IJCSS International Journal of Complex Systems in Science

Int. J. Complex Systems in Science
vol. **1(2)** (2011), pp. 191–201

A complex network approach to international commodity trade markets

Maximiliano A. Fernández[1,†], Javier Galeano Prieto[1] and César A. Hidalgo[2]

[1] *Grupo de Sistemas Complejos, Universidad Politécnica de Madrid*

[2] *The Media Lab, Massachussetts Institute of Technology*

Abstract. Adam Smith is considered the father of modern economics. His research on the Wealth of Nations[1] is the first scientific work that theorized about the complexity of economic systems and how an "invisible hand self-regulates markets and their behavior. In this way, we study the international commodity trade markets as complex networks. We analyze their topological properties, structure and temporal dynamics based on actual data. Our main premise states that a close analogy can be found between trade networks in economics and mutualistic networks in ecology. Indeed, both types of network are bipartite in nature and their constituting agents are motivated by self-interest. Thus, we apply the methodology developed for mutualistic ecosystems to trade networks. Minor gaps can be found in this methodology. We address such gaps by using well-known techniques from related scientific work [2, 6, 8, 9, 10, 11, 12, 13, 14], which effectively complement the premise. We confirm that mutualistic and trade networks share similar topological properties and structure. In this way, the evidence supports the fact that the premise is a realistic assumption.

† **Corresponding author:** max_fernandez1977@hotmail.com
Received: October 18, 2011
Published: October 24, 2011

1. About market theory

Economists often take for granted the microeconomic theory and, in particular, market theory. Although Adam Smith and other authors have already explained free market behavior more than two centuries ago, our understanding of such behavior is still a high-level explanation. In the same way that physicists understand the relationship between pressure and volume of an ideal gas, economists underestimate the complexity of market structure on a low-level perspective. In contract to physical phenomena, economic systems do not always follow a set of well-defined laws. For instance, economic systems tend to change their configuration and rules whenever a crisis appears. But under certain conditions, like those we find in commodity markets, complex network analysis may be of great help to provide new insights on economic complexity and an opportunity to potentially expand market theory. After all, the microeconomic theory does describe the basic markets in such a way that network graphs may easily be used to depict them (Figure 1). Now, even though this is not the first scientific work about trade networks, it is the first one to propose a bipartite approach and the existence of a close analogy with mutualistic systems.

2. Data analysis

We count on actual information about global commodity trading. This data is based on the UN Comtrade database. It includes 5039 products and 297 countries from 1995 to 2009, accounting for 127 trillion dollars in trade volume and $9{\times}10^7$ links in that period. It is also normalized due to reporting inconsistencies. We apply the key mutualistic indicators to the actual data. This set of mutualistic indicators include: a) the degree distribution $P(k)$, b) the strength-degree correlation $S(k)$, c) the nearest-neighbor degree distribution $Knn(k)$, d) the bipartite clustering distribution $C4_b(k)$, e) the average weight as a function of the end-point degree $\langle w\rangle(ki * kj)$, and f) the weighted interaction nestedness estimator η_w. In addition, we create two scenarios based on the RCA index, the revealed competitive advantage, which is defined by the expression:

$$RCA = \frac{x(c,i)/\sum_i x(c,i)}{\sum_c x(c,i)/\sum_{c,i} x(c,i)}; \tag{1}$$

where the term $x(c,i)$ is the exported value for commodity c in country i. The RCA serves as a link filter which enables us to separate the core from the periphery of a trade network. Moreover, the number of links as a function of the RCA shows a lognormal distribution. Based on our analysis, only 50

