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DBA5104 Introduction to Network Science & Analytics – Term Project Report

Topic: *Network Analysis on Global Offshoring and Tax Avoidance Behaviour*

This project used network analytics methodologies to construct and analyse the global offshoring network contained in the Offshore Leaks papers. The Offshore Leaks papers span over 80 years and contain relationships between more than 200 countries and territories worldwide. The key objectives of this project are: **(1)** To discover global offshoring network structures and behaviours; **(2)** To explore and test the network's resilience; and **(3)** To identify the top countries and financial regions.

A. Motivation & Background

I. Prevalence and Costs of Offshoring Activities

Financial offshoring activity is a worldwide phenomenon whereby individuals or businesses have relationships with financial institutions outside of their country of residence. While some of these activities are done under a legal context, many have been discovered to lean towards criminal activities such as money laundering, tax evasion and fraud. The tangible costs of these activities are colossal; it is estimated that countries worldwide lose over USD$427[1] billion in tax each year due to tax evasion and abuse. Multinational corporations shifted more than USD$650 billion – about 40% of their profit[2] – worth of profit into tax havens, while private tax evaders stored more than USD$10 trillion in financial assets offshore to avoid paying taxes. The social costs are also exigent, lower-income countries' tax losses are equivalent to nearly 52%[1] of their combined public health budget. Moreover, offshoring is a common phenomenon, prevailing in more than 190 countries[1].

Many governments are now willing to cooperate to combat offshoring by imposing region-wide sanctions or residual tax payments towards tax havens. After the Panama Papers, 24 countries were able to recoup USD$1.36 billion in back taxes[3]. G-20 countries plan to impose a universal global corporate tax rate[4]. However, these policies still fall short – recovering only 0.4% of the annual offshoring costs.

II. Application of Network Analytics to Offshoring Network

Prior to the release of the Offshore Leaks papers, studies on offshoring activities have been limited to qualitative studies as information on individuals' and corporations' offshoring activities are limited. After the Panama Papers were published, network analytics was adopted but its application has been limited to discovering and understanding activities in developed countries.

This study adds to the existing literature by not only establishing a global offshoring network but also testing its resilience, detecting communities and focusing on activities in developing countries more closely. Network analytics is suitable for this use case as it can capture complex relationships, identify clusters and run simulations on how to effectively attack the network with limited resources. Other methodologies limit their scope to detecting bad actors, ignoring a holistic overview of the network. In addition, disrupting the network

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[1] Written by Ludvig Wier, Postdoctoral researcher. "Tax Havens Cost Governments $200 Billion a Year. It's Time to Change the Way Global Tax Works." *World Economic Forum*, www.weforum.org/agenda/2020/02/how-do-corporate-tax-havens-work/.

[2] "$427 Billion Lost to Tax Havens Every Year." *Global Alliance for Tax Justice*, 20 Nov. 2020, www.globaltaxjustice.org/en/latest/427-billion-lost-tax-havens-every-year.

[3] McGoey, Sean, et al. "Panama Papers Revenue Recovery Reaches $1.36 Billion as Investigations Continue." *ICIJ*, 21 Apr. 2021, www.icij.org/investigations/panama-papers/panama-papers-revenue-recovery-reaches-1-36-billion-as-investigations-continue/.

[4] Meredith, Sam. "G-20's Global Crackdown Could Create a New Kind of Tax Haven." *CNBC*, CNBC, 16 July 2021, www.cnbc.com/2021/07/16/oecd-tax-reform-g-20s-crackdown-may-create-a-new-kind-of-tax-haven.html.

with minimal resources is key for policymakers as their authority toward tax evaders is limited. Lastly, a focus on developing countries is within reason, considering the magnitude of offshoring costs on their budget and that the creation of consortiums against offshoring is possible.

B. Dataset and Data Preprocessing

I. Original Dataset

The dataset was acquired from the ICIJ Panama Papers Offshore Leaks Database and contained information from all of the Offshore Leaks papers. There were 5 Offshore Leaks papers: Offshore Leaks (2013), Panama Papers (2016), Bahamas Leaks (2016), Paradise Leaks (2017) and Pandora Papers (2021). Each paper contained information on more than 100,000 entities or individuals along with their links to large intermediaries, offshore providers or law firms. The papers have a coverage of more than 200 countries. The dataset acquired combined entries from the aforementioned papers into 4 tables: **Entities**, **Intermediaries**, **Officers** and **Relationships**.

The **Entities** table has information on enterprises created in tax havens, including its general information and commercial registration; it contains 808,817 entries and 22 columns. The **Intermediaries** table provides insights into law firms or other intermediaries that offer offshoring services; the table has 26,768 entries and 11 columns. The **Officers** table corresponds to individuals or companies with a role in offshore entities, containing 746,949 entries and 8 columns. Lastly, the **Relationships** table contains existing relations between all of the tables mentioned with 3,273,524 entries and 8 columns.

