CIVENG263 Report: An Analysis of a global food supply chain by product (focus on coffee) and investigating impact of supply side disruptions

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Abstract: Food insecurity is contemporarily exacerbated by increased globalization in an ever growing world. More so, increased agricultural exchange between countries championed by advances in farming and logistics technology has led to more complex food networks. Certain economies especially regions with low agricultural yield rely on imports for food and are susceptible to food insecurity and negative disruptions to the global food network. Highly connected global food supply chains are extremely vulnerable as both local disruption could entirely cripple the global food network and lead to long term reduced food access globally. Understanding the impact of disruption on Agricultural supply chains becomes important in the analysis of the global movement of agricultural products. The aim of this project is to carry out an exploratory analysis on a global coffee demand and supply data set inorder to observe the changing trends in key network topological and robustness metrics over time. This analysis is a first step to understanding the effects of supply side disruptions on the movement of food at the global scale.

1 Introduction

Advancing technology and increased globalization in the last two decades have increased the complexity and thus uncertainty that exists within supply chains. It has been noted that supply chains vulnerability to disruption has increased while demand in most sectors has become increasingly volatile [1, 2]. This is particularly relevant in the case of Agricultural supply chains (ASC) that normally face high levels of stochasticity due to certain inherent characteristics including high long supply lead-times, seasonality, perishability, inherent uncertainties in their biological production processes, variable weather conditions, diseases among others[3]. In Agricultural and food supply chains, highly perishable grocery foods constitute up to 50% of all sales in retail food [4]. Supply chain managers particularly in retail groceries have a hard time managing perishable food products because of deterioration, wastage, spoilage, and a short shelf life [5, 6, 7]. In addition, the rise in 'tracking and tracing' interest within the supply chain community, coupled with animal welfare and food safety concerns present new areas of variability to be accounted for when analyzing agri-food chains. Additionally, the rising frequency and intensity of extreme climate events with continued temperature increases, and shifting rainfall patterns have accentuated volatility of crop and livestock yields thus rendering ASCs more vulnerable to external shocks such as natural disasters, pandemic outbreaks, etc [8, 9]. This increased uncertainty can only exacerbate already low-profit margins of perishable products.

Furthermore, the world's diet is highly dependent on only four grains: rice, wheat, corn, and soy. Another constricting factor is that 60% of these grains are produced by only five countries in very specific regions. Unexpected shocks to these production heavy countries could entirely cripple the ASC networks and reduce food access globally [10]. Certain economies, especially regions with low agricultural yield, rely on imports for food and are susceptible to food insecurity and negative disruptions to the global food network. On the African continent, roughly half of the population faces food insecurity presently where more than 250 million people are considered to be severely food insecure [11, 12]. In addition, the agricultural supply chain constitutes an essential part of many countries' economies. In sub-Saharan Africa, agriculture is also one of the most important economic sectors, making up 23 percent of the continent's GDP and provides work for nearly 60 percent of the economically active population [12]. In Asia, in the past decade, the number of small grocers has continued to grow reaching values of 13 million small grocers in four Asian countries: India, China, Indonesia, and the Philippines, with India alone hosting 6.6 million of them. This fragmented market system has remained convenient and hence competitive in these regions and is an essential part of creating local livelihoods, employment, and maintaining social hubs for the local communities [13]. Economic and social Interactions between countries are thus extremely important in the analysis of the global movement and accessibility of agricultural products.

There is very little research done exploring trends in network metrics trends over time. Previous work has focused on examining network metrics in static networks. The authors in [14] present a comprehensive review of the methodologies adopted in literature for modelling the topology and robustness of supply chain networks. By investigating dynamic trends, we can uncover important information about networks over time and allow analysts to evaluate and compare different topological network metric values and predict how these values change over time at the global scale. The author in [15]. explore changes in various centralities (betweeness, degree, closeness, eigenvector) over time to conduct network trend analysis. In [16], the authors present an extended network visualization tool which provide time series plots for the network metrics over time. This project aims to gain an understanding of historical trade flow data by product (focusing in Coffee) on the global scale by carrying out the following analysis: (1) Observing changes in the network over time by looking at how different topological metrics(centralities, clustering coefficients, network density) are changing dynamically with time. (2) Investigating trends in Robustness/ Vulnerability on network under random and targeted attack. (3) Implementing a Weighted network analysis where weights represents different trade flows.