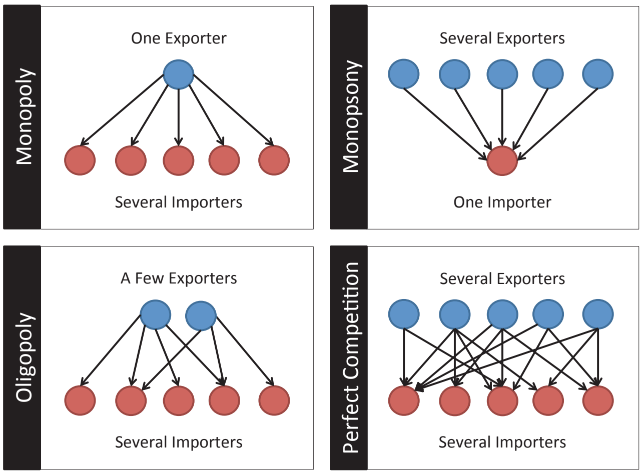

Figure 1: *Basic markets from a network point of view. Here, the monopoly, the monopsony, the olygopoly and the perfect competition markets are described by a network graph.*

percent of the links remain active when setting a filter of $RCA >= 10^{-3}$. However, 99.5 percent of the trade volume is still active in the remaining links. Finally, we also take advantage of the bipartite approach to visualize the trade matrix on a logarithmic scale.

Since performing the experiment for all the products and each year is a challenge given the large amount of data, we perform a selection process and define a sample of 35 highly representative products. We then repeat the experiment for each selected commodity, for each year, and for both scenarios. Now, trade networks evolve over time, changing in number of links and in trade volume, and reconfiguring its structure at the same time. We, however, focus on the topological properties we previously described. These properties are defined by the following expressions:

$$k_i^{importers} = \sum_i a_{ij} \tag{2}$$

$$s_i^{importers} = \sum_i a_{ij} w_{ij} \tag{3}$$

$$Knn_i^{w,importers} = \frac{1}{s_i} \sum_{j=1}^{N} a_{ij} w_{ij} k_j \tag{4}$$

$$C4b_i^{importers} = \frac{q_i}{Q_i} = \frac{q_i}{k_i^{nn} K_i (k_i - 1)/2} \tag{5}$$

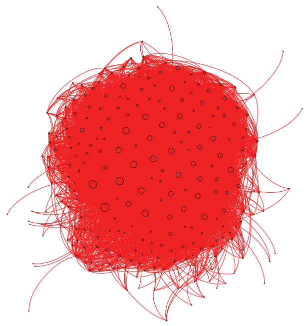

Figure 2: *Trade network graph for computers in 2000. We observe that the topology is highly dense in this case and no significant conclusions can be inferred from it.*

$$C4b_i^{w,importers} = \frac{\sum_{m,n} q_{imn}(\frac{\widetilde{w}_{im}+\widetilde{w}_{in}}{2})}{k_j^{nn} K_j(k_j-1)/2} \tag{6}$$

$$\widetilde{w}_{jm} = \frac{w_{jm}}{\bar{w}_i} = \frac{w_{jm}}{\frac{s_i}{k_i}} \tag{7}$$

All these indicators were defined for the importers. But given the bipartite nature of this work, we apply an identical set of indicators to the exporters as well.

3. Results

First of all, we process the network graphs for each selected commodity and then we apply the RCA filter, repeating the procedure for each period. Figure 2 shows the trade network for computers in 2008 without the RCA filter. In this case, we are unable to identify any community. Moreover, we are unable to perform significantly relevant analysis either. Figure 3, in contrast, shows the same trade network after the RCA filter is implemented, allowing us to extract more information than that of the previous case. We find a high correlation between the communities in trade networks and the geo-political reality as well as the regional proximity. For instance, the Arabian countries are located at the periphery of networks such as those of beer and other alcoholic beverages, and having virtually no presence in these commodities, whereas they are located at the core of the network in petroleum oil and its derivatives.

Secondly, we compute the basic topological properties, $P(k)$ and $S(k)$. The results show a remarkable behavior in both cases (Figure 4). On one hand, the degree distributions of both the importers and the exporters follow

