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Assessing Systemic Risk in the Network of COVID-19 Personal Protective Equipment Using Cascading Failure Agent-based Simulations

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Abstract: Network analysis allows us to simulate economic shocks in order to examine their effects on all the other countries in the trade network. In light of this, this paper aims to characterize the 2017 personal protective equipment (PPE) networks (as defined jointly by the WHO and WCO) by employing a two-part analysis, which involves: (i) using centrality measures to determine key nodes in the network, and (ii) employing the cascading failures model to propagate economic shocks in the network, then using cascade-based measures to identify key nodes and possibly characterize the underlying structure of the network. The agent-based simulation revealed that the PPE networks exhibit a core-periphery structure, characterized by a highly central and well-connected core and a sparsely-connected periphery. This allowed us to earmark core countries, which are more likely to be subject to systemic risk. Notably, we found a large core, suggesting that the networks are particularly vulnerable to systemic risk, with China posing the most systemic risk. We were also able to relate network centrality to systemic risk, finding a strong relationship between the two.

Key Words: network analysis; trade network; centrality; cascading failures model; core-periphery structure

1. INTRODUCTION

In the field of international economics, it helps to view international trade as a set of complex relationships between countries. This allows us to simulate economic shocks so as to observe their repercussions on the trade network in general. This is especially important in this era of supply shortages, economic sanctions and trade wars. Thus, network analysis provides us with a new lens through which we can view not only bilateral trade but inter-country relationships in general. The wealth of data from the World Trade Organization and the World Bank lends credence to employing this particular approach in trade analysis. Some databases even offer trade flow data at a more granular level, allowing us to examine trade networks for particular commodity groups.

As such, this paper aims to characterize the COVID-19 personal protective equipment (PPE) trade networks by employing a two-part analysis, which involves: (i) using centrality measures to determine key nodes in the network, and (ii) employing the cascading failures model to propagate economic shocks in the network, then using cascade-based measures to identify key nodes and possibly characterize the underlying structure of the network.

2. METHODOLOGY

2.1 DEFINITION OF TERMS

A *network* is simply a collection of nodes (or vertices) joined together by edges (or links). Edges can also be associated with a weight, which describes the intensity of the relationship between the two nodes.

Networks are often described by an *adjacency matrix* A, which is an $N \times N$ matrix (N being the number of nodes in the network), such that the element $A_{ij} = 1$ if an edge exists from node i to node j and and $A_{ij} = 0$ otherwise. Weighted networks are often associated with a *weight matrix* W where the values W_{ij} are the weights associated with the edges.

Centrality often refers to the importance of the node in a network. However, the notion of importance can differ depending on the network in question. One way to quantify the centrality of a node is often through its *degree*, which is the number of edges connected to it. In directed networks, it is useful to make the distinction between a node's in-degree and out-degree. The *in-degree* is the number of incoming edges connected to it, while the *out-degree* is the number of outgoing edges connected to it. The analog of the degree for weighted networks is the *strength*, and is computed similarly. A node may also be considered important because it is linked to other nodes that are themselves important. This is measured through the *eigenvector centrality*. Whereas the degree centrality treats all of a node's neighbors equally, eigenvector centrality takes into account the centralities of all its neighbors, and assigns weights to them accordingly.

The notion of a *core-periphery network structure* began with Borgatti & Everett (1999), whose model assumes two classes of nodes: one highly inter-connected group with many connections to nodes in the other group (the core) and another made up of nodes that are only loosely connected to the earlier group (the periphery). Because the core is very well-connected as opposed to the periphery, it is more prone to *systemic risk*; i.e., the risk of the entire system collapsing due to the collapse of a few nodes/components in the system.

2.2 METHODS

In the study, we constructed trade networks based on products that have been jointly identified by the World Customs Organization and the World Health Organization as essential COVID-19 medical supplies in the 2nd edition of its *HS Classification Reference for COVID-19 Medical Supplies* (2020). To limit the scope of the paper, we only examined the trade network for those products that have been identified as protective garments and the like, otherwise known as personal protective equipment (PPE) for the year 2017. The *HS Classification Reference* (2020) further subdivides this group into three sub-categories: (1) face and eye protection, (2) gloves and (3) others.