The rest of the paper is organized as follows. Section 2 discusses the methods implemented in the project. Section 3 describes the results and discussion. In section 4, we present our conclusions and discuss future work and extensions.

2 Data and Methods

2.1 Data : Global Coffee Network

Our data consists of historical ($1996 - 2017$) trade flow values (in USD) for different agricultural commodities such as coffee, rice, wheat etc obtained from a World Integrated Trade Solution database. The data set also contains historical tariff data for the same time period. The database was created by the World Bank in collaboration with the United Nations Conference on Trade and Development (UNCTAD) and in consultation with organizations such as International Trade Center, United Nations Statistical Division (UNSD) and the World Trade Organization (WTO). The data can be accessed from the following link: https://wits.worldbank.org/about_wits.html

2.2 Data Analysis

Notation:
Nodes - Trading Countries

Edges - Coffee Trade transaction between nodes(countries)
Weights - dollar value of coffee traded

Table 1: Global Coffee Time Series Data

Characteristic	Value
min year	1996
max year	2017
Year range	22

2.3 Visualizing Static Network

We focus on a subset of our data set for visualizing our network. In fig 1look at a random subset of the Coffee supply chain data set from 2015 on the left of the figure. The in-degree and our degree distribution of the network instance is presented on the left of the same figure. From this image we note that a small number of countries are responsible for a large fraction of the coffee supply in the network. As we can see only a small number of nodes with large sizes (indicating large supply ability) and most other nodes being very small(little or no supply capacity). We can also see this behavior when looking at the degree distribution, where majority of the out-degree(representing supply) values are concentrated around values 0, with a relatively low number of nodes have out-degree values greater than 0.

A summary of the statistics for the instance selected for our visualization can be found in Table 2 below.

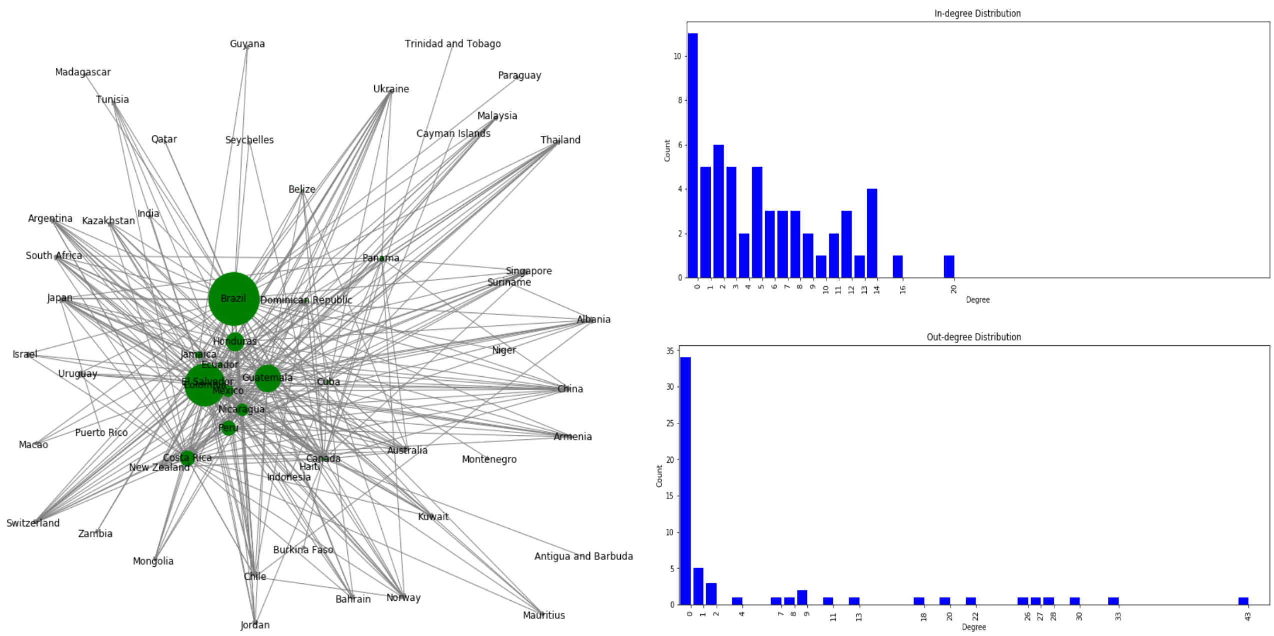

Figure 1: Visualizing Subset of Coffee supply chain Network in 2015. To the Left, is the Supply chain Network with nodes sizes Weighted by supply capacity. To the right, are the in-degree and out degree distributions.