II. Data Preprocessing Steps

The following steps were done to prepare the dataset:

1. Cleaned and collated the names of the countries in the dataset.
2. Dropped unnecessary columns, saving only base and jurisdiction locations.
3. Connected entities with their officers and intermediaries using the relationship dataset.
4. Created edge lists and assigned suitable weightage for the different relationships.

III. Network Construction

The nodes in the network are countries while the edges are the relationships that these countries have with each other. The final dataset contains 196 countries or independent states with 338,124 unique edges and 5 relationship types that were weighted based on importance to the network. For this study, a directed network was adopted since identifying capital inflow and outflow between countries is key to understanding offshoring behaviours.

The different relationship types are as follows:

1. Entity Jurisdiction – links the entity's base location to its jurisdiction
2. Officer to Base – links the base of an entity's officer to the entity's base
3. Officer to Jurisdiction – links the base of an entity's officer to the entity's jurisdiction
4. Intermediary to Base – links the base of an entity's intermediary to the entity's base
5. Intermediary to Jurisdiction – links the base of an entity's intermediary to the entity's jurisdiction

Relationships were weighted according to importance:

- **Officer/Intermediary to Base** edges were given the lowest weightage of 0.5 as they gave visibility to individuals involved but do not represent direct authority or activities.
- **Officer/Intermediary to Jurisdiction** edges were given a standard weightage of 1 as they represent stakeholders' ability to exercise authority in the jurisdiction through the entities.
- **Entity to Jurisdiction** edges were given the highest weightage of 2 as they represent the offshoring activities done through the entities.

The relationship weightage was parameterized with the following final edge weight formula.

Total weight (in and outflow) for an individual territory i:

$$T_i = \sum_{k=1}^{5} \sum_{j=1}^{196} \mathbb{1}_{ij} \times W_{ijk} + \mathbb{1}_{ji} \times W_{jik}$$

$T_i = Total\ weight\ of\ territory\ i\ (in\ and\ outflow)$

$W_{ijk}, W_{jik} = Weight\ of\ each\ relationship\ k\ between\ i\ and\ j\ territories$

$\mathbb{1}_{ij}, \mathbb{1}_{ji} = Indicator\ variable\ where\ 1\ if\ territory\ relation\ between\ i\ and\ j\ exists,\ 0\ otherwise$

$i = selected\ territory\ (fixed);\ j = all\ territories\ (196\ total);\ k = relationships\ (5\ total);$
$where\ i \in [1, 196],\ j \in [1, 196],\ i \neq j$

Three network permutations were done to gain more insights on the global offshoring behaviours:

1. **All Relationships Network** included all relationship types. This was the benchmark network.
2. **All Jurisdiction Network** included only relationships that signify locations where individuals or entities have jurisdictions over. It excluded Officer to Base and Intermediary to Base relationships. This network captured the locations where individuals and corporations actually exercise offshoring activities through the entity that they were involved in.
3. **No Intermediary Network** included only Officer relationships. This network focused on activities done by private individuals.

C. Proposed Methodology

I. Network Metrics

An overview of each network was derived by extracting 6 network metrics which give different visibility to the network structure and behaviour.

1. **Weighted In-Degree** measures a territory's offshoring inflow.
2. **Weighted Out-Degree** measures a territory's offshoring outflow.
3. **Page Rank** indicates a territory's importance within the network.
4. **Hub Score** measures a territory's interaction with other territories with high offshoring inflow.
5. **Authority Score** measures how much a territory received offshoring inflow from other territories that have high offshoring outflow.
6. **Betweenness** indicates the importance of a territory to the cohesiveness of the network.

II. Community Detection

Community detection helps identify unique groups of territories that are closely connected to each other. Community detection algorithms can be classified as either agglomerative or optimization-based. The former (e.g. Walktrap algorithm) first considers each node as its own community and progressively builds larger communities based on minimising the random walks between nodes. The objective function of optimization community detection algorithms is modularity maximisation. Modularity is a metric that calculates how connected a node is to its community versus other communities. Some popular examples are the Spinglass, Leading Eigenvector, and Infomap algorithms.

To select the most suitable algorithm, the Question-Alignment approach was followed: chosen algorithms were adopted based on specific research questions or objectives of this study rather than speed or optimality[5]. Each algorithm was tested for each type of network, and each community was individually investigated to find key insights and conduct network disruption attacks. The best community detection algorithms were chosen based on size, interpretability and insights.

III. Network Disruption

Two deletion strategies, Random Deletion and Targeted Deletion, were employed. Random Deletion was done to test and provide a benchmark for the general resilience of the network. Meanwhile, Targeted Deletion was done to simulate how to effectively disintegrate the network. For targeted deletion, nodes and edges were sorted by weighted in-degree before removing the ones with the highest degree first. The attack simulations done are summarised in the table below:

Table 1: Summary of Network Disruption Strategies adopted

	Node Removal	Edge Removal	Network Permutations			Community Algorithms Used	
			All Relationships	All Jurisdictions	No Intermediary	Spinglass	Leading Eigenvector
Random Attack	✅						
Targeted Attack	✅	✅	✅	✅	✅	✅	✅

For all attacks, four network metrics – Degree, Betweenness, Page Rank and Authority Score – were tracked to understand how the network persists.

