Temporal Network Analysis of International Trade Flows

Ben Hinshaw, Umut Ozturk, Harsh Choudhary, Kevin Cao

Math 76 – Dartmouth College

Abstract
This research paper introduces a distinctive approach to the study of international trade by utilizing methodologies from network science. Trade economists do not traditionally use tools from network science in order to derive inferences about international trade; however, the international trade network is a complex system characterized by interdependencies and intricate patterns that are difficult to interpret through traditional analysis. To unravel these complexities, we develop a robust methodology for constructing and analyzing the international trade network from a network science perspective. In particular, we analyze network properties, conduct time-series analysis, examine the effects of random failures and targeted attacks, and perform community detection on an intertemporal trading network. We find that there are numerous economic insights that can be derived from network analysis that traditional economic analyses might overlook. As such, a network science approach can be a powerful tool in informing economic policy and strategic planning for international trade relations.

Introduction
Our search for networks related to economics was motivated by our shared background in the field and interest in international finance. We found trade to be an extremely compelling area and came across a promising temporal dataset that could reveal insights on how these relationships evolve with time.

International trade is more relevant than ever; in an increasingly globalized world, it is what drives the global market economy. In today's world, it is very rare to look around and not find something that was not manufactured in another country. Furthermore, trade is a popular area of economic research, particularly in the context of globalization. There are several topics that can be analyzed with respect to trade flows such as global value chains, environmental issues and climate change, e-commerce and digital trade, wealth disparities, and the development of market economies across the globe.

In our paper, we wanted to leverage our dataset to explore the following:

1) Time Series Analysis
Sought to apply a model like ARIMA to our network to predict future network characteristics, such as eigen centrality, based on past trade flows in our dataset.

2) Random Failure And Targeted Attacks
Sought to assess how our network would respond to an attack where a selection of

nodes or countries would fail and cease their interaction with the global trade network. For instance, if there was a random crisis in a particular country, what would be the implications for the broader trade network. Similarly, what would be the effect of a targeted terrorist attack on global powers.

3) Community Detection
Sought to find clusters of countries who are more strongly connected with each other in terms of trade.

Literature Review
Our work in this paper builds upon the notion of analyzing international trade using the tools of network science and applying certain methods that have not been used before.

The International Trade Network: weighted network analysis and modeling by K Bhattacharya et al J. Stat. Mech. (2008) uses scaled link weight distribution to assess whether centrality in the network and the GDP of the countries have a relationship. The paper finds out that the countries that dominate international trade are actually shrinking in terms of total share of the global trade network, suggesting that the international trade network is getting more interconnected. We test this hypothesis in this paper by using ARIMA and community detection methods.

Dynamics and Evolution of the International Trade Network by Fagiolo et al (2007) assesses betweenness centrality and weight distribution in international trade networks to see how node statistic distributions have evolved over the past 20 years, which they found to be stable. We run similar analysis on a broader time horizon, and use alternative methods to assess the same centrality measures like eigenvector centrality.

Forecasting International Trade: A Time Series Approach by Keck et al. (2010) where they develop a regression model to represent the imports of the countries and run ARIMA on this model to predict the import inflows in the upcoming 2-6 quarters. As this was the only paper that employed ARIMA on an international trade network, we decided to contribute to literature by applying the same methodology on eigenvector centrality scores of the countries.

Attack Vulnerability of Complex Networks by Holme et al (2002) outlines certain methods to employ attacks on networks and ways to assess the vulnerability of networks that are complex (multilayer, with high connectivity scores). They find that the most effective methods of network attacks are those that attack the nodes by their descending order of centrality, where the centrality scores are recalculated after each iteration. We also utilized this method in our project and compared its results to randomly launched attacks, and we confirmed that international trade networks behave in similar ways to the complex networks described in this paper. This gives us insight on what would happen to global trade if a country faced an unexpected crisis of some sort and was unable to participate in trade relations with other countries. Differently from this paper, we looked at eigenvector centrality instead of betweenness centrality as our network is well connected if weights are not taken into account, and the share of the volume of the trade a country is involved in is a more relevant information for the purposes of this paper.