Table 2: Summary Statistics of Data

Characteristic	Value
Number of Nodes	58
Number of edges	319
Network Density	0.096
Time Resolution	1 year
Spatial Resolution	Country level

2.4 Dynamic Network Analysis

In order to make sense of our time series network data, we investigate trends of some topological network metrics including number of nodes and edges, network density and clustering coefficient over time. These measures are selected because they can give us information about the overall changes in size, structure and potentially complexity in our network.

Nodes and Edges: In figure 2, we note that the number of nodes (countries) represented in the network steadily increased from less than 170 countries to over 200 countries between 1996 and 2006. Then the number countries trading coffee seemed to have reached an equilibrium somewhere between 200 and 210 countries trading every year. We do not consider the final year in this data set because the data collected was incomplete for this year.

It make sense for the number of nodes in the network to eventually plateau because there is only a finite number of countries in the world and a smaller subset of these countries trade coffee. The lower number of nodes seen in the initially years could be as a result of incomplete reporting, where in the earlier years not all countries trading where reported. We also note that coffee has becoming increasing popular in many countries in the Asian region that previously preferred tea. These changes in consumer preferences may also account for the steady rise in number of countries producing and trading coffee.

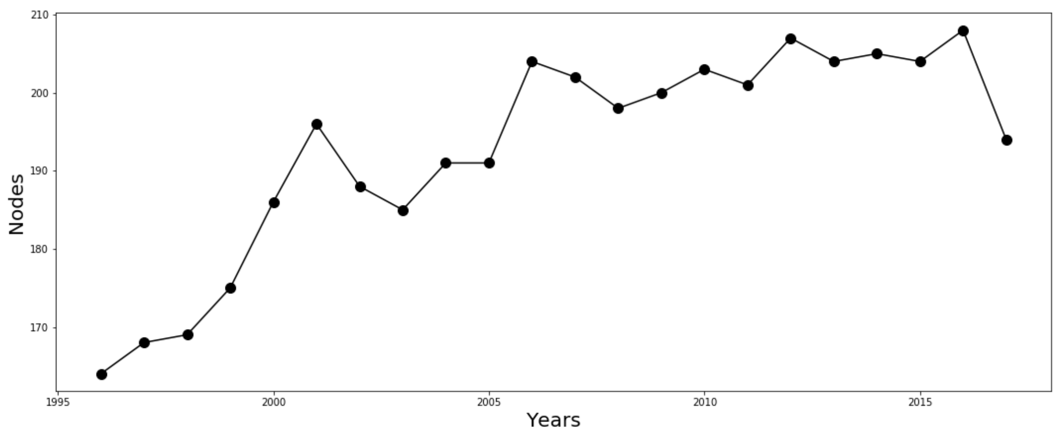

Figure 2: Number of nodes in network over time

Figure 3 presents and image of the number of edges of trading transactions between countries over time. We note a steadily increasing trend in number of connections. This is almost expected as the number of nodes have also increased over time. But this could also reflect that the complexity of the network is increasing as there are more interconnections between the nodes over time.