D. Results and Insights

I. Overall Network Structure and Behaviours

This section discusses the different networks created and country rankings to gain insights on network structure and behaviours.

a. Constructed Network Overview

Interestingly, all three networks – All Relationship (benchmark), All Jurisdiction and No Intermediary – created contain 195 territories. It is observed that the degree distribution of the benchmark network is heavily skewed to the right and roughly follows the power law distribution. This indicates that the network behaves more closely to a scale-free network that typically comprises large hubs and is prone to targeted attacks[6].

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5 Smith, Natalie R., et al. "A Guide for Choosing Community Detection Algorithms in Social Network Studies: The Question Alignment Approach." *American Journal of Preventive Medicine*, Elsevier, 17 Sept. 2020, www.sciencedirect.com/science/article/abs/pii/S0749379720302166.

6 Perera, Supun, et al. "Network Science Approach to Modelling the Topology and Robustness of Supply Chain Networks: a Review and Perspective - Applied Network Science." *SpringerOpen*, Springer International Publishing, 10 Oct. 2017, appliednetsci.springeropen.com/articles/10.1007/s41109-017-0053-0.

Within the benchmark network, known tax haven territories like Panama, Cayman Islands and British Virgin Islands are likely to be large hubs.

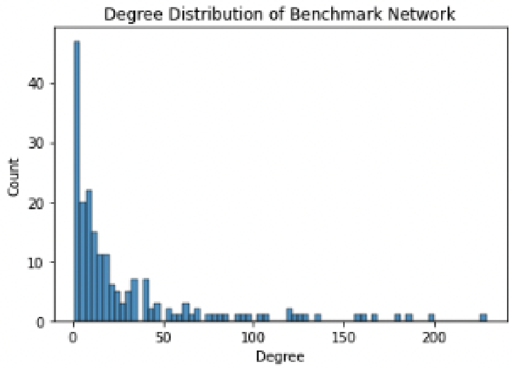

Figure 1: Degree distribution of Network

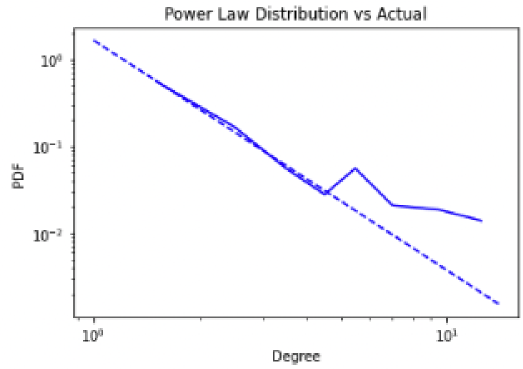

Figure 2: Actual network vs power law comparison

b. Offshoring Territories Rankings and Insights

i. Top Ranked Territories

Top 10 countries ranked based on the 6 metrics adopted for the benchmark network can be found in Table 2. Unsurprisingly, 39 out of 60 rankings represent known tax havens like the British Virgin Island and Panama. In addition, 12 out of 60 rankings represent countries known for tax evasion like the United Kingdom and China.

Further classification can be done however, as **four metric-ranked groups** can be identified:

- **Hub Territories (HT)** are those with high hub scores and weighted out degrees, indicating high offshoring outflow activities. There are 4 plausible reasons why a spike in offshoring might occur in these territories:
    1. High risks of **political or financial instability**, as evident in Hong Kong and Taiwan.
    2. The territories have a **stringent capital constraint or control**, which instil fear in wealthy individuals, as seen in China.
    3. The territories are **capital rich** with assets to invest overseas, as can be seen in Singapore and Luxembourg.
    4. The territories intentionally provide infrastructure for offshoring, becoming a **base for shell companies**. This can be seen in Jersey, an offshoring base whereby shell companies are established and used to conceal ownership or to smurf large cash sums – common techniques in money laundering schemes[7].

- **Authority Territories (AT)** are those with high authority scores and weighted in degree scores, indicating territories with high offshoring inflow. Known tax haven territories, such as British Anguilla, feature heavily in this list. Other territories like Russia also have special administrative regions with heavy tax breaks which make it appealing to set up companies there[8].

- **Highly Active Territories (HAT)** are territories that are top-ranked in every metric like the United Kingdom and Panama. These territories are highly embedded in the offshoring network.

[7] *Ingenique Solutions*, www.ingenique.net/the-most-common-money-laundering-schemes-how-professional-firms-stay-ahead-of-criminal-activity/.

[8] KPMG, 2019. https://assets.kpmg/content/dam/kpmg/ru/pdf/2019/06/ru-en-special-administrative-regions-new-tax-planning-opportunities.pdf

- **Bridging Territories (BT)** are territories with high betweenness which means they are enablers of shell companies or capital flows. While it is natural that highly active territories are here, other territories like the Cook Islands and the United Arab Emirates also appear. They are known tax havens for smaller regions – for Australia[9] and the Middle East[10] respectively.

