73-449: Social, Economic, and Information Networks — Tax Havens : Network Effects and Policy Interventions

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0.1 Introduction

A tax haven is a jurisdiction where individuals and companies can get a more favorable tax rate on their assets than another jurisdiction. Typically, a tax haven is a country with a favorable tax regime, although it can also be a territory embeded within a country. Individuals and companies often want to set up entities within tax havens for two reasons. The first reason is that the tax regime within a haven is often helpful for retaining a large amount of financial assets for a company. The second reason is that tax havens typically have looser laws on financial transparency when compared to other jurisdictions, and so companies can use entities within tax havens to perform transactions in a less regulated environment than their typical jurisdiction.

Tax havens have been a source of controversy in developed and middle-income countries in recent years. Governments have been concerned by the many large private institutions that choose to set up entities within tax havens such as Switzerland, the Bahamas, and Panama. This concern comes from two issues. The first issue is that when companies set up entities within these tax havens, a lot of tax revenue that would come from domestic financial transactions is lost due to the offshoring of certain business components; this is often considered tax evasions in the eyes of governments. The other reason is that the lack of financial transparency in these tax havens allows certain informal economies to develop around the world, such as the financial backing of the drug trade.

Upon initial consideration of these issues, it becomes apparent that the financial relationships formed by domestic companies and offshore entities to be a topic for network analysis. My first question is, what aspects of the tax haven network give legal and financial intermediaries social capital in the network? If we are able to identify these aspects of the network, we would be able to identify the responsibility that domestic intermediaries have in building networks for tax evasion. My second question is, what are some policy interventions we can do to reduce the strength of this network? If we begin to build some of these policy interventions, we may be able to find mechanisms to reduce global tax evasion and fight illicit economies.

0.2 The Dataset

The source of my data comes from International Consortium of Investigative Journalists (ICIJ). ICIJ is a non-governmental organization that connects investigative journalists from around the world to address cross-border crime and corruption. This organization has created the Offshore Leaks Database, a graph database that displays the major players in the financing and operation of tax haven entities and the relationships among these players. This database was formed by ICIJ using three document sources. The first source is the Offshore (China) Leaks, a document leak in 2013 that provided information on tens of thousands of tax haven clients from Hong Kong and Mainland China. The second source is the Panama Papers, a leak in May of 2016 that featured information on individuals transacting with the Panamanian law firm Mossack Fonseca. The last source is the Bahamas Leaks, a cache of documents that was exposed in September of 2016 that contained the financial transactions of hundreds of thousands of Bahamian entities.

The raw dataset contains 4 different types of agents:

- **Entity**: A company, trust, or fund created in a low-tax, offshore jurisdiction by another agent.
- **Officer**: A person or company who plays a role in an offshore entity.
- **Intermediary**: A financial or legal go-between for a given individual using an offshore entity.
- **Addresses**: An agent's postal address.

There are 281 different relationship types represented in this database, but this amount of relationships is mainly a result of data quality issues and are not truly 281 distinct relationships. For example, some of the most common relationships in this network are disambiguation relationships, such as "same name as" or "similar address to." As another example, some of these relationships need to be textually aggregated, such as when "shareholder of" and "shareholder" are represented as two different relationships when they are in fact the same relationship.

In order to perform a meaningful analysis on this dataset, I took several steps to reduce this network into a more interpretable form.

1. First, I removed all agents who did not represent meaningful financial stakeholders in the network. This meant that I had to removing all addresses from the network.
2. I then removed all relationships that did not represent business-oriented transactions. This meant deleting all edges that were related to disambiguation in the network.
3. I then removed all edge types that were not in the top 20 edge types. Thankfully, the top 20 edge types represented 99.5% of the edge type distribution after removing all disambiguation edges.
4. I then removed all agents who were not in the largest weakly connected component. This was done for the purpose of having interpretable metrics on distance and paths for the network. This largest weakly connected component comprised 81.53% of all agents in the network after removing all addresses.
5. I then collapsed all directed relationships into the undirected "does business with" relationship. This was done for the purpose of making our network measures as interpretable as possible. This is a simplification that could be altered in future research.

This left me with an undirected network with three different agent types (Officers, Entities, and Intermediaries) and edges representing the "does business with" relationship.