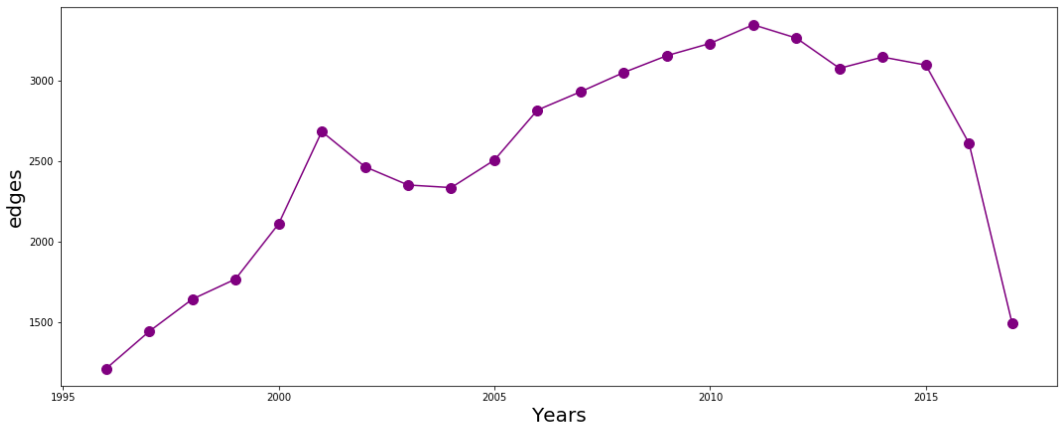

Figure 3: Number of edges in network over time

Network density: This measure is defined as the ratio of undirected edges to nodes and the trends in its values are shown in figure 4. We note overall an increase in the network density over time which could signal an increase in the complexity of the network over time which could be expected because of how increasingly interconnected the world is becoming.

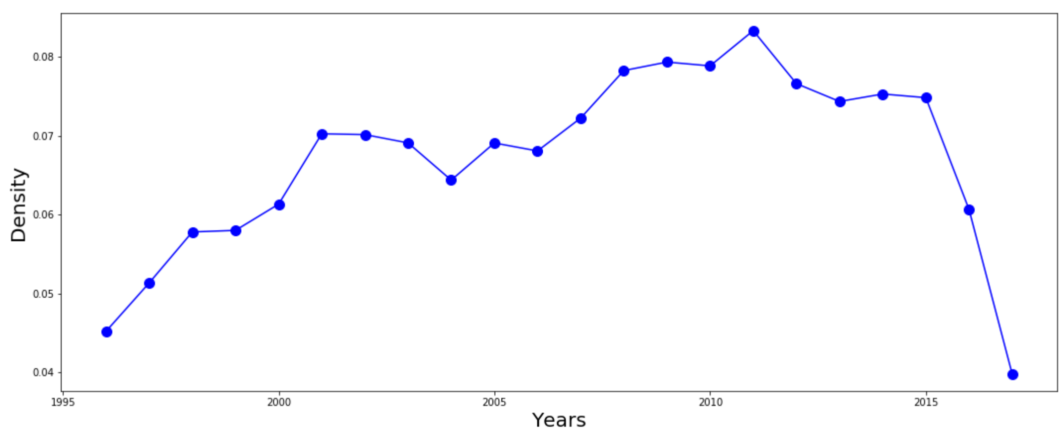

Figure 4: Network density over time

Clustering Coefficient: It is a measure of the degree to which nodes in a graph tend to cluster together. The occurrence of multiple small clusters versus no clusters may represent the difference between a decentralised versus centralised structure. In terms of robustness. Usually decentralised structure may recover more easily from shocks on the global scale. However, highly dependent local areas may suffer disproportionately more from a shock. Thus, more clusters on the other had could signal more vulnerability if we have a small number of high demand and/or supply clusters within the network