Table 2: Top 10 Countries from All Relationship/Benchmark Network (Colour Coded based on Metric-Ranked Groups)

Rank	Weighted In Degree	Weighted Out Degree	Page Rank	Hub Score	Authority Score	Betweenness
1	British Virgin Islands (AT, HAT, BT)	Hong Kong (HT, BT, HAT)	British Virgin Islands	Hong Kong	British Virgin Islands	Cook Islands (BT)
2	Panama (HT, AT, HAT)	Switzerland (HT)	Panama	Switzerland	Panama	China (HT, BT)
3	Seychelles (AT)	Taiwan (HT)	Barbados	Jersey (HT)	Seychelles	Hong Kong
4	Bahamas (AT)	Jersey	Bahamas	Taiwan	Bahamas	United States (BT)
5	Niue	China	Hong Kong	United Kingdom (HT, AT, HAT, BT)	Samoa	Singapore (BT)
6	United Kingdom	Luxembourg (HT)	United Kingdom	Singapore	Niue (AT)	Panama
7	Hong Kong	United Kingdom	Seychelles	China	United Kingdom	British Virgin Islands
8	Samoa	Panama	Russia	Panama	Russia (AT)	Canada (BT)
9	Russia	Singapore	Niue	Guernsey	British Anguilla (AT)	United Arab Emirates (BT)
10	British Anguilla	United States	Bermuda	Luxembourg	Hong Kong	United Kingdom

Legend
White = Repeated territory or territory belonging to no metric-ranked group; Grey = Territory belongs to 1 metric-ranked group; Yellow = Territory belongs to 2 groups; Orange = Territory belongs to 3 groups; Red = Territory belongs to 4 groups

ii. Lowest Ranked Territories

Notably, African countries had lower ranks when sorted by weighted outdegree. However, it is interesting that countries that are known to be most corrupt such as Namibia, Djibouti, Uganda, Sudan and Malawi, were in the lowest ranks. This is contradictory to earlier findings where countries with political or financial risks had higher offshoring outflows. A plausible hypothesis is that the number of wealthy individuals in Africa, and thus by extension, offshoring activities, are lower as compared to other regions[11]. This is supported by the finding that suggests that wealthy individuals in Africa practice offshoring just like wealthy individuals in other regions[12].

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[9] "Tax Havens - Complete Guide of Setting up an Offshore Corporate Structure." *Sewell & Kettle*, 31 Jan. 2022, sklawyers.com.au/blog/offshore-tax-havens/#How-do-offshore-tax-havens-compare-to-Australia?-Case-Study:-British-Virgin-Islands.

[10] *Bloomberg.com*, Bloomberg, www.bloomberg.com/news/articles/2022-02-02/what-uae-s-new-tax-means-for-its-business-hub-status-quicktake.

[11] "Panama Papers and the Looting of Africa." *Global Alliance for Tax Justice*, 31 Aug. 2016, www.globaltaxjustice.org/en/latest/panama-papers-and-looting-africa.

[12] Smith, Natalie R., et al. "A Guide for Choosing Community Detection Algorithms in Social Network Studies: The Question Alignment Approach." *American Journal of Preventive Medicine*, Elsevier, 17 Sept. 2020, www.sciencedirect.com/science/article/abs/pii/S0749379720302166.

iii. Other Interesting Insights

A couple of interesting insights could be derived from other network permutations:

1. **Increasing number of tax haven territories in all jurisdiction networks.**
   The All Jurisdiction network shows similar results except that 4 known tax havens – Isle of Man, Cayman Islands, Malta and Belize – are also featured. Interestingly, Nevada appears in the authority score top 10. This state in the United States is tax-friendly, and it is possible that instead of offshoring, individuals or corporations in the U.S may choose to onshore interstate here.

2. **Russia has high weighted in-degree for officer relationships from territories near China and high weighted out-degree to many tax haven territories.**
   Russia receives a high influx of officers from Taiwan, China and Hong Kong and shows high offshoring activities outflow towards the British Virgin Islands, Bermuda, Seychelles and the Cayman Islands. This indicates that Russia is the preferred country to exercise offshoring activities for individuals within regions surrounding China.

3. **Southeast Asian countries have a high weighted out-degree in no intermediary network.**
   Indonesia, Philippines and Malaysia rank in the top 10 for weighted out-degree in no intermediary network but did not rank highly in other networks. This suggests that most offshoring activities in these regions were done directly by private individuals. This aligns with the fact that offshoring infrastructure or services are not readily available in Southeast Asia; this also explains why Southeast Asia has high out-degree to other regions and low in-degree.