Trade data for the PPEs during 2017 was collected from the UN Comtrade database via the tradedownloder tool by Eoin O'Keefe. We cleaned the data using the Pandas package in Python to make it amenable to the construction of a trade network. Using the functions in the NetworkX package, we then characterized the resulting network, computing the the out-strength and out-eigenvector centralities of each node in the network.

Based on the basic model suggested by Burkholz & Schweitzer (2019), we implemented an agent-based model on the constructed networks by simulating a one-time exogenous shock on a country's exports. This is meant to simulate countries limiting PPE exports to other countries, as has been the case for China (Horwitz, 2020) and the United States (Lewis et al., 2020), among others. The simulation is based on the cascading failure model, which has been used effectively to simulate power failures in electrical grids (Motter & Lai, 2002). Based on this model, countries will limit exports of PPEs to other countries in an effort to prioritize domestic demand. As a result, the exports from the origin country to its partner countries will decrease in a proportionate manner. With the decreased exports, the partner countries will consequently decrease their exports to their own partner countries to continue satisfying domestic demand. The shock will continue to cascade until a country can no longer decrease its exports to iterations, during which the simulation terminates This is repeated for all such countries in the trade network. Two parameters define this model, as in Gephart et al. (2016): the *shock parameter*, governing the amount by which the exports decrease in the origin country and the *spread parameter*, governing how much of the shock spreads to other country.

After performing the agent-based simulation, we examined the impact of the cascade on the network using two metrics: cascade size and cascade depth. The *cascade size* denotes the number of unique affected nodes in the cascade (Loser & Segel, n.d.). The *cascade depth* refers to the number of iterations it takes for the shock to cascade through the network until the simulation terminates. We examined both metrics for different shock and spread parameter values and found a core-periphery divide between the nodes, to be discussed in the results section.

Based on the model proposed by Li et al. (2014), we calculated a minimum shock threshold for each country in the networks. This *minimum shock threshold* represents the minimum amount of shock needed for a country to be considered a core node, setting the spread parameter to 1 (i.e., all of the shocks are transmitted). The definition of a core node is heuristic and primarily rests on the results obtained from the cascade size and cascade depth. The calculations were done using a modified bisection search algorithm. Using the rank-size distribution of the computed minimum shocks, we then used threshold shock values (which are also heuristic) to determine which nodes constitute which group.

3. RESULTS AND DISCUSSION

3.1 CENTRALITY MEASURES

3.1.1 STRENGTH CENTRALITY

The strength centrality quantifies how central a node is in terms of the number of nodes it shares an edge with, taking into account the weight of each edge. Calculating the strength centrality per node yields Figure 3.1.

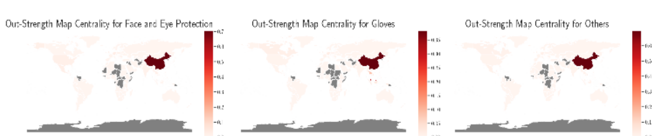

Figure 3.1. Out-strength centrality maps for the 2017 Face and Eye Protection, Gloves and Others networks

Having done so, we can see from the choropleth map that China is absolutely dominant in terms of out-strength centrality, having a 70.58%, 38.34% and 69.97% market share over total exports for Face and Eye Protection, Gloves and Others, respectively.

3.1.2 EIGENVECTOR CENTRALITY

As opposed to strength centrality, eigenvector centrality is often used as a measure of influence/prestige. Eigenvector centrality accounts for a node's neighbors and how well-connected they are. Thus, the higher the eigenvector centrality of a node, the more well-connected its neighbors are.