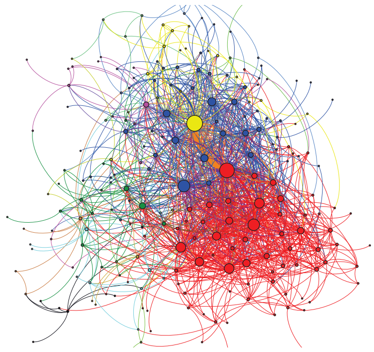

Figure 3: *Trade network graph for computers in 2008. RCA filter has been implemented here.*

a power-law pattern. Unfortunately, we deal with the problem finite-size data when computing the results at commodity level. The resulting exponents for the importers (columns) and the exporters (rows) are not necessarily the same and, in general, quite different. On the other hand, the strength-degree correlation has a much cleaner pattern than that of $P(k)$. The $S(k)$ correlations also follow a power-law form. The β exponents we obtain are higher than one, providing evidence that, in trade networks, highly-connected nodes tend to have higher trade volumes. In other words, the rich get richer. From a dynamic perspective, we may argue that an exporter will have higher degree whenever a competitive advantage exists. This advantage, in turn, will attract new importers and more transactions from current importers, so that the trade volume increases exponentially over time. This mechanism is likely to explain the values of $\beta > 1$. It also means that importers of large quantities of a given commodity tend to buy from several sources. Exporting countries of large volume are very likely to be highly connected too.

Thirdly, after processing the performance of Knn(k), we find that trade networks present an assortative behavior in general. However, a few specific commodities do not. This makes sense from an economic thinking standpoint. The profit maximization principle states that a firm or an individuo will act in order to secure the highest possible benefit. This idea manifests itself when realizing that highly connected countries tend to be associated to those that are alike. It also shows that the main market force, competition, is always present in the topology.

The previous analysis about Knn(k) is not complete though. We need to account for the clustering coefficient behavior before drawing a definitive conclusion. We use a bipartite clustering definition, as previously stated. This implies that we look for closed loops of exporter-importer-exporter and vice

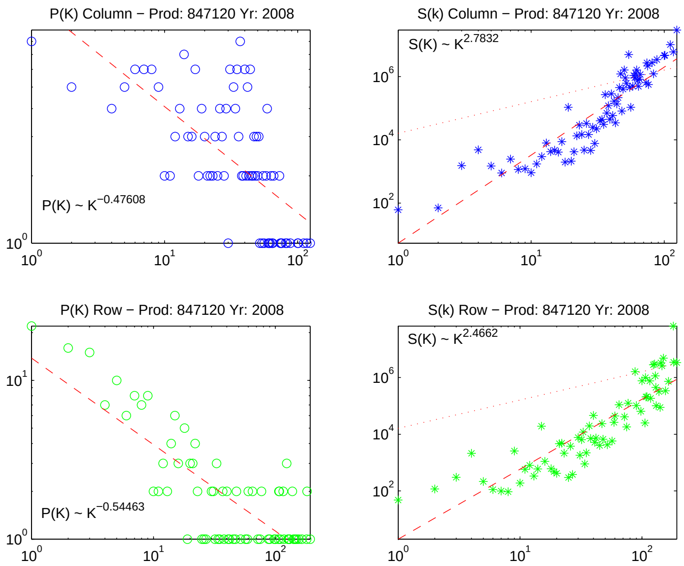

Figure 4: *P(k) and S(k) for computers in 2008. No RCA filter applied. In blue, we show the performance of the importers. In green (on the bottom charts), we find the results for the exporters. The dashed lines represent in all cases the best-fit curves or power laws.*

versa. But despite the technical definition, we focus on the exporting and importing countries and their ability to form clusters as a function of the degree. The evidence suggests that highly connected nodes are less likely to form clusters. In contrast, less connected countries tend to form larger clusters. The clustering distribution follows a power law with negative exponents. Trade networks also show two clustering zones: an initial one with a low value exponent and a final one with higher exponent. This, in combination with the existence of assortative mixing, depicts an idea of bipartite trade networks that follow every single principle in microeconomic theory; as such behavior has a common root in self-interest, profit maximization and market bargaining power. Less connected exporters will try to reach the importing "hubs" so that they have a higher share in the market, but the network topology (assortative behavior plus negative clustering exponent) makes it intrinsically harder for them to accomplish such objective, maintaining the status quo. The results obtained for the average weight as a function of the end point degree is a mere confirmation of the previously stated conclusion. This distribution also follow a power law with positive θ exponents at all times.