Data

Our data is sourced from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII), a French institute for international economics. It represents 73 years (1948-2020) of international bilateral trade relationships between more than 100 countries. Our dataset includes over 2 million total data points, where each data point is characterized by the year, importer, exporter, and trade volume.

Our dataset was filtered in several ways to make it salubrious for analysis. First, we filtered out data that reflected less than a million dollars of annual trade flow as such links were unlikely to be even marginally relevant relationships. Furthermore, we had to exclude the early years in the dataset as there was limited reporting of trade data by many countries during those years, which would have provided largely distorted results. As a result, the data we used going forward represents the trade flows between countries that exceeded $1m USD (standardized to 2016 dollars) during the years 1984 to 2016.

Additionally, we leverage historical interest rate, growth, and exchange rate data sourced from the World Bank and the Bank for International Settlements (BIS) in order to analyze the relationship between trade network characteristics with mainstream macroeconomic metrics. This data is specifically used for our analysis of network science tools to predict exchange rates.

Methodology

A. Time Series Analysis

ARIMA is a popular method for univariate time-series data forecasting. In this paper, we apply the model to examine and predict the change in trade eigenvector centrality scores for specific countries over time: USA, China, Switzerland. First, we obtain a dataframe with the index as year and one column as the eigen centrality scores of the country. Next, we use the Dickey-Fuller Test to find the appropriate differencing (d) such that the series is stationary. We then leverage the Autocorrelation Function (ACF) to identify the order of the moving average term (q). Similarly, we use the Partial Autocorrelation Function (PACF) to identify the order of the autoregressive term (p). Finally, we apply ARIMA with the derived parameters (p, d, q) from above. The 95% confidence interval of predictions are also calculated.

Another related application we explored was related to a network-based theory of the exchange rate. Economists and traders have long desired to develop a robust theory that can encapsulate exchange rate movements; with a $6.6 trillion market cap a day, the sheer size and scope of the foreign exchange market demonstrates the importance of exchange rate modeling. Current exchange rate theory is largely centered on the IS/LM/UIP model, which faces a severe limitation in the sense that you need to somehow calculate the expected future exchange rate before being able to calculate the present exchange rate. Alternatively, we aim to derive our own exchange rate theory from economic intuition, which is derivative of the law of supply and demand in foreign exchange markets.

According to pure economic intuition, we can break the exchange rate down to 3 factors that affect the supply and demand of currencies: interest rates, investment flows, and trade desirability. More specifically, higher interest rates make investing in a country's bonds more attractive due to greater returns, so more people would want to buy the country's currency in order to be able to invest those bonds. The significance of investment flows can be attributed to the fact that economic growth attracts foreign capital as it increases the perceived returns on any investment (also decreased risk of expropriation). We use annual growth in real GDP to represent this factor. Lastly, in regard to desirability, if a country exports more to other countries, that means many global consumers will need to buy the country's currency in order to be able to purchase the country's products. Trade desirability can be represented by trade network eigenvector centrality.

Now to apply this theory and attempt to predict exchange rate from these 3 factors, we use the following regression:

$$Y_{ER\_it} = \beta_0 + \beta_1 \ln(X_{eigencentrality\_it}) + \beta_2 \ln(X_{interest\_it}) + \beta_3 X_{growth\_it} + \mu_{it} + \lambda_{it} + \varepsilon_{it}$$

Here, we use country fixed effects μ_{it} to control all time-invariant characteristics of each country and year fixed effects λ_{it} to account for global economic fluctuations that affect each country. We also clustered standard errors (on country) ε_{it} to account for the fact that observations in the same country but in different years are not always independent (e.g. an economic shock can have lasting effects).

Lastly, we also looked into the relationship between the relative importance of a country in our trade network on annual growth in real GDP. We thought this was valuable as the relationship between export-driven centrality scores on growth could inform economic policy. Further, establishing this relationship can be helpful when assessing the economic distress caused by a random failure in a trading network. To capture this relationship, we use the following time-series regression:

$$Y_{growth\_it} = \beta_0 + \beta_1 \ln(X_{eigencentrality\_it}) + \text{controls} + \mu_{it} + \lambda_{it} + \varepsilon_{it}$$

We run this modified regression with different controls in order to test the true strength of the causal relationship between eigenvector centrality and growth of real GDP.