II. Community Detection

The ability to detect communities is crucial for policymakers, as it enables them to better target certain countries when drafting new preventive measures.

a. Chosen Community Detection Algorithms

i. Spinglass Algorithm

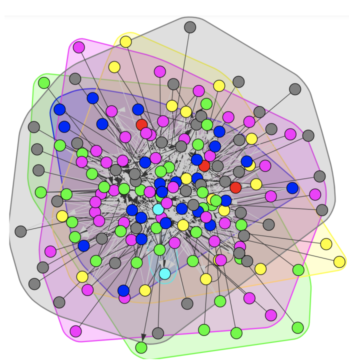


Figure 3: Spinglass plot

This algorithm gave the most number of insightful clusters. South America and Central America were clustered together as shown under the mapped overview for all networks. Other communities were more spread out geographically – Europe was especially divided. Labuan and Malaysia tended to form a separate community, indicating that Labuan (a Malaysian territory) was being used for offshoring but mostly by Malaysia. The highest in degree for each community were Caribbean territories implying their popularity as offshoring destinations.

a. Mapped Overview of Spinglass Communities

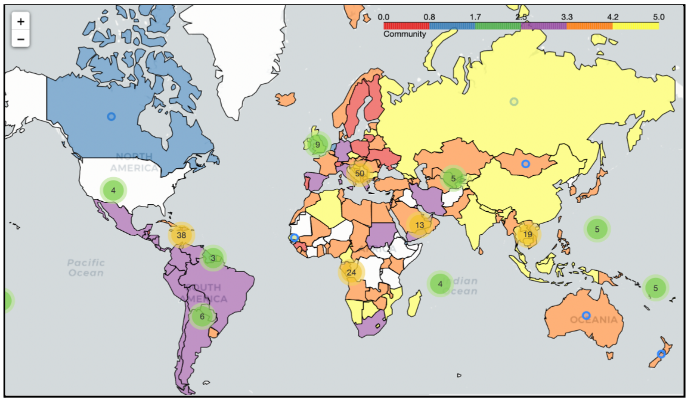


Figure 4 : All Relationship/Benchmark Network, Spinglass

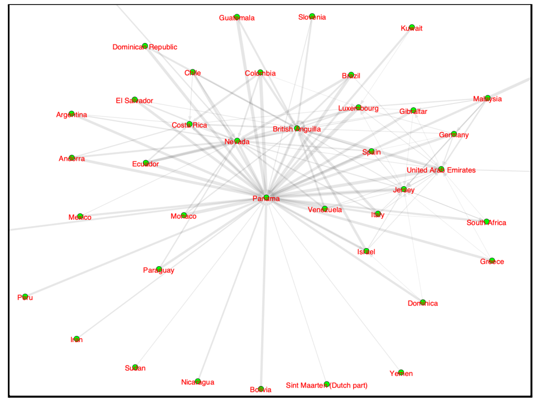
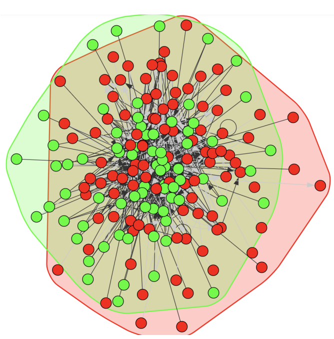


Figure 5 : Community 3 Subplot

Spinglass assigned a majority of South and Central American countries, including Brazil, Bolivia, Mexico and Argentina to the same community. From the subplot visualisation in Figure 5, it is apparent that the offshoring activities in this community revolved around Panama. British Anguilla also had few in-degrees but surprisingly, no other popular nearby tax haven territories like Bermuda, Bahamas and the British Virgin Islands appeared in this community.

In 2014, Brazil and Argentina were identified as one of the most prevalent territories to offshore their business operations to reduce costs. More than half of Central and South America's businesses were offshored and tax services represented 58% of the offshoring activities. Interestingly, 82% of the businesses, which consider conducting outsourcing activities, preferred to onshore than offshore[13]. This is because they considered the region to be politically stable and thriving economically at the time. As such, most offshoring activities were in fact, onshoring, from this region into Panama. Panama was chosen as it was a territory which is "local, culturally similar, and socially-linked" to Central and South America[14]. It is thus a trusted territory by wealthy individuals within the region, mostly due to its proximity and cultural similarity. This finding validated the behaviour found by the community detection algorithm.



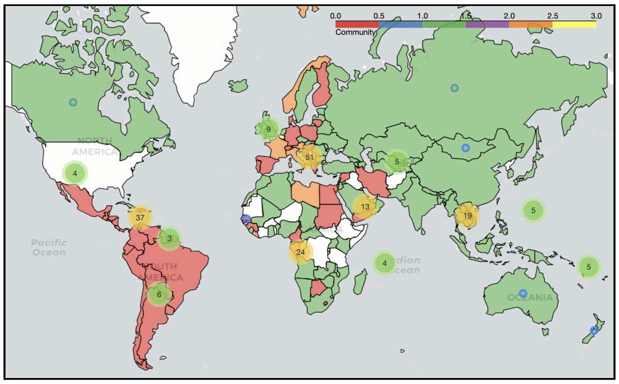
ii. Leading Eigenvector Algorithm

Figure 6: Leading Eigenvector plot

There were 2 notable communities - with Europe, North & South America in one and most of Eurasia and Australia as another. There was high modularity between the clusters; in addition, Panama & Bahamas featured as part of Community 0, with the other Caribbean territories - e.g. the British Virgin Islands appearing in Community 1.