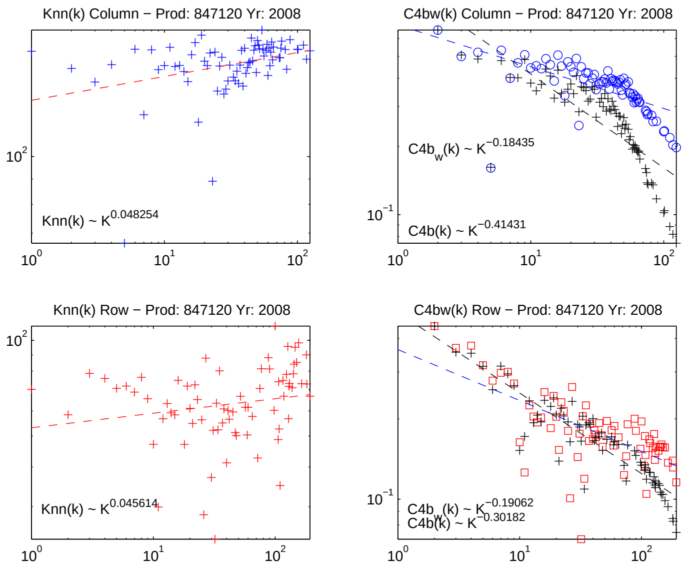

Figure 5: *Knn(k) and C4b(k) for computers in 2008. The upper charts show the properties for importers, showing an assortative behavior and a negative bipartite clustering exponent. Exporter charts (bottom).*

Finally, we compute the weighted interaction nestedness estimator and visualize the bipartite matrix as a supporting reference. The majority of results for η_w are higher than 0.5, a fact that reinforces the similarities with mutualistic systems. Some commodities show nestedness estimator values that are close to that of a perfectly nested network ($\eta_w = 1$). In order to minimize the problem of finite-size data, we also compute the degree distribution for all products and all periods in the database. In this way, we find that the distribution is better described by a truncated power law of the form $P(k) \sim k^{-\gamma} e^{-k/kc}$. Indeed, a correlation with an $R^2 = 0.99992$ shows again that a very strong relationship with the mutualistic systems exist. This fact will have a specific and important economic meaning in the conclusions.

4. Conclusions

So, in trade networks, like in mutualistic ones, the P(k) follows a truncated power law. But, what does that really mean? In the introduction, we have implied that the presence of a hub would indicate the existence of either a monopoly or a monopsony. These are extreme cases and an idealization. But, commodity trade markets are well known because they are very close to be a perfect competition market, where several buyers and sellers exist, and no one has power over the market. A truncated power law supports this idea since the distribution has a cut-off before an extremely connected node might appear. This is clear evidence about the way commodity markets are organized. No hubs are created as either a consequence of the bargaining process or an emergent phenomenon.

Regarding the bipartite approach, we proved that, like in mutualistic networks, a highly nested structure is present in trade networks. Such emergent organization can be the results from no other source than a strong analogy and the same basic rules that evolve in both systems. We will not argue about the processes that lead to such behavior in this work. Instead, we propose an idea of a common root cause that may partially explain this, at least. Self-interest may well be that root cause. Ecologic systems are the result of evolution, a purely cyclic process of natural selection. And species in these systems have a main goal: the survival and growth of its own species. In this way, the mutualistic strategies appear as a natural response to accomplish such objective. As a consequence, mutualistic networks are highly stable and robust.

Commodity markets, on the other hand, evolve from a different premise or goal, profit maximization, which is another form of self-interest. The economic theory explains that profit maximization is essential to secure a business survival and growth. Clearly, self-interest itself is the common element that makes the analogy between mutualistic and trade networks fairly valid, in addition to the topological evidence shown in the results section. This is an opportunity for further research.

The adoption of two scenarios, with and without RCA filter, turned out to be the right decision from a process point of view. We realized that the power law exponents at the core of a trade network better reflects the topological properties of the main countries and that the errors for those exponent are lower, increasing the accuracy of the experiment.