B. Random Failure and Targeted Attacks

Next we analyzed the impact of random failures and targeted attacks on the 2012 international trade network. The random attacks removed n random nodes, while the targeted attacks removed the top n nodes by gross exports. We analyzed the effect of both of these manipulations through the network's average clustering coefficient.

C. Community Detection

Before we began this part of our analysis, we read in our dataset as a multilayer network of networkx graphs, where each year of data corresponds to a graph or layer in our network. In order to find strongly connected clusters of countries, we use the Louvain best partition algorithm. Ultimately, to visualize and interpret our findings on a world map we leverage the plotly express scatter geo package.

Results

A. Time Series Analysis

The Dickey-Fuller test on all three time series yielded an optimal first differencing to reject the null hypothesis that the series are nonstationary. Moreover, all three countries resulted in an autoregressive order p = 2 when plotting the partial autocorrelation function. The results from the autocorrelation function, however, were different for each country. Thus, we run ARIMA with slightly different moving average order parameters (q) for each of the three countries.

To summarize our selection of parameters:

- US projections were run with the parameters (p, d, q) = (2, 1, 9).
- Chinese projections were run with the parameters (p, d, q) = (2, 1, 11).
- Swiss projections were run with the parameters (p, d, q) = (2, 1, 7).

Results from our Dickey-Fuller tests, autocorrelation functions, and partial autocorrelation functions can be viewed along with our code in our github repository, in addition to our slide deck.

Using these parameters, here are the 10-year forecasts for each country along with their 95% confidence intervals, which are shaded in.