0.3 Analysis

I was primarily interested in studying the placement of intermediaries within the network. To answer my first question, I wanted to compare measures of brokerage for intermediaries (i.e. betweenness centralities) with measures of closure for intermediaries (i.e. embeddedness, clustering coefficients). Given that intermediaries are meant to financially connect agents across many different countries, I was expecting that intermediaries would have social capital from brokerage. To answer my second question, I wanted to perform policy interventions where I would remove certain intermediaries or intermediary-entity relationships and study how the network is dismantled. I was expecting that it would take only the removal of a few intermediaries to collapse the structure of this network.

0.3.1 Summary Statistics

The network has around 724000 nodes and around 910000 edges. Unfortunately, this suggests that some of the network measures we should be calculate would be too computationally expensive for me to find using simple methods, and so we would need to use estimation methods for certain network measures. Upon looking at the distribution of leak sources for my nodes (see Figure 2), I see that most of my agents were found via the Panama Papers, but there is still a substantial amount coming from the Bahamas Leaks and the Offshore Leaks. We see that a really small portion of our agents are intermediaries (see Figure 3), which is why many of the network measures we see for intermediaries will be surprising given their small representation in the network (see Network Measures). In terms of countries and territories represented in the network (see Figure 4), we see that some of the typical tax havens are common in our dataset, such as Hong Kong (HKG), the British Virgin Islands (VGB), and Switzerland (CHE). Interestingly, we see that about 10% of our agents are from non-identifiable countries/territories (XXX). For future research, it may be useful to use the structure of the network to infer the countries of these agents.

0.3.2 Network Measures

Intermediaries have relatively high degree when compared to other agents in the network (see Figure 5), which is surprising given their small representation in the network (see Summary Statistics). This suggests that intermediaries have many direct businees partners, which may lend some power to intermediaries in terms of available clientele. Due to the large size of the network (see Summary Statistics), I had to find a computationally reasonable way to compute betweenness centrality for our agents. I ended up using an estimation method that sampled around 350 nodes in our network for computing paths for betweenness centrality. Unfortunately, we see that betweenness centrality is generally low across all agent types (see Figure 6). This either suggests that our estimation was not effective or that intermediaries may not be essential for connecting distant communities in the network.

For studying embeddedness, I realized that calculating average link embeddedness for a node would be computationally difficult given that some nodes have extremely high degree (see Figure 5). Thus, I felt that a simpler method for calculating some measure of closure for a node was to study the clustering coefficients of our agents. Interestingly, we see that all intermediaries have a clustering coefficient of 0 (see Figure 6). This suggests that intermediaries are in extremely fragile parts of the network, since their high degree can disconnect many agents if they are removed from the network. We also see that intermediaries are only adjacent to entities in this network. I would argue that this is potentially a data quality issue, since most intermediaries transact with entities under the request of a legal or financial client. That being said, addressing this data quality issue is slightly out of the scope of this project, and may be an avenue of future research (see Discussion).

0.3.3 Policy Interventions

Given the fragility in the placement of intermediaries in the network, I started to consider certain interventions to dismantle the network by taking advantage of this fragility.

At first, I considered a scenario in which the governments of the world ban intermediaries from interacting with offshore entities. This essentially removes all intermediaries from the network. This intervention shatters our network into 287000 components, and the largest connected component contains only 22% of agents in the remaining network. The average degree of this network also shifts from 2.5 to 1.4, which suggests that on average most agents have fewer direct business connections than before. When we consider how extremely disconnected our network becomes after this policy intervention, it is apparent that if we prevent a large number of financial and legal intermediaries from engaging with entities, we can weaken the number of accessible entities for agents in the network. However, given the fact that it seems unrealistic for all governments across the world to commit to this ban, I thought that it would be important to consider some more realistic scenarios.

I then considered a scenario where China decides to prevent its domestic intermediaries from interacting with offshore entities. This removes only Chinese intermediaries from the network, which is about 5% of available intermediaries. I considered this policy because China is the only country in this network that has a history of extensive market intervention in the financial sector. This intervention shatters the network into 2300 components, but 99% of the remaining agents are within the largest connected component and the average degree in the network stays about the same. This suggests that while the Chinese ban can damage the connectivity of certain parts of the network, this ban does not reduce the accessibility of many tax havens in the network. It is apparent that this problem can't be tackled by the policies of only one country.