[13] King, Dominic. "Outsourcing: Driving Efficiency and Growth." *Grant Thornton International Ltd. Home*, www.grantthornton.global/en/insights/articles/Outsourcing-driving-efficiency-and-growth/.
[14] Julius Bauer, 2014. https://www.juliusbaer.com/index.php?eID=dumpFile&t=f&f=3692&token=c46f2c571d4ab42e913f8534cd7fee21c4be0ef3

a. Mapped Overview of Leading Eigenvector Communities



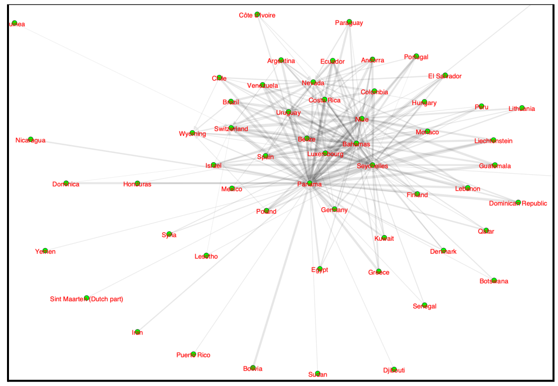


Figure 7 : Benchmark Network, Leading Eigenvector

Figure 8: Community 0 Subplot

This algorithm divided Latin America, Eurasia and Europe into different communities, similar to the Spinglass algorithm. However, the Latin American community appeared to have more territories and density. Panama was the most dominant tax haven territory in this network as shown in Figure 8. Network disruption was simulated on this community to gain insights into the effect of dominant tax haven removal.

III. Network Disruptions and Insights

As discussed in the proposed methodology section, random and targeted deletion were conducted based on weighted in-degree of nodes and edges. Attacks on certain communities were also explored.

a. Random and Targeted Attacks on Nodes

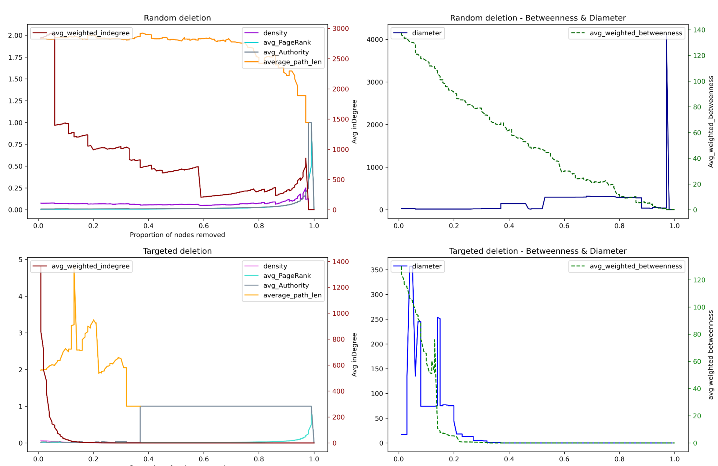


Figure 9: Result of attack on Nodes graph

The network was quite resilient to random attacks, as shown by the graphs below in Figure 9. However, when the nodes were specifically targeted, the network failed rapidly with average weight indegree experiencing a sharp decline when just a small proportion (less than 10%) of high in-degree nodes were removed.

b. Targeted Attack on Edges

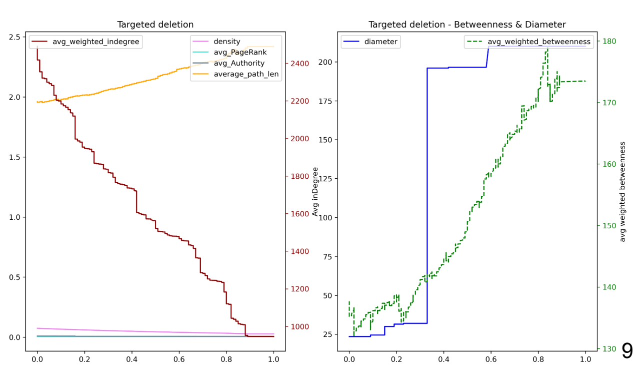


Figure 10: Attack on Edges graph

Targeted attacks were done on edges. The result shows that the network only starts to fail when more than 40% of the edges are removed. This reflects the real world scenario where authorities spend a lot of resources to prosecute individuals and/or entities (edges) with minimal impact.

c. Community Attacks

Targeted attacks on selected communities were attempted to simulate the destruction of specific offshoring networks.

I. Typical Community (Leading Eigenvector - Jurisdiction relationship, Community 0)

This community was selected to simulate the removal of a dominant tax haven territory, Panama. In it, Panama had a high inflow of offshoring activities as demonstrated in the middle chart which shows an inflow from 87 countries into Panama. Contrastingly, there were only 8 offshoring outflows from Panama. These outflows were into other tax havens, suggesting possible hops to further conceal offshoring activities.