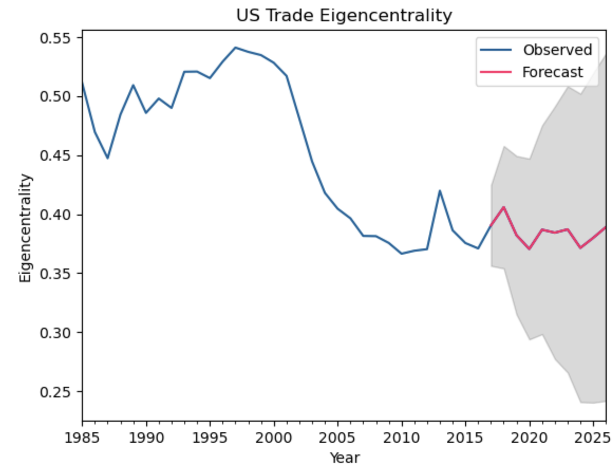

Figure 1. US Trade Eigencentrality

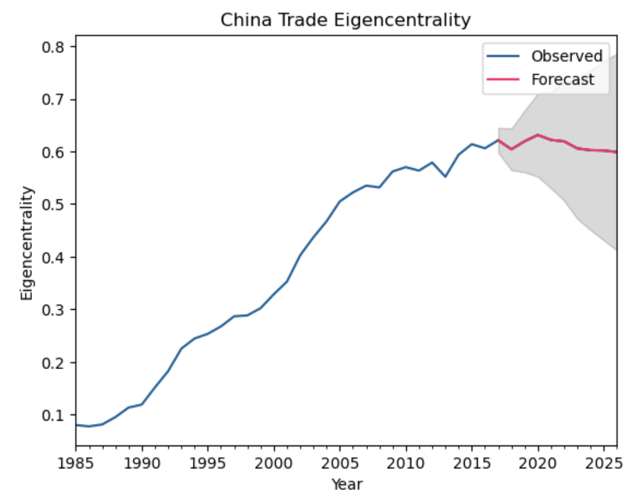

Figure 2. China Trade Eigencentrality

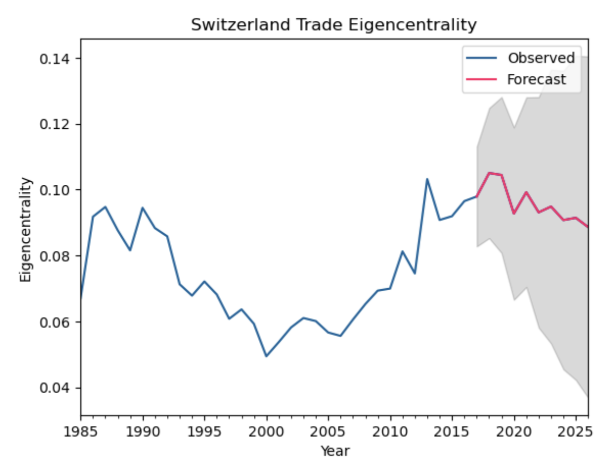

Figure 3. Switzerland Trade Eigencentrality

The eigenvector centrality of a country in the global trading network represents the country's dominance in international trade. As evidenced from these plots, the influence of the United States in international trade has diminished significantly from 1984 to 2016, while the influence of China in international trade has strengthened sixfold over that same time period. Meanwhile, Switzerland's eigenvector centrality has hardly changed over that time span.

The 10-year ARIMA projections suggest the US will likely stay at its current, lowered level of trade dominance. China, on the other hand, will likely peak at its current level of trade dominance. Switzerland will also likely stay around its historical levels of trade dominance.

Next, we explored the relationship between trading eigenvector centrality and exchange rates via time-series regression.

ln_e_usd	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	.15005	.0838148	1.79	0.075	-.015355	.315455

ln_e_usd	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	.0798518	.2067055	0.39	0.701	-.3345678	.4942714
ln_interestrate	.1160977	.1109365	1.05	0.300	-.1063166	.338512
gdpgrowth	.0179409	.0106487	1.68	0.098	-.0034084	.0392902

Figure 4. Exchange Rate Regression Output

The first regression, which was run to isolate the relationship between trade eigencentrality and exchange rates, demonstrates a relatively strong relationship between the two, albeit not necessarily direct. Significant at the 10% level, it appears that a 1% increase in trade eigenvector centrality has a 0.15% increase in the exchange rate.

After adding all three variables as originally intended, this one-to-one relationship between trade eigenvector centrality and exchange rate is weakened, though the coefficient remains positive. While the relationships between none of the three variables and exchange rate are exceptionally strong, these results do suggest that there is a relationship between these variables, and that perhaps this relationship is not best modeled by linear regression. Later, we propose alternatives in our discussion section.

Lastly, we analyze the time-series relationship between growth in real GDP and trade eigenvector centrality. We first ran the time-series regression with no controls, and then we ran the regression with exchange rate and interest rate as controls.

gdpgrowth	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	.934423	.2669208	3.50	0.001	.4076662	1.46118

gdpgrowth	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ln_eigen	1.36918	.4531004	3.02	0.004	.460768	2.277591
ln_e_usd	.184214	.1293275	1.42	0.160	-.0750719	.4435
ln_interestrate	-.1410645	.1537765	-0.92	0.363	-.4493678	.1672388

Figure 5. Centrality and Growth Regression Output

In both regressions, the relationship between trade eigenvector centrality and growth in real GDP is very statistically significant, even at the $\alpha = 0.01$ level. We can interpret these findings as a 1% increase in trade eigencentrality yields a 1.369% increase in growth in real GDP, holding other factors constant. In general, we find that trade dominance is associated with increased economic growth.

B. Random Failure

In the following 2 graphs, we visualized the results of our random failure and random attacks. While the random attack is decreasing the average clustering coefficient of the 2012 network, the relative change is small, only a decrease of ~4% after removing 48 nodes. On the other hand, by attacking the top 48 nodes, we decrease the average clustering coefficient of the network by ~30%. The results of this study show us that the network is quite robust against random failures. In other words, the world economy is unlikely to be significantly affected by a country ceasing trading. On the other hand, while it is very unlikely, a targeted attack on the most important nodes by gross exports is likely to have more significant results on the network.

A future direction which we were unable to explore due to a lack of data availability is the robustness of specific sectors. We would expect the rare earth elements (REEs) sector to be much more vulnerable to targeted attacks than say the consumer goods sector as the raw materials and means of production for REEs are much more concentrated in a few countries.

