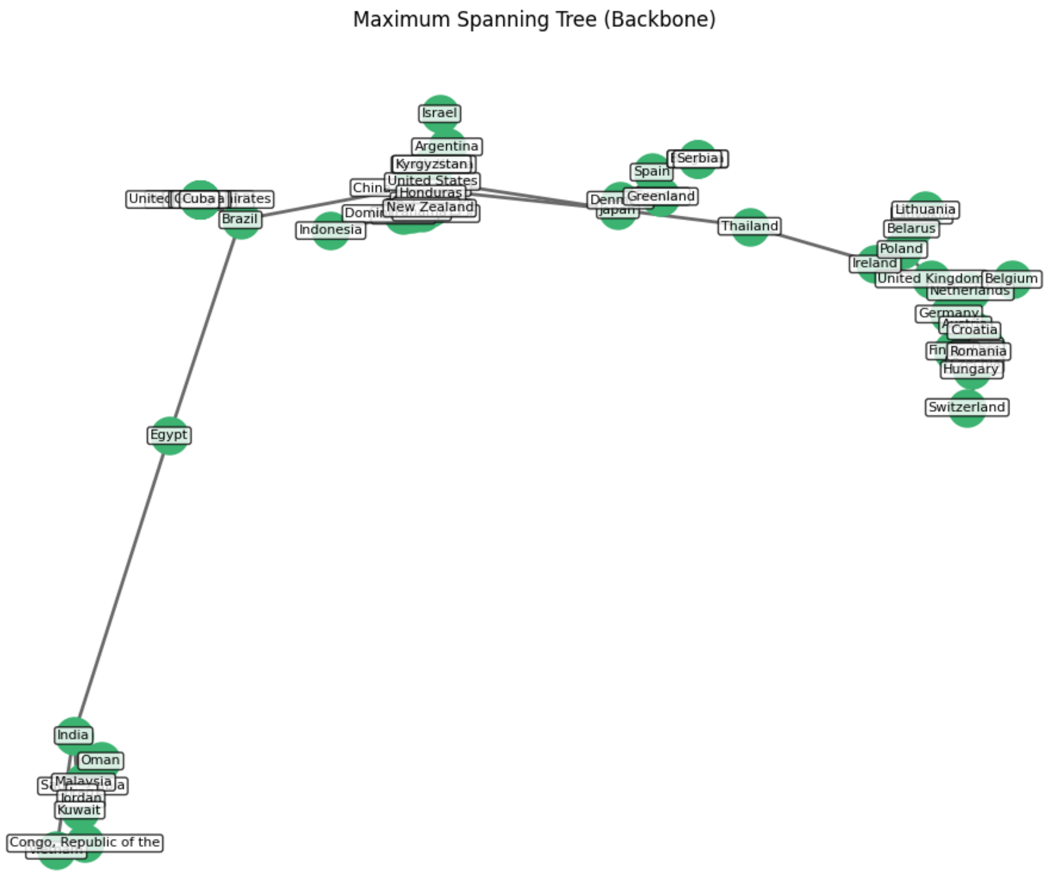

Figure 7: Maximum Spanning Tree

3.7.1 Linear / Chain-Like Structure

In the displayed MST (Figure 7), many nodes are arranged in what appears to be a chain or series of small branches rather than a dense cluster. This suggests that the network's dominant trade flows (when reduced to one spanning tree) do not form many large hubs, but instead create relatively direct, high-value connections. A single path might stretch across multiple continents, with smaller sub-branches for regionally concentrated trade links.

3.7.2 Key Nodes in the MST

Certain nodes (e.g., Brazil, India, United States) serve as junctions where multiple branches converge. This is consistent with earlier analyses identifying these countries as major exporters or importers, underlining their significance in connecting otherwise distant regions. Disruptions in these high-weight edges could fracture the MST and, by extension, the wider trade network's most essential routes.

Overall, the MST highlights a relatively small set of links that collectively ensure the connectivity of the entire pruned network. Countries that appear central in this tree have disproportionate influence on the flow of goods, reinforcing the concentration trends noted in previous sections.

3.8 Community Detection (Greedy Modularity)

We apply a greedy modularity algorithm to the undirected version of the pruned network. This method groups nodes into communities where intra-community connections are denser or more significant than inter-community links, thereby revealing natural "clusters" of trade relationships.