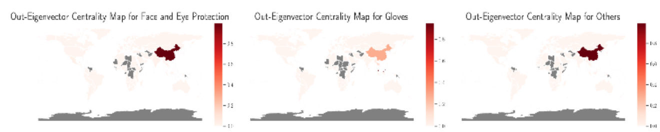

Figure 3.2. Out-eigenvector centrality maps for the 2017 Face and Eye Protection, Gloves and Others networks

From Figure 3.2, we see that China has a significantly higher out-eigenvector centrality than the rest of the countries for all PPE product groups. This means that China remains an important hub in the PPE trade network even after taking into account the importance of its immediate trade partners, thus highlighting the important role China plays in the PPE value chain.

Overall, based on the centralities, the trade networks seem to exhibit a core-periphery structure – a small well-connected core consisting of only a few nodes, surrounded by a large periphery of sparsely-connected nodes. We will see if this hypothesis holds water in the following section.

3.2 SHOCK PROPAGATION

We can now use the model outlined in Chapter 2 to evaluate how perturbing different nodes will affect the network, using the two metrics discussed to measure these effects. Because we have two variable parameters (the shock and spread parameter), we run run the simulation for shock and spread parameters of 0.1, 0.5 and 0.9 and check the distribution for different values.

3.2.1 DISTRIBUTION BASED ON SHOCK AND SPREAD PARAMETERS

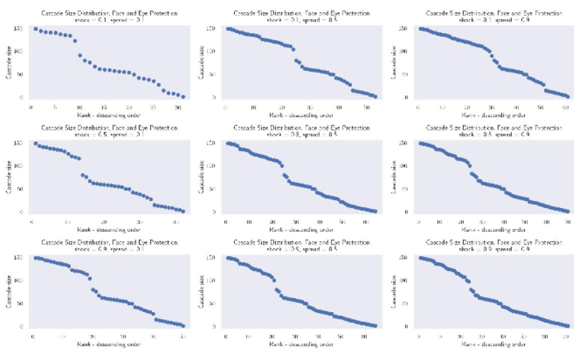

Figure 3.3. Cascade size rank-size distribution for the Face and Eye Protection network for different shock and spread parameters.

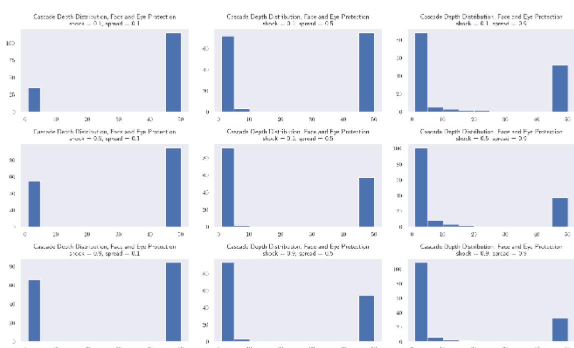

Figure 3.4. Cascade depth rank-size distribution for the Face and Eye Protection network for different shock and spread parameters.

We see from Figure 3.3 that cascade size is somewhat uniformly distributed across the range of values over which they occur.

The same is not true for the cascade depth, however. The cascade depth only seems to take on a number of values regardless of the values assigned to the shock and spread parameter. More notably, we see a large break in the distribution regardless of the values assigned; the simulation does not seem to terminate (i.e., takes 50 iterations in total) after setting some of the nodes as starting nodes while it does so in less than 10 iterations for some of the other nodes. This shows that we can use the cascade depth as a heuristic with which to identify core and peripheral nodes in the network. The bimodality in the cascade depth distribution lends better credence to our earlier core-periphery hypothesis. In the next section, we take advantage of this observation to distinguish between core and peripheral nodes.

3.2.2 IDENTIFYING CORE AND PERIPHERAL NODES

We can now designate each node as either a core or peripheral node. As we can see from Figure 3.4, however, the designation depends on the value of both the shock and spread parameter. To get around this problem, we follow Li et al. (2014) and compute for the minimum value of the shock parameter required to designate a node as a core node, setting the spread parameter equal to 1.

