Does a Nation's Level of Import Interconnection Correspond to its Global Power Status?

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Introduction

Does the United States’ decreasing export-import ratio mean the end of the top global status that it has enjoyed for decades? According to the Observatory of Economic Complexity, there is no doubt that the United States is increasingly becoming an importer nation (2017). Simultaneous production growth in the EU and China has seemed to challenge the US’ assumed top economic position (Bryan 2015). Correspondingly, concerns over increased import reliance have been brought to the forefront of US domestic politics (History 2018). This leads to questions over how a nation’s level of import interconnection relates to its global influence and power. This paper will utilize both a network and linear model involving 31 economies linked to their primary import sources to address the proposition that particularly important import source nations typically have higher measures of international status. Power, Influence, Human Development Index (HDI), and Competitiveness metrics will represent global status and will be referred to in total as Power Status Rankings. The initial hypothesis is that the number of economies relying on a specific country for imports has a significant negative linear correlation with that aforementioned country’s rank value in the Power Status Rankings. Furthermore, I find that the number of sources a nation primarily imports from and the level of its partners’ interdependence are not significantly linked to the Power Status Rankings. These results may suggest that nations facing decreasing export trends rethink their trade strategies and will address topical claims that free trade can have deeper impacts than initially apparent.

Framing of Imports and Power Issue

In this section, I will lay out the theoretical foundations behind why import interdependence intuitively captures a sense of relative power, and contextualize the salience of the issue in the US. To begin, the principle of comparative advantage claims that everyone has a comparative advantage at producing something relative to someone else (Landsburg 2019). In other words, although two nations may be able to produce cars, one nation will have a lower opportunity cost in producing each additional car relative to the other. If both countries trade, with the more efficient nation specializing in car production and the other giving it up, both countries theoretically should be better off economically than if they both produced cars and did not trade. However, by giving up car production the importing nation becomes reliant on the exporting country, giving the latter nation some amount of power in their relationship. Essentially, importing does not have only economic impacts, but geopolitical implications as well. Thus, using imports as a proxy for productivity reliance should provide a sense of relative power networks.

In recent decades, there seems to be some who subscribe to this thinking in the US, as politicians and citizens alike have raised opposition to the nation’s rising trade deficit (Bartash 2018). Public opinion polls show that in 2014, 50% of Americans believed trade destroyed jobs, compared to a global median of only 19%, revealing considerable skepticism over the theoretical mutual benefits of importing (Stokes 2014). Further, anti-free trade sentiments boiled over in the 2016 US elections with both Democratic challenger Bernie Sanders and Republican Donald Trump running on populist/anti-trade platforms (History 2018). Finally, recent backlash against trade agreements such as the Trans-Pacific Partnership signals that this issue will not disappear anytime soon (Palmer 2016). Thus, there is obvious value in investigating the potential links between imports and power status.

Description of Network and Linear Models

Before applying the network and linear models to the issue of international import dependence, I will define and highlight relevant components of the models. A network model represents how different things, nodes, are connected through edges (represented as lines) (Clipperton 2019). An edge symbolizes a legitimate connection between two nodes and can be directed (one-sided relationship) or undirected (mutual connection). Nodes connected by edges are called neighbors (Clipperton 2019). Further, a swath of network statistics contextualizes each network. In degree is how many edges are directed into a single node, and out degree is how many edges are directed out of a node (Clipperton 2019). Clustering coefficient is the proportion of a node’s pairs of neighbors that are linked (Clipperton 2019). These will be the three relevant statistics used in this paper’s analysis.

Uses of network models include identifying significant nodes, understanding the general geographic distribution of nodes, or seeing if any particular communities exist. Limitations might arise if the chosen nodes do not have an obvious link that can be reliably represented as an edge. For example, Facebook friends are mutually linked (you are either friends or not). A key assumption of this model is that connections/edges are indicative of the same type of relationship for each node. When this assumption is violated (e.g., If you ask each node to link to their “favorite” person but you have not given a standard definition of what constitutes favorite) network statistics could be skewed and lead to the identification of communities that do not belong together. Specific limitations of the model’s application to imports will be mentioned in the conclusion.