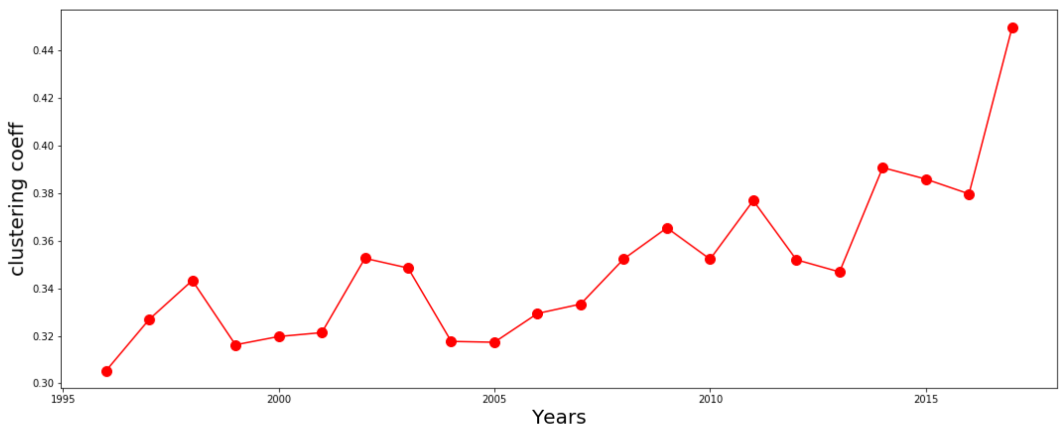

Figure 5: Network clustering coefficient over time

3 Results and Discussion

3.1 Defining Disruptions

1. **Capacity (Node) Disruptions.**These disruptions are captured by adding or removing nodes from the network. In this work, we focus primarily on modelling the disruption by node removal from the network. This is because in a food supply chain, node removal which usually represents decreased production capacity has more significant impacts and occur more frequently in practice compared to node additions. Node disruptions may be random, where nodes selected for removal are done in a random manner or targeted. In targeted attacks, the nodes are ranked based on some externally defined metric and the nodes are removed based on this ranking system with the most important nodes being removed first.

2. **Flow (Edge) Disruptions.** Another commonly modeled disruption in supply chain networks involves capturing the temporary loss in connection between 2 nodes (an

edge). i.e if edge $< u, v >$ is disrupted, then for a whole time step, $x_{u,v} = 0$. We do not model edge disruption in our current analysis but we hope to include this form of disruption in future works. It is common to make assumptions about what happens to the goods being transported along the disrupted edges. For instance we may assume that an edge disruption only implies that goods are delayed rather than destroyed. This assumption is reasonable as material destruction during an edge disruption have a much lower chance of occurrence and thus account for a much smaller volume of goods compared to delay (traffic and other transportation delays).

3.2 Network Vulnerability under targeted attack

In order to investigate the impacts of disruption on our network, we implement a robustness/ vulnerability metric proposed in [17], that compares the robustness of the network under targeted attack, by ranking the nodes by different centrality measures (Degree, Betweeness, Closeness) and the Random case. The robustness measure denoted, R is defined as follows;

$$R = \frac{1}{N} \sum_{i=1}^{N} \sigma(\frac{i}{N}) \tag{1}$$

where N is the size of the original network and N_ρ be the network that results from removing a fraction of the vertices according to some specified procedure. Then $\sigma(\frac{i}{N}) = \frac{|N_\rho|}{N}$ is the ratio of giant component (formed after removing a fraction of $\frac{1}{N}$ nodes) size relative to total network size and $\frac{1}{N}$ is the normalisation factor. For any network and method of vertex removal, $R \in [0, \frac{1}{2}]$. As such a vulnerability measure, V is also defined as follows:

$$V = \frac{1}{2} - R \tag{2}$$

The robustness under random attack is also considered in black line.

Results displayed in figure 6 suggest that the network is less vulnerable to random attacks than more targeted attacks using different centrality measures. The results for the three targeted attacks seem to have vulnerability values that are relatively close in magnitude. However, we also note that using the betweeness centrality for ranking the nodes has the highest vulnerability.

3.3 Vulnerability Trends Analysis

In this section, we explore the changed in vulnerability over time under the various forms of targeted attacks discussed in section 3.1. We also include the case of random disruption to the nodes in the network. Fig 7 displays the changes in the coffee supply chain network