	Node_indice	Nodes	In_Degree
6	6	Panama	33039.0
1	1	Bahamas	5526.0
5	5	Niue	5204.0
4	4	Nevada	1151.0
52	52	Labuan	422.0
16	16	Belize	101.0
3	3	Costa Rica	78.0
85	85	State of Delaware	62.0
7	7	Uruguay	36.0
14	14	Wyoming	35.0

	Edge_indice	Edges_weight	Vertex_source	Vertex_target
235	235	11590	Switzerland	Panama
142	142	5584	Luxembourg	Panama
258	258	2653	Uruguay	Panama
23	23	2256	Bahamas	Panama
156	156	1402	Monaco	Panama
...	...	...	...	...
215	215	1	Slovenia	Panama
208	208	1	Saint Lucia	Panama
133	133	1	Libya	Panama
226	226	1	Sudan	Panama
74	74	1	Djibouti	Panama

	Edge_indice	Edges_weight	Vertex_source	Vertex_target
178	178	1589	Panama	Niue
173	173	1120	Panama	Bahamas
176	176	82	Panama	Nevada
174	174	40	Panama	Belize
179	179	7	Panama	Uruguay
180	180	5	Panama	Wyoming
175	175	5	Panama	Costa Rica
177	177	2	Panama	New Zealand

Figure 11: Community 0 - Panama Top node by in-Degree, as a Target, and Source

Disrupting access to Panama massively crippled the network as shown in the graphs below. The network started to fail when ~10% of the nodes were removed. This was a stark contrast to attack on edges, where nearly 40% removal was needed to destroy the network.

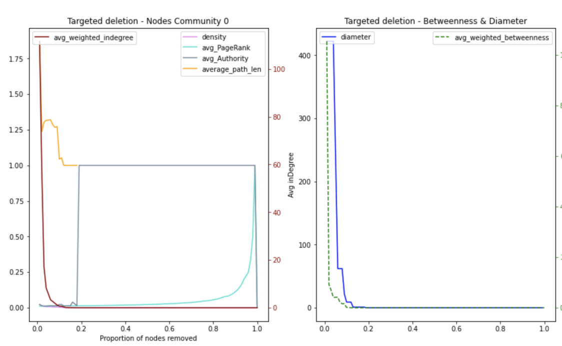


Figure 12: Attack on Nodes Community 0

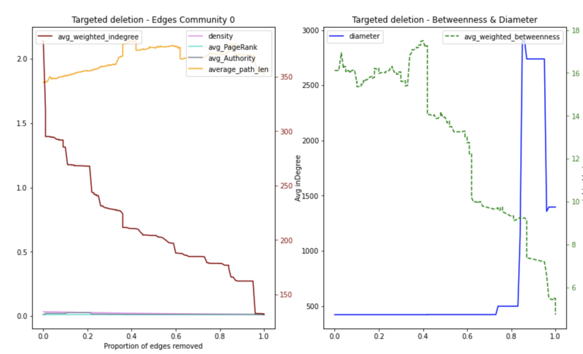


Figure 13: Attack on Nodes Community 1

ii. Atypical Community (Spinglass - No Intermediary relationship, Community 4)

This community excluded typical Caribbean tax havens. Instead, it was composed of highly active offshoring territories like the United Kingdom and China, and capital rich tax haven territories such as Ireland and Singapore.

	Node_indice	Nodes	In_Degree
1	1	United Kingdom	5729.0
5	5	Russia	3699.0
2	2	United States	1357.0
8	8	Ireland	1211.0
7	7	Cyprus	1101.0
4	4	China	852.0
14	14	Latvia	453.0
16	16	Singapore	174.0
18	18	Cook Islands	93.0
9	9	Netherlands	51.0

	Edge_indice	Edges_weight	Vertex_source	Vertex_target
184	184	918	Singapore	United Kingdom
183	183	593	Singapore	Russia
185	185	244	Singapore	United States
180	180	204	Singapore	Ireland
177	177	195	Singapore	Cyprus
174	174	106	Singapore	China
181	181	91	Singapore	Latvia
175	175	48	Singapore	Cook Islands
182	182	8	Singapore	Netherlands
178	178	4	Singapore	Czech Republic
176	176	2	Singapore	Croatia
179	179	1	Singapore	Georgia

	Edge_indice	Edges_weight	Vertex_source	Vertex_target
26	26	69	China	Singapore
225	225	32	United States	Singapore
95	95	25	Indonesia	Singapore
215	215	13	United Kingdom	Singapore
166	166	9	Russia	Singapore
38	38	6	Cook Islands	Singapore
83	83	5	India	Singapore
51	51	5	Cyprus	Singapore
153	153	4	Philippines	Singapore
107	107	2	Japan	Singapore
189	189	1	Slovakia	Singapore
195	195	1	Sri Lanka	Singapore
139	139	1	Netherlands	Singapore
31	31	1	Congo	Singapore

Figure 14: Singapore in Top 10 Countries, as a Source, and as Target

In this community, Singapore played an important role, appearing both as an offshoring activities' source, as well as a target. Given the figures, Singapore is likely to function as an intermediary, given higher outflow (as a source) than it receives. Similar to previous attack simulation, the removal of Singapore as a node was more effective removing edges given its role as a 'transit hub' for illegal offshoring activities.