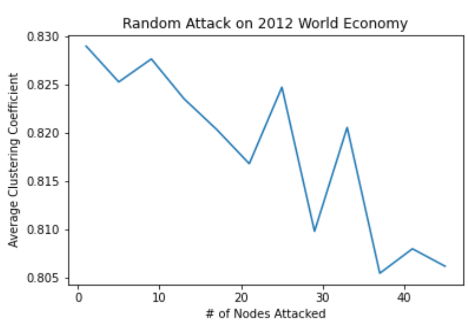

Figure 6. Random Failure

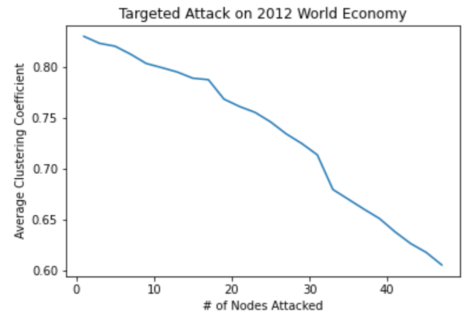

Figure 7. Targeted Attack

C. Community Detection

We were able to generate insightful visualizations that illustrate the communities countries form with their trade relationships over time. For the sake of space, we will limit the discussion here to five key shifts we observed.

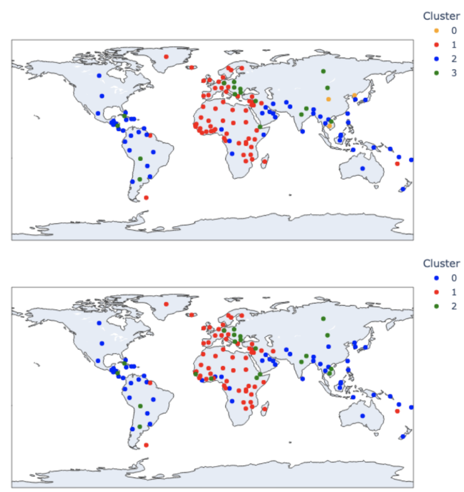

Figure 8. Global Trade Clusters 1986, 1987

First, from 1986 to 1987 (Figure 8) we saw a reduction in the number of clusters from 4 to 3. We believe this shift, in which the cluster with China collapses into the one with the majority of the Americas and South Asia, could be connected to IMF structural rebalances, Deng Xiaoping's economic liberalization of China, and the collapse in oil prices due to OPEC policy.

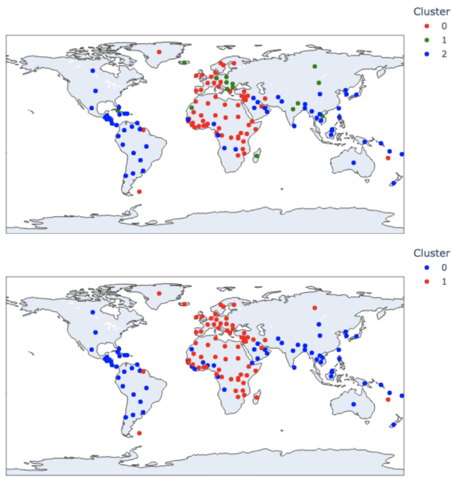

Figure 9. Global Trade Clusters 1990, 1991

Second, from 1990 to 1991 (Figure 9) we saw a further reduction in the number of clusters from 3 to 2. We believe this shift, in which Europe unites, Russia joins the Europe cluster, and India joins the Americas and South Asia cluster, could be associated with the collapse of the Soviet Union, the 1991 Indian Financial Crisis, and the Global Recession from the savings and loan crisis.

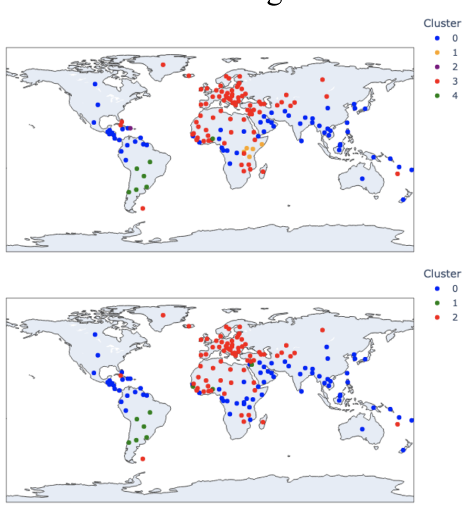

Figure 10. Global Trade Clusters 1997, 1998

Third, from 1997 to 1998 (Figure 10), there was another consolidation in clusters from 5 to 3. Here, SE African countries join the N. America and S. Asia cluster. We believe that movements around this time could be related to the Asian Financial Crisis.