Moving on to the secondary model, a linear model describes a relationship which assumes that variation in certain individual variable(s) are associated with constant changes in a corresponding dependent variable (Clipperton 2019). A key use of a linear model is linear regression, in which a linear model is applied to data and the line that best fits is generated. Specifically, OLS (Ordinary Least Squares) refers to the method utilized to minimize error in finding the best estimate (Clipperton 2019). Significance values reveal how likely the observed relationship is to occur out of random chance. Each calculated coefficient, which represents the magnitude of the effect that a one unit change in that independent variable has on the dependent variable, has a corresponding significance value (Clipperton 2019). If this value is below an accepted value (I will use .05 in this paper), then we can have confidence in the relationship holding weight.

Furthermore, bivariate regression involves one independent variable and a dependent variable. In multivariate regression, there is more than one independent variable (LaMorte 2016). In this case, the coefficient associated with an independent variable estimates the magnitude of change in the dependent variable for a single unit change of this specific independent variable, while keeping all other independent variables constant (LaMorte 2016). Coefficients are also known as slope and are written in front of the independent variable(s). Finally, the intercept yields the initial value of the dependent variable prior to any change in the independent variable(s).

Finally, an important limitation of linear regression analyses is that these generated lines are just estimates and due to error (measurement mistakes, etc.) they will almost never perfectly fit real-world data. Even when a significant relationship is discovered, linear models cannot prove that the change in the independent variable is what directly caused the change in the dependent, merely that a correlation exists (Clipperton 2019).

Application of Network and Linear Models

This section will explain model designs and why the network model (and linear model) was chosen to relate import sources to power. Firstly, assuming that each node represents a single nation, a network model enables representation of legitimate one-sided trade relationships between countries as directed edges. Further, network statistics provide multiple measures of the import connectivity and relative power of the nations. This will be instrumental in testing if the same nodes highlighted by the network are typically those among the top of the Power Status Rankings.

To detail the network design, a representative sample of 31 countries makes up the nodes, and each node has edges directed to the sources (other nodes) that make up its top 20% of imports. The nation sample contains a cross-section of developing, middle ground BRIC, and developed countries. Import share is defined as the share of total merchandise trade accounted for by a partner in a given year (World Bank 2017). Each node, say the UK, is linked to as many nodes necessary until the top 20% of its import volume is accounted for. So, since Germany is its largest import source, making up 13.99% of British imports, and the next largest source is China with 9.33%, the top 20% threshold would be reached. The UK has edges directed into Germany and China. By design, some nations will have edges directed to only one economy, and others may have three edges directed out of them.