In the resulting visualisation (Figure 8), we see a few distinct clusters (colour-coded):

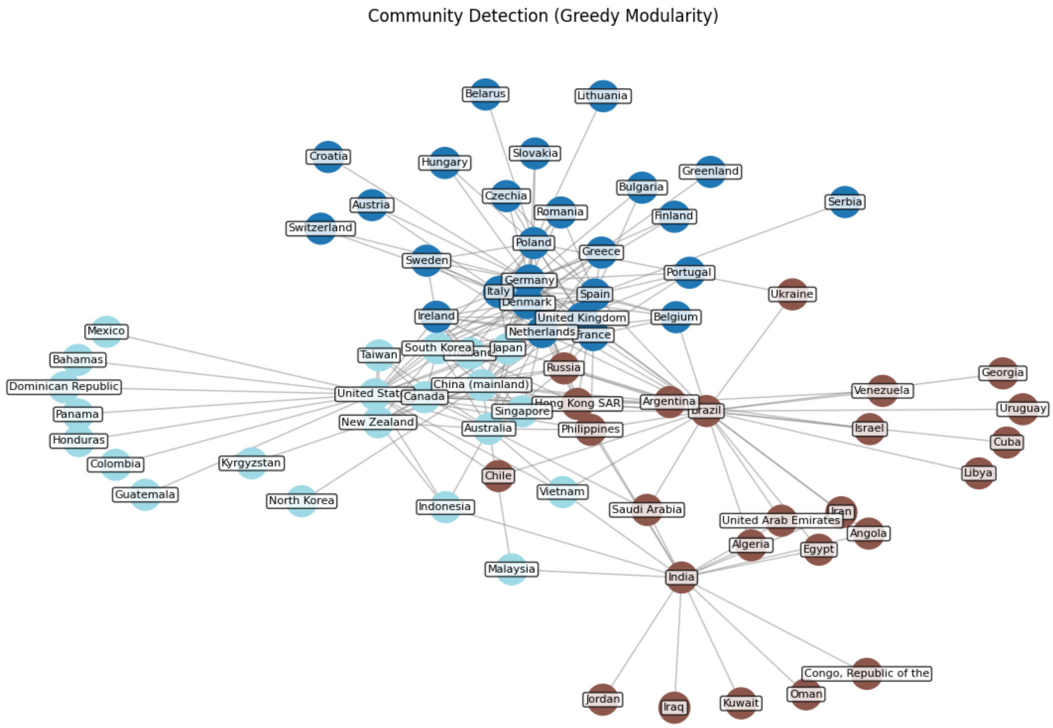

Figure 8: Community Detection Graph

- A light blue cluster that primarily includes countries in or near **Central America** which trade heavily with the United States. Several large countries also appear in this cluster such as China (mainland), Canada, Japan, South Korea, and Australia, although the Central American segment remains almost exclusively linked to the United States, likely due to geographic proximity.
- A large **Europe-centric cluster** (darker blue) with dense trade connections amongst themselves.
- A third major cluster (in brown), which is more geographically scattered. Larger countries such as Russia, Brazil, Argentina, and the Philippines appear near other clusters and act as bridges to smaller nodes. In particular, Brazil connects both South American and certain Middle Eastern countries; some of the latter also have strong links to India, which itself serves a set of nodes (e.g. Jordan, Iraq) that are not well connected to other countries.

The Community Graph appears to be well rooted in reality and is successfully carving out important relationships from the dataset, such as:

- **Regional or Cultural Factors**: shared borders or cultural/economic alliances (e.g., EU membership, historical trade ties) often lead to denser intra-community trade.
- **Influential Exporters**: countries such as Brazil or the United States might appear in or near multiple clusters if they maintain high-value links across different regions, sometimes blurring strict geographical divisions.
- **Policy and Logistics**: tariffs, free trade agreements, or shared logistics corridors can reinforce community structures, leading certain sets of countries to cluster together.

3.9 Robustness (Node Removal)

We performed two separate node-removal experiments to assess how the network's connectivity changes under different disruptions by comparing its Largest Connected Component (LCC) before and after removal.

3.9.1 Removing Top Five by Eigenvector Centrality

- Nodes removed: Japan, the United Kingdom, South Korea, China (mainland), and the Netherlands.
- LCC: decreases from 73 to 66.

These high-eigenvector nodes (which largely overlap with the top five by In-Degree) are well-connected to other influential countries, but removing them detaches only a modest set of peripheral nodes. The bulk of the network remains intact, suggesting that while these hubs are important, alternative routes still exist for many participants.

3.9.2 Removing Top Five by Out-Degree

- Nodes removed: Brazil, Germany, the United States, Spain, and the Netherlands.
- LCC: decreases from 73 to 53.

This more substantial drop reflects the critical role of major exporters. High out-degree nodes are top suppliers in the network; when they disappear, many importers, especially those heavily reliant on these exporters, lose their primary or only connection to the rest of the system. Consequently, the network fragments more severely.