We also analyze the dynamics of trade networks. We find similar results and conclusions in comparison to previous related work in the field. Nevertheless, we feel that further analysis of the time series is required to either confirm or reject the validity of our conclusions.

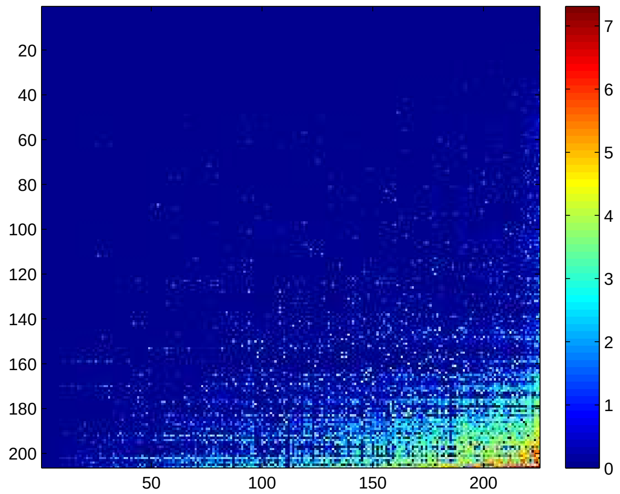

Figure 6: *Bipartite matrix visualization for computers in 2008. Exporters are located on the Y-axis and importers on the X-axis. The matrix has been ordered by increasing trade volume in a logarithmic scale.*

5. Acknowledgements

We would like to thank the Economic Complexity Observatory at MIT and César Hidalgo for providing the data that made this possible. Special thanks to Javier Galeano and Juan Manuel Pastor for their contribution with the WINE software package.

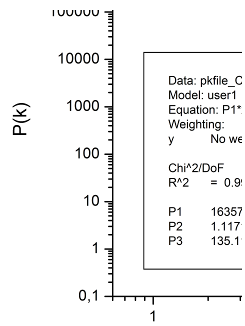

Figure 7: *Degree distribution for all commodities from 1995 to 2009. We show the actual results in green dots. The red line describes the best fit curve, a truncated power law, with* $R^2 = 0.99992$

References

[1] Adam Smith, *An Inquiry into the Nature and Causes of the Wealth of Nations*. London (1776).

[2] C. A. Hidalgo et al., *The Product Space Conditions the Development of Nations*. Science 317, 482 (2007).

[3] L. Gilarranz et al., *The Architecture of Weighted Mutualistic Networks*. On press.

[4] J. Galeano et al., *Weighted-Interaction Nestedness Estimator (WINE): A new estimator to calculate over frequency matrices*. Environmental Modelling & Software 24, Issue 11 Pag. 1342-1346 (2009).

[5] J. Bascompte et al., *The Nested Assembly of Plant Animal Mutualistic Networks*. PNAS, Vol. 100 (2004).

[6] C. Campbell et al., *A Network Model for Plant Pollinator Community Assembly*. PNAS, Vol. 108 (2010).

[7] A. Barrat et al., *The Architecture of Complex Weighted Networks*. PNAS, Vol. 101 (2004).

[8] M. A. Serrano et al., *Topology of the World Trade Web*. Phys. Rev. E 68, 015101(R) (2003).

[9] M. A. Serrano et al., *Patterns of Dominant Flows in the World Trade Web.* J Econ Interac Coord. (2007).

[10] G. Fagiolo et al., *The World Trade Web: Topological Properties, Dynamics, and Evolution.* Phys. Rev. E 79, 036115 (2009).

[11] G. Fagiolo et al., *Patterns of Dominant Flows in the World Trade Web.* J Evol Econ (2010) 20:479-514.

[12] A. Chakraborty et al., *Weighted Trade Network in a Model of Preferential Bipartite Transactions.* Phys. Rev. E 81, 016111 (2010).

[13] T. Squartini et al., *Rewiring World Trade. Part I: A Binary Network Analysis.* arXiv:1103.1243v2 (2011).

[14] T. Squartini et al., *Rewiring World Trade. Part II: A Weighted Network Analysis.* arXiv:1103.1249v2 (2011).