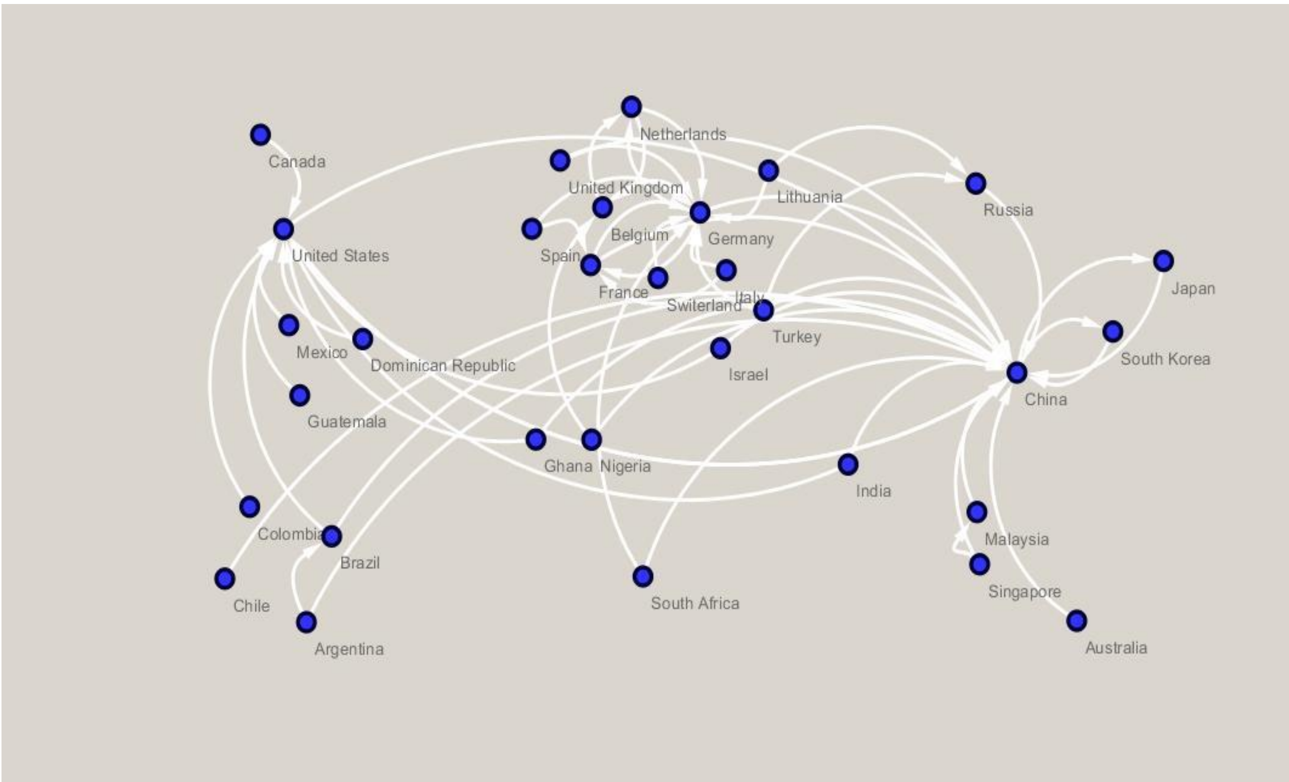
Thus, in degree reveals how many nations rely on a node in their top 20% of imports, enabling the initial hypothesis to be tested. The out degree of a node is how many countries it relies on for its top 20% of imports, which should provide a measure of how varied each nodes' import sources are and if this impacts power status. Finally, clustering coefficient should provide a measure of how much the economies that a node is linked to are reliant on one another. It is included to understand if nations that are more connected within small groups typically are less globally important.

The network statistics are being tested for significant relationships with the Power Status Rankings through the use of multivariate linear regression. The four measures of Power Status Rankings are Power, Influence, Human Development Index, and Competitiveness. Influence and Power come from the 2019 US News and World Report rankings, HDI comes from 2018 UN Data, and Competitiveness from Knoema in 2018. Power takes into account economic, political, and military measures, and was included to represent a more hard power definition of status. Influence measures cultural influence and global connectedness, and was chosen to represent soft power status. The final two metrics, HDI and Competitiveness are more inclusive. Both were chosen to represent development without solely stereotypical militaristic and economic measures, as HDI and Competitiveness also include social indicators such as life expectancy and education levels.

Four multivariate regressions will be run, with the independent variables being in degree, out degree, and clustering coefficient every time. The dependent variable will be one of the four Power Status Rankings in each case (so Power first, Influence next, etc.). Each metric of the Power Status Rankings will have the 31 nodes ranked, so a value closer to one is better. Multivariate regression will reveal the impact that each network statistic has on the chosen Power Status Ranking keeping the other two statistics constant, which will be instrumental in confirming that any potentially significant relationships are truly linked to the specified statistic.