3.9.3 Results of the node-removal experiment

The two node-removal experiments reveal distinct vulnerabilities in the meat trade network. Removing the top five nodes by eigenvector centrality, comprising Japan, the United Kingdom, South Korea, China (mainland), and the Netherlands, resulted in a modest decrease in the largest connected component, from 73 to 66 nodes. This suggests that while these nodes are influential and well-connected, their removal primarily affects peripheral connections, with many alternative pathways still preserving overall connectivity.

In contrast, when the top five nodes by out-degree were removed, namely Brazil, Germany, the United States, Spain, and the Netherlands, the network's largest connected component dropped significantly from 73 to 53 nodes. This more pronounced fragmentation indicates that major exporters, which are identified by high out-degree values, serve as critical supply hubs. Their removal disrupts many importers that rely heavily on these key trade relationships, leading to a more substantial breakdown in network connectivity.

Together, these findings underscore that both importer and exporter hubs are crucial to the global meat trade system; however, the network is particularly sensitive to disruptions among leading exporters. This increased vulnerability among exporters highlights the importance of diversification strategies for importers and the need for robust logistical networks to mitigate potential disruptions in global trade flows.

3.9.4 Spectral Analysis (Laplacian Eigenvalues)

3.9.5 Laplacian Matrix

The Laplacian L is defined as $L = D - A$, where D is the degree matrix and A is the adjacency matrix of the undirected version of the pruned network. Examining its eigenvalue distribution helps us understand connectivity and clustering properties.

3.9.6 Eigenvalue Distribution

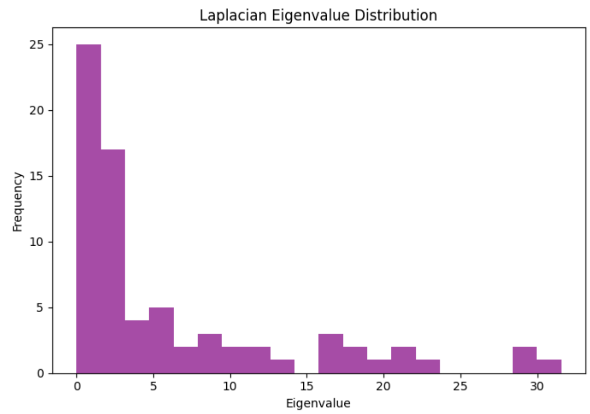

Figure 9: Laplacian Eigenvalue Distribution

The histogram (Figure 9) shows a peak near 0, followed by a tail extending to around 30. Typically, the number of zero eigenvalues equals the number of connected components in the graph, so a single peak at or near 0 suggests the network is largely one connected component (as also reflected by the largest connected component size of 73).

In our analysis, the Laplacian eigenvalue distribution shows that while there are a few small non-zero eigenvalues (notably the second smallest, known as the "Fiedler value"), these do not translate into a network that is easily fragmented. Although very small eigenvalues can theoretically signal that a network is on the verge of splitting into sub-networks, our robustness tests indicate otherwise. For example, removing the top five nodes by eigenvector centrality reduced the largest connected component only from 73 to 66 nodes, while removing the top five nodes by out-degree (primarily major exporters) resulted in a larger reduction, from 73 to 53 nodes. This disparity underscores that although there is some underlying substructure, the network overall remains resilient: even when key nodes are removed, significant alternative pathways preserve much of the network's connectivity.

4 Conclusion and Outlook

Our comprehensive analysis of the global meat trade network reveals a highly concentrated system in which a relatively small number of countries dominate the majority of trade flows. Although the dataset initially encompasses 246 countries, our pruning process, retaining edges that account for 90% of the total trade, reduces the network to 73 key nodes. Notably, only 17 major exporters account for 80% of the exports in 2022, highlighting a significant concentration on the supply side. This concentration is reflected in our dependency analysis, which shows that many importers rely heavily on a single exporter, thus signalling potential vulnerabilities in the trade network.

Centrality measures provide further insight into the system's structure. Our metrics indicate that while influential nodes emerge on both the import and export sides, exporters such as Brazil, Germany, and the United States play an especially critical role in sustaining global supply chains. In our node removal experiments, we compared two scenarios. Removing the top five nodes by eigenvector centrality (Japan, United Kingdom, South Korea, China (mainland), and the Netherlands) reduced the largest connected component from 73 to 66 nodes, a modest decline. In contrast, removing the top five nodes by out-degree (Brazil, Germany, United States, Spain, and the Netherlands) resulted in a much more pronounced fragmentation, with the largest connected component shrinking from 73 to 53 nodes. These contrasting outcomes underscore that, while both importers and exporters are important, the network is particularly sensitive to disruptions among the leading exporters.