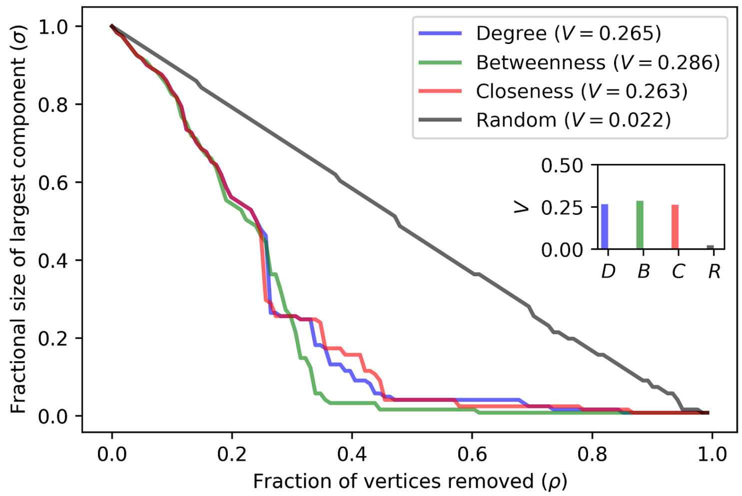

Figure 6: Vulnerability Measure using centrality and percolation theory under targeted attack

vulnerability to disruption under targeted attacks. We use random selection in addition to degree, betweeness and closeness centralities to rank the importance of nodes in the network for our targeted attacks. Overall, we note that through time, the network is less vulnerable to random attacks than different targetted attack. The three types ranking metric employed for our targeted attacks tend to behave quite similarly. We note that the vulnerabily seems to change over time in a range of at most 50% from mean. We see drops in system vulnerability especially under targeted attack between the years 2000 and 2002.

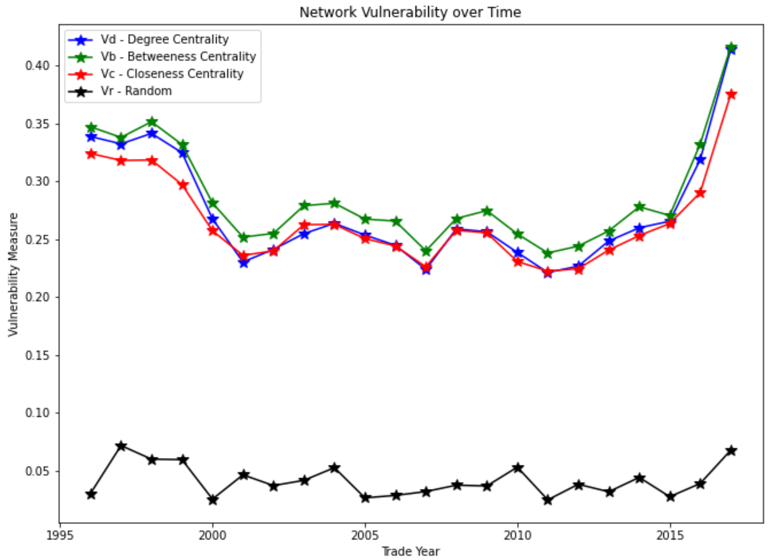

Figure 7: Network Vulnerability over Time under various kinds of targeted attack including ranking nodes using betweeness, closeness and degree centralities

Degree and Weighted degree Analysis: In this section, we look into the degree distribution of the network and also present its weighted degree distribution in a manner similar to the weighted network distribution figures in [18]. We see that in general, the probability distribution P(w) that any edge has a weight w follows a power-law decay. This power-law decay is also seen in the regular degree distribution, although the spread of the points on the plots are further apart.

In the future, I plan to fit exponent to power law and look at its trends over time.

4 Conclusion and Future works

In summary, we present an exploration of coffee supply chain data by investigating changes in the network over time. We also explore the networks' vulnerability and how this value changes over a time period of 22 years. From our data, we find some evidence suggesting an increased complexity in coffee supply chain network over time based on the increasing trends in number of nodes, edges and network density over time. In addition, the coffee supply chain network vulnerability is dynamic over time and changes by up to 30% in each time period. We also find that the network is less vulnerable to random attacks than targeted attacks using different centrality measures over time. The three ranking metric employed for targeted attacks tend to behave quite similarly. Though the targeted attacks using betweeness centrality tend to have higher vulnerability than its other 2 counterparts over time.