Network Statistics and Linear Regression Results

Global Import Source Network



Network Statistics

Country	In degree	Out degree	Clustering Coefficient
United States	10	1	0.04444444
Canada	0	1	0
Mexico	0	1	0
United Kingdom	0	2	0.5
France	3	2	0.25
Germany	10	3	0.07272727
Netherlands	2	2	0.5
Belgium	2	2	0.33333333
Switerland	0	1	0
China	19	3	0.03508772
South Korea	1	1	0
Japan	1	1	0
Brazil	1	2	0.5
Russia	2	1	0.16666667
India	0	2	1
Nigeria	0	2	0
Turkey	0	3	0.33333333
Italy	0	2	1
Israel	0	2	1
Spain	0	2	1
Australia	0	1	0
South Africa	0	2	0.5
Argentina	0	2	0.5
Chile	0	1	0
Colombia	0	1	0
Singapore	0	2	0.5
Lithuania	0	2	0
Guatemala	0	1	0
Ghana	0	2	1
Dominican Republic	0	1	0
Malaysia	1	1	0.5

Power Regression Results

Linear Regression

Model Fit Measures

Model	R	R^2
1	0.454	0.206

Model Coefficients

Predictor	Estimate	SE	t	p
Intercept	30.96	11.07	2.797	0.009
Indegree	−3.01	1.33	−2.261	0.032
Outdegree	4.40	7.65	0.575	0.570
Clustering Coefficient	−19.55	13.66	−1.431	0.164

Influence Regression Results

Linear Regression

Model Fit Measures

Model	R	R^2
1	0.449	0.202

Model Coefficients

Predictor	Estimate	SE	t	p
Intercept	33.03	10.74	3.075	0.005
Indegree	−2.81	1.29	−2.177	0.038
Outdegree	2.75	7.43	0.370	0.714
Clustering Coefficient	−15.16	13.26	−1.143	0.263

Human Development Index Regression Results

Linear Regression

Model Fit Measures

Model	R	R^2
1	0.214	0.0458

Model Coefficients

Predictor	Estimate	SE	t	p
Intercept	0.87209	0.05732	15.215	< .001
Indegree	0.00637	0.00690	0.923	0.364
Outdegree	−0.03568	0.03964	−0.900	0.376
Clustering Coefficient	0.00954	0.07075	0.135	0.894

Competitiveness Regression Results

Linear Regression

Model Fit Measures

Model	R	R^2
1	0.418	0.175

Model Coefficients

Predictor	Estimate	SE	t	p
Intercept	24.91	15.41	1.617	0.118
Indegree	−4.23	1.85	−2.285	0.030
Outdegree	14.33	10.65	1.345	0.190
Clustering Coefficient	−10.20	19.02	−0.537	0.596

Results Analysis and Insights

The results consist of two parts, the network model (made in Cytoscape) with summary statistics and the Jamovi linear regression data. I will first analyze the former followed by the latter. The next and final section will discuss the implications of the results for the overall issue.

First analyzing the network statistics, it seems that they loosely support preconceived power assumptions. Specifically, the United States, Germany, and China were the three nodes with the highest in degrees, (10, 10, and 19 respectively) meaning that they were the nodes with the most nations relying on them. Correspondingly they were all in the top five for Power and Influence, although not for HDI or Competitiveness. In addition, out degree was 1 for 12 out of the 31 nodes, revealing that more nations were reliant on only one nation for at least 20% of their top imports as opposed to having edges directed into two or three sources. This indicates a high level of overall dependency in the network, suggesting many nations today have pursued policies that favor economic benefits even at the cost of high dependency on one nation.

Additionally, the US, Germany, and China had the lowest nonzero clustering coefficient values, meaning that a lower proportion of their neighbors relied primarily upon each other. Many other nodes had clustering coefficients of zero, usually those with out degrees of 1, which suggests that the one source they were connected to was not as well connected with its neighbors either. All other nodes with nonzero clustering coefficients had values greater than the US, Germany, and China. This indicates that these middle-level nations, such as France and South Africa, were part of more interconnected groups with their neighbors as opposed to the aforementioned three which were not tied as closely to their immediate neighbors and had broader connections across the network.