Community detection further enriches our understanding by revealing distinct clusters within the network. Our analysis identified clusters that align with regional or cultural ties, such as a Central American cluster closely linked to the United States and a Europe-centric cluster with dense intra-regional connections, as well as a more geographically dispersed group where key exporters like Brazil and India serve as bridges. This community structure highlights not only the inherent regional grouping in global meat trade but also the complex role of certain countries that connect diverse regions.

Looking ahead, further research could integrate economic indicators and geopolitical risk assessments to forecast the impact of external shocks, such as the introduction of new tariffs or trade disputes, on the trade network's stability. Dynamic network models that account for temporal changes could provide a more nuanced understanding of how shifts in trade policies or disruptions in major exporting countries might reshape global meat trade flows. Overall, our findings emphasise the need for importers to consider diversification strategies, while policymakers should be aware of the potential systemic risks posed by concentrated supply channels.

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A Appendix - Additional Tables

Node	Closeness	Betweenness	Eigenvector	PageRank
Brazil	0.014	0.006	0	0.012
Russia	0.155	0	0.194	0.019
Thailand	0	0	0	0.011
Japan	0.209	0	0.345	0.026
China (mainland)	0.174	0.03	0.251	0.022
United States	0.156	0.033	0.167	0.021
India	0	0	0	0.011
Vietnam	0.115	0	0.046	0.013
South Korea	0.169	0	0.279	0.023
Canada	0.104	0.002	0.049	0.015
Ireland	0.098	0.002	0.082	0.013
United Kingdom	0.169	0	0.288	0.021
Hong Kong SAR	0.167	0	0.193	0.021
Denmark	0.108	0.007	0.181	0.016
Australia	0.125	0.011	0.11	0.016
New Zealand	0.08	0	0.018	0.012
Germany	0.156	0.035	0.247	0.021
France	0.12	0.001	0.211	0.017
Egypt	0.031	0	0	0.012
Mexico	0.099	0	0.028	0.012
Netherlands	0.156	0.023	0.247	0.02
Argentina	0.014	0	0	0.011
Poland	0.098	0.01	0.115	0.013
Belgium	0.119	0	0.184	0.015
Italy	0.116	0.004	0.2	0.016
Malaysia	0.096	0	0.018	0.012
Iran	0.031	0	0	0.012
Spain	0.116	0.007	0.2	0.016
Venezuela	0.028	0	0	0.012
Sweden	0.115	0	0.178	0.016
Austria	0.102	0	0.074	0.012
Portugal	0.108	0	0.15	0.014
Taiwan	0.132	0	0.12	0.017
Singapore	0.137	0	0.129	0.017
Philippines	0.143	0	0.122	0.015
Indonesia	0.115	0	0.049	0.014
Saudi Arabia	0.103	0	0.018	0.013
United Arab Emirates	0.031	0	0	0.012
Chile	0.102	0	0.028	0.012
Angola	0.031	0	0	0.012
Israel	0.028	0	0	0.012
Colombia	0.099	0	0.028	0.012
Iraq	0.014	0	0	0.011
Czechia	0.105	0	0.093	0.013
Ukraine	0.081	0	0.019	0.012
Dominican Republic	0.099	0	0.028	0.012
Romania	0.108	0	0.127	0.014
Uruguay	0.019	0	0	0.011
Hungary	0.102	0	0.06	0.012
Switzerland	0.102	0	0.074	0.012
Jordan	0.014	0	0	0.011
Kuwait	0.014	0	0	0.011
Guatemala	0.099	0	0.028	0.012
Greece	0.111	0	0.179	0.015
Algeria	0.031	0	0	0.012
Honduras	0.099	0	0.028	0.012
Finland	0.102	0	0.071	0.012
Slovakia	0.102	0	0.06	0.012
Libya	0.019	0	0	0.011
Lithuania	0.074	0	0.019	0.011
Bulgaria	0.102	0	0.074	0.012
Oman	0.014	0	0	0.011
Croatia	0.099	0	0.041	0.011
Bahamas	0.099	0	0.028	0.012
Panama	0.099	0	0.028	0.012
North Korea	0.105	0	0.042	0.013
Kyrgyzstan	0.105	0	0.042	0.013
Greenland	0.079	0	0.03	0.011
Georgia	0.019	0	0	0.011
Belarus	0.074	0	0.019	0.011
Congo, Republic of the	0.014	0	0	0.011
Cuba	0.019	0	0	0.011
Serbia	0.083	0	0.033	0.011

Figure 10: Centrality Measures by Country