In the future, we hope to carry out the following analysis:

- Introducing edge disruptions into the analysis.
- Integrating operational metrics specific to coffee supply chain to measure vulnerability
- Weighted Network Analysis : Including volume of products moving between nodes. For now, the vulnerability metric ranks connections between nodes equally, however certain connections are more important than others because they carry more volume.
- Exploring local impacts of disruption and disruption propagation. The Current vulnerability measure looks at impacts of disruption at the global scale. It is also important to understand what is happening locally to individual nodes as disruptions occur
- Expand product space (include other agricultural products)

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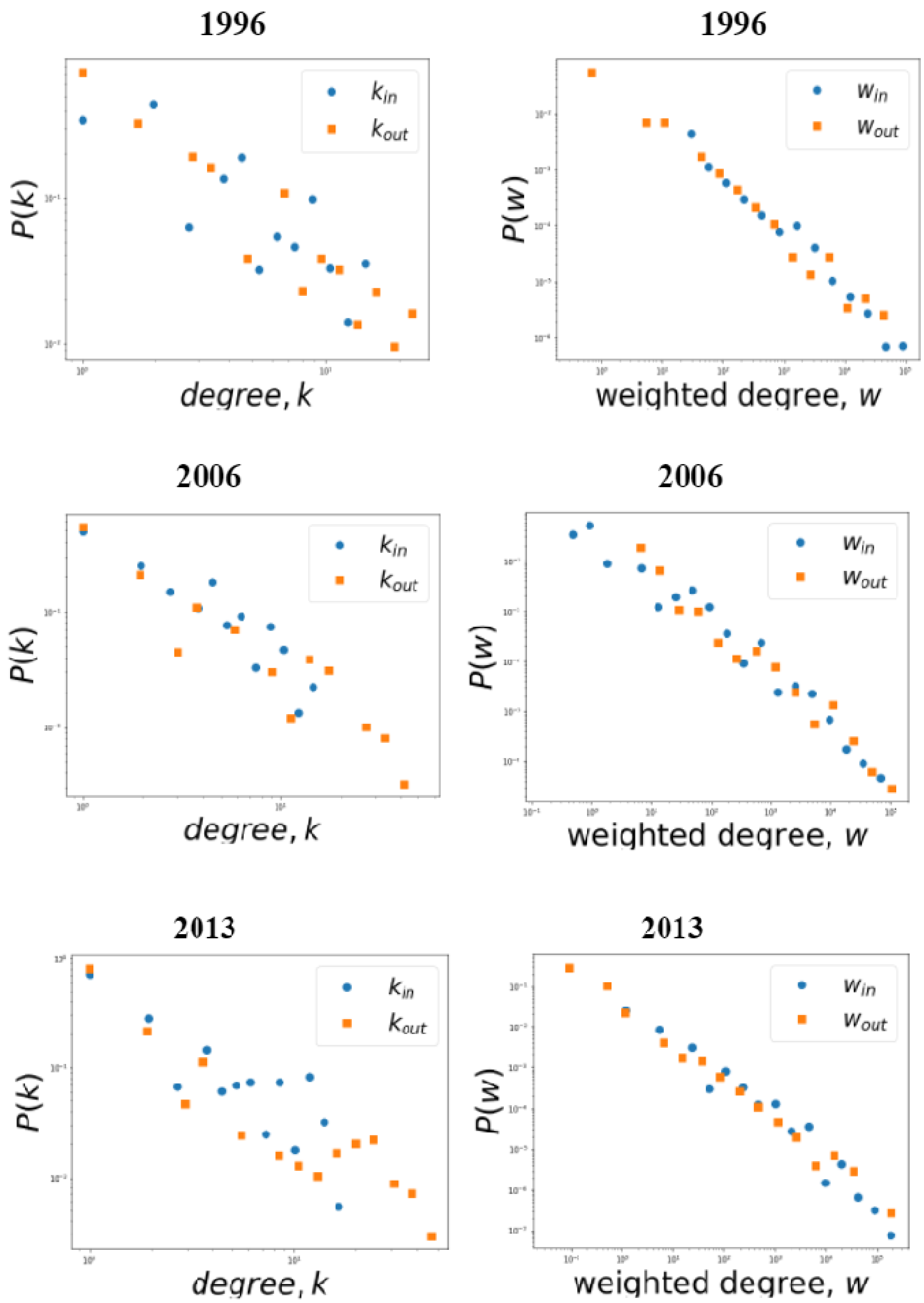

Figure 8: log-log plot of Degree distribution (left) and log-log plot of weighted degree distribution for the coffee supply chain network in years 1996, 2006 and 2013 respectively