Now on to the linear model results, which mostly support the initial hypothesis. In other words, in degree was significantly correlated to Power, Influence, and Competitiveness. The corresponding significance values for in degree were below .05 in the specified multivariate regressions (.032, .038, and .030 respectively). Additionally, the coefficients for in degree were -3.01, -2.81, and -4.23 for Power, Influence, and Competitiveness respectively. The negative sign suggests that on average, as in degree of a node increases by 1, its numerical value on the respective ranking gets closer to 1. This is essentially the hypothesis, which is that as the number of nations that rely on a node increases, the international status of that node increases as well.

Further supporting the hypothesis, out degree and clustering coefficient were not significantly correlated with any of the Power Status Rankings. This suggests that out degree, representing the number of nations that make up the top 20% of a country's imports, does not have an obvious relation to a nation's power rankings. Specifically, it appears that importing from only one country for the top 20% imports, or having a high level of dependency, does not have a negative impact on status. Clustering coefficient not revealing a significant relationship could indicate that being a part of a highly interconnected community may just demonstrate a high regional or local level of preference (or trust), and does not disqualify or make it more likely for a nation to have higher power status.

Finally, HDI did not yield a significant correlation with any of the network statistics, which suggests that level of import interconnection may not be linked with development. Considering HDI takes into account only one economic productivity indicator (Gross National Income), with other factors being educational and life expectancy standards, this is not too unbelievable (United Nations 2018). On the other hand, one may argue that industrialized nations typically should provide a higher standard of living. However, BRIC countries such as

India and Russia provide evidence to the contrary, as they are rapidly industrializing but also face high levels of poverty (Anikin & Tikhonova 2016).

Conclusion and Further Extensions

So, this paper broke down complex global power relations through the lens of imports. Initial results suggest that being the primary import source for many nations is a better indicator of the power status of a country rather than the variety in its own sources or the level of its import sources’ interdependence. Perhaps national governments understand this seeming lack of an impact on hegemony from high dependence, as nearly half of the sample relied on only one nation for their top 20% of imports.

Further, these results seem to lend some support to arguments that decreasing exports (lowering the number of nations reliant on a country) in favor of imports hurts status. This insight could help address the aforementioned concerns in the US by being extended to future policy decisions. In other words, considering not only the projected economic benefits from free trade but also the spillover effects on international status before engaging in agreements.

However, as a final note, it is important to keep in mind that a key limitation of the linear model, and this paper, is that the identification of a significant relationship does not mean causation. Before utilizing these insights on a mass level, deeper analysis of the issue should be undertaken by perhaps accounting for potential outside factors impacting power status, such as political events or economic recessions. Furthermore, the network model’s limitations could be addressed by differentiating edges for distinct types of goods or including a larger threshold and nation sample. In either case, although initial results provided some significant outcomes and mostly supported the initial hypothesis, they still serve as a starting point to embark on a more detailed investigation of the relationship between trade and power.

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Country	Power	Influence	UN HDI	Competitiveness
United States	1	1	13	1
Canada	12	10	12	12
Mexico	38	26	74	46
United Kingdom	5	4	14	8
France	6	6	24	17
Germany	4	5	5	6
Netherlands	26	21	10	28
Belgium	25	19	17	21
Switerland	14	16	2	4
China	3	3	86	13
South Korea	10	13	22	15
Japan	7	7	19	5
Brazil	30	27	79	72
Russia	2	2	49	43
India	17	15	130	58
Nigeria	46	57	157	115
Turkey	16	20	64	61
Italy	18	9	28	31
Israel	8	8	22	20
Spain	23	11	26	26
Australia	15	17	3	14
South Africa	31	33	113	67
Argentina	55	39	47	81
Chile	67	53	44	33
Colombia	50	59	90	60
Singapore	20	28	9	2
Lithuania	76	66	35	40
Guatemala	64	77	127	96
Ghana	57	75	140	106
Dominican Republi	69	73	94	82
Malaysia	58	43	57	25