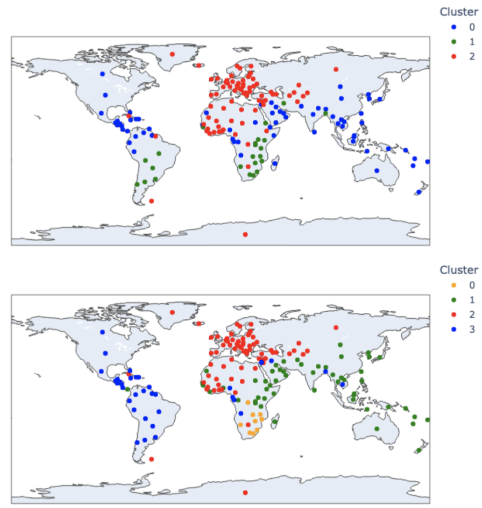

Figure 11. Global Trade Clusters 2000, 2001

Fourth, from 2000 to 2001 (Figure 11), we saw an increase in the number of clusters from 3 to 4. Here, S. African countries form their own clusters while the Americas unite. We believe these changes could be driven by a recovery from the Asian Financial Crisis and post- 9/11 economic slowdown.

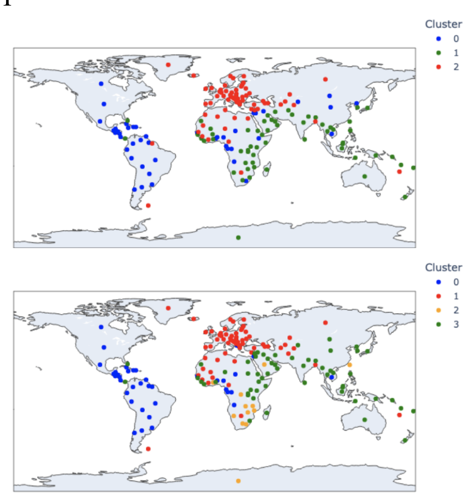

Figure 12. Global Trade Clusters 2008, 2009

Lastly, from 2008 to 2009 (Figure 12), we observed another increase in the number of clusters from 3 to 4. Once again, the S. African countries break off into their own cluster and China notably joins the cluster with India. These shifts can likely be related to the 2008 Financial Crisis. While some countries continue to change clusters in the coming years, the number of global clusters remains constant up until 2016, where we see some consolidation.

Discussion

We find that our results from our network analysis on international trade allow us to view trade in a different light than using traditional economic analysis tools. Our results make sense in the context of economic intuition, meaning that network analysis on economic networks is perfectly reconcilable with mainstream economic thinking.

For our time-series analysis, the shifts in centrality, particularly the diminishing influence of the United States and the significant surge in China's dominance, align with the contemporary narrative of the shifting power dynamics in international trade. Interestingly, the Swiss trading network's stability reflects the country's resilient economic and trade policy that has enabled it to maintain a steady position in international trade. One may naively think that Switzerland's dominance in the exportation of financial services may force its export volume to be prone to global financial fluctuations and crises; however, Switzerland does feature numerous other exports such as pharmaceuticals, machinery, electronics, and watches. World Bank data indicates that financial services only accounted for 10% of Swiss exports, which may lead to the conclusion that proper diversification in exports may help countries' trade volumes become more resistant to economic shocks.

It should also be noted that the 10-year ARIMA projections highlight an impending stabilization of current trade network dynamics, suggesting a period of relative stability in international trade dynamics. This finding is important for both investors and policymakers as they prepare for the future landscape of international trade.

Our first set of time-series regression analysis depicts a notable relationship between trade eigenvector centrality and exchange rates. We find that an increase in trade centrality corresponds with a positive shift in the exchange rate; in other words, countries with greater trade dominance may have stronger currencies than countries with weaker trade dominance. However, the relationship's complexity, as indicated by the attenuated relationship when all variables are considered, strongly suggest that these relationships and dynamics are not adequately represented by a time-series linear regression. We strongly encourage future exploration of this relationship using non-linear modeling techniques, or potentially even using machine learning to capture these interdependencies.