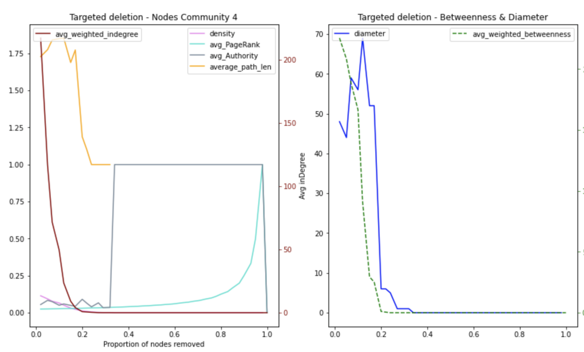


Figure 15: Attack on Nodes Community 4

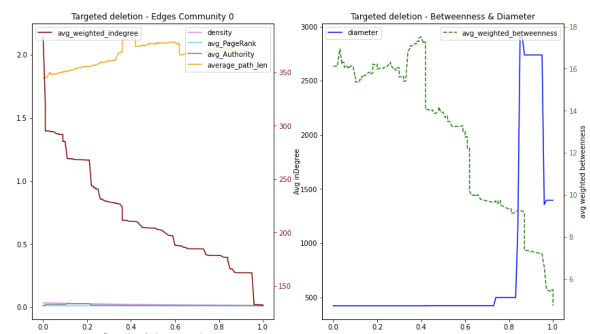


Figure 16: Attack on Edges Community 4

E. Conclusion and Recommendation

I. Consideration for Policymakers

This study found four interesting insights which policymakers could consider to reduce offshoring activities.

1. Impose localised policy based on the region's offshoring behaviours.

Trust-based regions like Latin America were tightly knit, and so, region wide preventive policies could be effective. A focus on curbing local and culturally similar tax havens, like Panama, could also be fruitful. Developed regions like Europe interact with other regions. Therefore to effectively combat offshoring, a collaboration with other regions might be needed. Similarly, Southeast Asia also interacted with other regions, but most activities were offshoring outflow as the region does not have the necessary structure to support offshoring activities. In such a case, policies that target the region, especially those that target individuals will be ineffective – as proven by the edges deletion simulation. Instead, Southeast Asia should collaborate with other regions to impose sanctions towards tax havens.

2. Focus on highly active territories might be needed to disrupt the network.

Extremely active countries like the United Kingdom, Panama and Hong Kong participate both as the source and targets for offshoring activities. To successfully combat global offshoring activities, cooperation from these countries is vital because as shown by the simulation, removal of dominant offshoring territories is the most effective and cost-efficient way to cause network failure.

3. Tax haven territories should be differentiated between capital rich versus offshoring bases.

Renowned tax haven territories like Panama, Jersey and Singapore can be differentiated into capital rich and offshoring bases territories as they exhibit different behaviours. Singapore experiences high offshoring outflows and inflows from and to many regions, while Panama and Jersey show a high outflow to other tax havens. Singapore is capital rich and has the infrastructure to support not only offshoring activities, but also business operations – comparable to Switzerland. Meanwhile, Panama and Jersey are mostly focused on becoming offshoring bases by offering loose Know Your Customer (KYC) standards and anonymity. Singapore, like Switzerland, is not listed in the European tax blacklist because it exerts political influence[15]; on the other hand, Panama and Jersey are always listed.

Thus, different measures should be taken when addressing these different types of tax haven territories. To restrain capital rich tax haven territories, political pressure might be needed as imposing sanctions might not be possible. Meanwhile, to limit offshoring bases territories, sanctions and tax penalties seem to be enough.

4. Preventive policies should focus on cooperation and restraining activities between countries rather than targeting individuals.

While one can identify communities and regions where disruption would help curb offshoring practices, there are some aspects that should be considered. The simulations run show that node removal is more effective than edge removal. Policy wise, preventing all offshoring activity from specific regions may not be as practical. Edge removal is more likely to be practised where policy between two regions is changed to prevent offshoring between them. This requires cooperation between regions to be effective.

II. Limitations & Future Steps

The current study measures the amount of offshoring between countries based on importance (weight for each relationship) and the number of interactions. A key factor that is missing is information on how much capital flows between territories involved. This would allow a more accurate measure of the offshoring activity between countries. Furthermore, the current dataset has limited information on when entities are established and shut down. Attaining this data would be helpful for causal analysis. Understanding this information can help determine the effectiveness of policies that combat offshoring and investigate whether there are shifts in offshoring behaviour in certain regions as a result of policy changes and world events.

This report contains an initial network analysis based on publicly available ICIJ data. Further enrichment, such as collating the amount of offshoring capital flows as edge weights, can be done to understand offshoring behaviour better. Network disruption on such a network can show the impact of certain policies in terms of how much tax money can be saved. This network can be continually built on as more information becomes publicly available, giving a more complete view of offshoring behaviour between regions around the world.

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[15] "EU List of Non-Cooperative Jurisdictions for Tax Purposes." *Consilium*, 11 Apr. 2022, www.consilium.europa.eu/en/policies/eu-list-of-non-cooperative-jurisdictions.