Source	Target
United States	China
Canada	United States
Mexico	United States
United Kingdom	Germany
United Kingdom	China
France	Germany
France	China
Germany	China
Germany	Netherlands
Germany	France
Netherlands	Germany
Netherlands	Belgium
Belgium	Netherlands
Belgium	Germany
Switerland	Germany
China	South Korea
China	Japan
China	United States
South Korea	China
Japan	China
Brazil	China
Brazil	United States
Russia	China
India	China
India	United States
Nigeria	China
Nigeria	Belgium
Turkey	China
Turkey	Germany
Turkey	Russia
Italy	Germany
Italy	France
Israel	United States
Israel	China
Spain	Germany
Spain	France
Australia	China
South Africa	China
South Africa	Germany
Argentina	China
Argentina	Brazil
Chile	China
Colombia	United States
Singapore	China

Singapore	Malaysia
Lithuania	Russia
Lithuania	Germany
Guatemala	United States
Ghana	China
Ghana	United States
Dominican Republi	United States
Malaysia	China

Country	Indegree	Outdegree	ClusteringCoefficient
United Stat	10	1	0.04444444
Canada	0	1	0
Mexico	0	1	0
United King	0	2	0.5
France	3	2	0.25
Germany	10	3	0.07272727
Netherland	2	2	0.5
Belgium	2	2	0.33333333
Switerland	0	1	0
China	19	3	0.03508772
South Kore	1	1	0
Japan	1	1	0
Brazil	1	2	0.5
Russia	2	1	0.16666667
India	0	2	1
Nigeria	0	2	0
Turkey	0	3	0.33333333
Italy	0	2	1
Israel	0	2	1
Spain	0	2	1
Australia	0	1	0
South Afric	0	2	0.5
Argentina	0	2	0.5
Chile	0	1	0
Colombia	0	1	0
Singapore	0	2	0.5
Lithuania	0	2	0
Guatemala	0	1	0
Ghana	0	2	1
Dominican	0	1	0
Malaysia	1	1	0.5

SUID	AverageShortestPathLength	BetweennessCentrality	**ClosenessCentrality**
196	1.66666667	0.01724138	0.6
198	2.25	0	0.44444444
199	2.25	0	0.44444444
200	1.875	0	0.53333333
202	1.85714286	0.0045977	0.53846154
204	1.57142857	0.04827586	0.63636364
205	2.14285714	0.01034483	0.46666667
206	2.14285714	0.00344828	0.46666667
207	2.375	0	0.42105263
197	1	0.08908046	1
208	1.66666667	0	0.6
209	1.66666667	0	0.6
210	1.5	5.75E-04	0.66666667
211	1.75	0.00229885	0.57142857
212	1.5	0	0.66666667
213	1.875	0	0.53333333
214	1.77777778	0	0.5625
215	2.25	0	0.44444444
216	1.5	0	0.66666667
217	2.25	0	0.44444444
218	1.75	0	0.57142857
220	1.875	0	0.53333333
221	1.6	0	0.625
223	1.75	0	0.57142857
224	2.25	0	0.44444444
225	1.6	0	0.625
227	2.22222222	0	0.45
228	2.25	0	0.44444444
229	1.5	0	0.66666667
230	2.25	0	0.44444444
226	1.75	0	0.57142857

ClusteringCoefficient	Degree	Eccentricity	EdgeCount	Indegree
0.04444444	11	2	11	10
0	1	3	1	0
0	1	3	1	0
0.5	2	3	2	0
0.25	5	3	5	3
0.07272727	13	2	13	10
0.5	4	3	4	2
0.33333333	4	3	4	2
0	1	3	1	0
0.03508772	22	1	22	19
0	2	2	2	1
0	2	2	2	1
0.5	3	2	3	1
0.16666667	3	2	3	2
1	2	2	2	0
0	2	3	2	0
0.33333333	3	3	3	0
1	2	3	2	0
1	2	2	2	0
1	2	3	2	0
0	1	2	1	0
0.5	2	3	2	0
0.5	2	2	2	0
0	1	2	1	0
0	1	3	1	0
0.5	2	2	2	0
0	2	3	2	0
0	1	3	1	0
1	2	2	2	0
0	1	3	1	0
0.5	2	2	2	1