Our second set of time-series regression analysis demonstrates a remarkably significant relationship between trade centrality and the annual growth in real GDP. The results indicate that trade dominance, as measured by eigenvector centrality, directly contributes to economic growth, affirming the importance of maintaining and developing strong international trade relations. Economists and policymakers can use this conclusion to better shape trade policy. While there are numerous other factors to consider when debating free trade versus protectionism, our results suggest that free trade is the better policy when the focus is solely on maximizing economic output and growth.

When it comes to our simulations of random failures, our findings provide valuable insights on the inherent robustness of the international trade network. The relatively small change in the average clustering coefficient following random attacks indicates the network's resilience against attacks or disruptions, which in economic terms represent some sort of financial or political crisis within a country. This robustness can be attributed to the highly interconnected nature of international trade – which is largely attributed to an increasingly globalized world – where many combinations of trade routes and partners provide alternatives and redundancies that buffer against isolated attacks and disruptions.

In contrast, targeted attacks on the most influential nodes led to a much larger decrease in the average clustering coefficient. While this decrease does not match the extent to which a scale-free network might behave in such a scenario – which again demonstrates the relative robustness of the global trading network – it does demonstrate that some sort of orchestrated disruption targeting the most dominant countries in international trade can present potentially severe consequences to the global economy. Such a scenario may come in the form of a war between major powers, a pandemic, a natural disaster, an economic sanction or embargo, a targeted cyberattack, or any sort of large-scale change in political or economic thinking. While these scenarios are relatively improbable, understanding these vulnerabilities can help guide risk assessment and contingency planning in international trade.

Our study of random failures and targeted attacks prompts further exploration into the vulnerability of specific sectors within the international trade network. Potential directions include the examination of the rare earth elements (REEs) sector and oil. Given the concentrated nature of REEs and oil production in a few countries, these sectors might be more susceptible to targeted attacks. With the right granular data, one could potentially further explore the vulnerabilities within the trading networks of these specific sectors.

Regarding our analysis of community detection on the trading network, we find that the clusters formed by a best partition of each of the countries within our trading network can be explained by economic events. It is noteworthy that changes in community structure over time reflect global economic shifts. For example, the establishment of new trade agreements (e.g. NAFTA, ASEAN) and the impact of global financial crises are all mirrored in the evolving structure of the trading network. Ultimately, our community detection analysis further underscores the importance of applying network science methods to study international trade, offering new perspectives and insights that traditional economic analyses may tend to overlook.

Looking ahead, there are a few different directions we could take this paper. First, when it comes to our time series analysis, we could apply the LSTM model for more robust, flexible predictive models – especially for exchange rate forecasting. Second, we could explore how tradeflow and economic growth may evolve following random failure or targeted attacks on our network using the ARIMA predictive model. Third, we may examine implications from network link prediction on the hypothetical addition of a new country or new relationships following an attack. While this last avenue would be an interesting endeavor, we would likely have to procure more granular data to make it feasible.

Contributions

Because of previous research experience, K.C. took primary responsibility for the time series analysis. Otherwise, all authors assisted with research, ideation, analysis, interpretation, direction, and the preparation of presentation materials and this final report.

Link to our github repository: https://github.com/kevincow/MATH76TradingNetwork

1. Bhattacharya, Kunal, et al. "The international trade network: weighted network analysis and modeling." *Journal of Statistical Mechanics: Theory and Experiment* 2008.02 (2008): P02002.
2. Fagiolo, Giorgio, Javier Reyes, and Stefano Schiavo. "Dynamics and evolution of the international trade network." *Complex Networks: Results of the 2009 International Workshop on Complex Networks (CompleNet 2009)*. Springer Berlin Heidelberg, 2009.
3. Holme, Petter, et al. "Attack vulnerability of complex networks." *Physical review E* 65.5 (2002): 056109.
4. Keck, Alexander, Alexander Raubold, and Alessandro Truppia. "Forecasting international trade: A time series approach." *OECD Journal: Journal of Business Cycle Measurement and Analysis* 2009.2 (2010): 157-176.