In this case, we define a *core node* as one which requires at most 10 iterations to terminate, which is consistent with Figure 3.4. The shock parameter is then computed using a modified bisection search algorithm which is run for 100 iterations, during which the computed values for the minimum shock parameter have been found to converge. After this, we rank the nodes based on the minimum shock parameter. We can then set a threshold shock parameter and designate all countries with a smaller minimum shock parameter as core nodes, with the rest being designated as peripheral nodes.

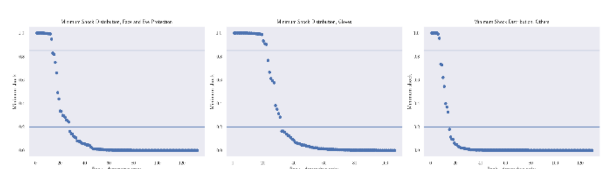

Figure 3.5. Minimum shock parameter rank-size distribution for the Face and Eye Protection, Gloves and Others trade networks

From the figure, we see a clear gap between the minimum shock values for core and peripheral nodes. We set a threshold value of 0.85 to distinguish between these two groups. Note however that in doing so, we end up with a largely heterogeneous core, with a large variance in the minimum shock value. Thus, in the interest of keeping as tight a core as possible, we also set a threshold value at 0.2, where we also find a significant gap. In doing so, we have separated our countries into three main groups. Those with a minimum shock value higher than 0.85 form the periphery of our outgoing network, meaning that the failure of any one of these countries does not significantly affect the outgoing network at all. Those with a minimum shock value lower than 0.2 form the inner core and the failure of any one of these countries carries with it a significant amount of systemic risk. Those countries that have minimum shock values in between the two occupy an intermediate position of the network and form the outer core. These countries may be valuable to look at, as the effect of their failure may be mitigated by similarly positioned nodes coming in to "substitute" for them. We can visualize the geographic distribution of core and peripheral nodes using a choropleth map, as in the following figure.

Figure 3.6. Core-periphery maps for the Face and Eye Protection, Gloves and Others trade networks

The figures show that the PPE trade networks exhibit a very large core and a small periphery, indicating that the PPE networks are somewhat fragile. Furthermore, we have found very little minimum shock parameters for China in particular, indicating that it takes only a small perturbation to Chinese supply to cause failure in the PPE trade networks, at least as defined by this paper.

From the log plots in Figure 3.7, we find that the relationship is strongly linear with respect to the strength centrality and moderately linear with respect to the eigenvector centrality. This suggests that the centrality of a node is a strong determinant of its systemic risk in the network.

4. CONCLUSION

This paper uses agent-based simulation and network science to characterize the 2017 PPE trade networks.

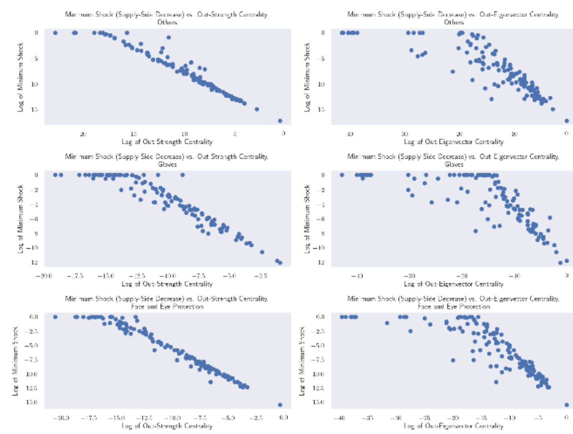

Figure 3.7. Log-log plots of minimum shock vs. in-strength and in-eigenvector centrality

We found that the trade network exhibits a core-periphery network structure, with a large, highly-central core and a small, sparsely-connected periphery. This indicates that the PPE trade network is vulnerable to supply-side decreases, with China in particular being very susceptible. We have also been able to relate network centrality measures and the minimum shock parameter (the paper's proxy for systemic risk), finding a significant relationship between the two.

5. ACKNOWLEDGMENT

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