IsSingleNode	name	NeighborhoodConnectivity	NumberOfDirectedEdges
FALSE	United States	3.3	11
FALSE	Canada	10	1
FALSE	Mexico	10	1
FALSE	United Kingdom	15	2
FALSE	France	8.5	5
FALSE	Germany	3.818181818	13
FALSE	Netherlands	7	4
FALSE	Belgium	5	4
FALSE	Switerland	11	1
FALSE	China	2.947368421	22
FALSE	South Korea	19	2
FALSE	Japan	19	2
FALSE	Brazil	10.33333333	3
FALSE	Russia	8	3
FALSE	India	14.5	2
FALSE	Nigeria	11	2
FALSE	Turkey	11	3
FALSE	Italy	7.5	2
FALSE	Israel	14.5	2
FALSE	Spain	7.5	2
FALSE	Australia	19	1
FALSE	South Africa	15	2
FALSE	Argentina	11	2
FALSE	Chile	19	1
FALSE	Colombia	10	1
FALSE	Singapore	10.5	2
FALSE	Lithuania	7	2
FALSE	Guatemala	10	1
FALSE	Ghana	14.5	2
FALSE	Dominican Republic	10	1
FALSE	Malaysia	10.5	2

NumberOfUndirectedEdges	Outdegree	PartnerOfMultiEdgedNodePairs	Radiality
0	1	1	0.78333333
0	1	0	0.54166667
0	1	0	0.54166667
0	2	0	0.725
0	2	1	0.74166667
0	3	2	0.8
0	2	2	0.575
0	2	1	0.58333333
0	1	0	0.55833333
0	3	3	0.90833333
0	1	1	0.66666667
0	1	1	0.66666667
0	2	0	0.725
0	1	0	0.69166667
0	2	0	0.71666667
0	2	0	0.69166667
0	3	0	0.73333333
0	2	0	0.56666667
0	2	0	0.71666667
0	2	0	0.56666667
0	1	0	0.66666667
0	2	0	0.725
0	2	0	0.675
0	1	0	0.66666667
0	1	0	0.54166667
0	2	0	0.675
0	2	0	0.575
0	1	0	0.54166667
0	2	0	0.71666667
0	1	0	0.54166667
0	1	0	0.675

selected	SelfLoops	shared name	Stress	TopologicalCoefficient
FALSE	0	United States	15	0.14736842
FALSE	0	Canada	0	0
FALSE	0	Mexico	0	0
FALSE	0	United Kingdom	0	0.6
FALSE	0	France	8	0.34
FALSE	0	Germany	48	0.15810277
FALSE	0	Netherlands	9	0.58333333
FALSE	0	Belgium	3	0.42424242
FALSE	0	Switerland	0	0
FALSE	0	China	87	0.10736842
FALSE	0	South Korea	0	0
FALSE	0	Japan	0	0
FALSE	0	Brazil	1	0.43055556
FALSE	0	Russia	4	0.40350877
FALSE	0	India	0	0.60416667
FALSE	0	Nigeria	0	0.52631579
FALSE	0	Turkey	0	0.44
FALSE	0	Italy	0	0.68181818
FALSE	0	Israel	0	0.60416667
FALSE	0	Spain	0	0.68181818
FALSE	0	Australia	0	0
FALSE	0	South Africa	0	0.6
FALSE	0	Argentina	0	0.57894737
FALSE	0	Chile	0	0
FALSE	0	Colombia	0	0
FALSE	0	Singapore	0	0.55263158
FALSE	0	Lithuania	0	0.6
FALSE	0	Guatemala	0	0
FALSE	0	Ghana	0	0.60416667
FALSE	0	Dominican Republic	0	0
FALSE	0	Malaysia	0	0.55263158