I then considered a policy scenario where the US and the UK engage in light regulation on the number of intermediary-entity connections per intermediary in their country. This policy scenario caps the degree of US and UK intermediaries at 5. Any intermediary in these countries that has over 5 adjacencies must choose which adjacencies to keep at random. I considered this policy because there is a history of cooperation among developed countries to commit to light regulation in each economy. This policy shatters our network into 12000 components, but 97% of the remaining nodes are within the largest connected component and the average degree only shifts slightly from 2.45 to 2.5. While the multi-country effort seems to have damaged some parts of the Atlantic part of the network, it was not very effective due to its inability to damage the East Asian part of the network.

0.4 Discussion and Future Research

It seems as though intermediaries have social capital in this network from having many direct business connections with entities and being placed in very unclustered groups of entities. While these aspects of intermediaries would suggest that their social capital cannot be characterized by closure, it is uncertain whether intermediaries could have social capital characterized by brokerage since our betweenness measures for intermediaries are weak (see Analysis, Network Measures). After testing several different policy interventions, it seems as though the most effective methods for breaking apart the network was to remove a meaningful number of intermediaries across many geographical regions in the network. Thus, the best direction for policymaking on dismantling this network would be to form a strong multinational coalition for regulating intermediary-entity relationships.

There are several possible avenues of future research. One avenue is to study this dataset with more computationally efficient algorithms. If we had more resources for computing power on this large graph, many of our calculations on embeddedness and betweenness centrality could be more accurately measured and not just estimated. Another avenue of research is to study the structure of the network to infer what relationships exist between intermediaries and officers. Given the peculiarity of the lack of adjacencies between intermediaries and officers on this network, it may be useful to use certain statistical methods to infer likely connections between intermediaries and their likely clients. Finally, another avenue of research would be to test policy interventions in a more robust manner. If we were to add some level of randomness to policy decisions using Monte Carlo simulations, we may be able to make more probabilistic statements on the effect of governmental choices and create more meaningful suggestions on how to weaken the tax haven network.

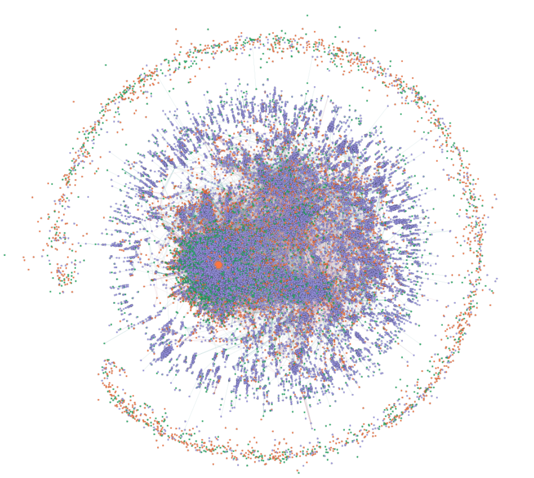

Figure 1: A visualization of our final dataset with the removal of nodes with a degree of less than 5. Nodes are sized by degree and nodes are colored by agent type, where entities are purple, officers are orange, and intermediaries are green.

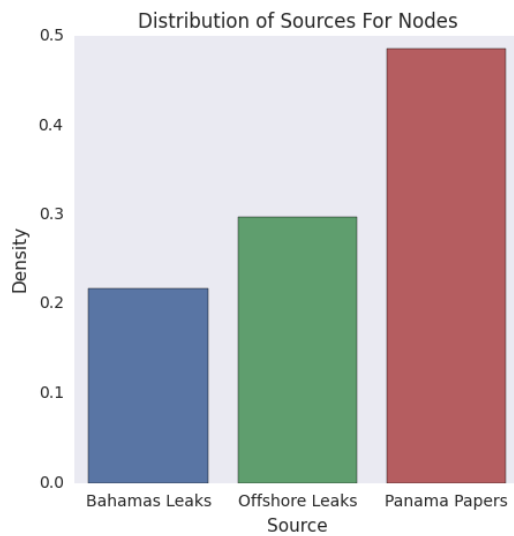

Figure 2: Distribution of Leak Source for nodes in the canonical network.

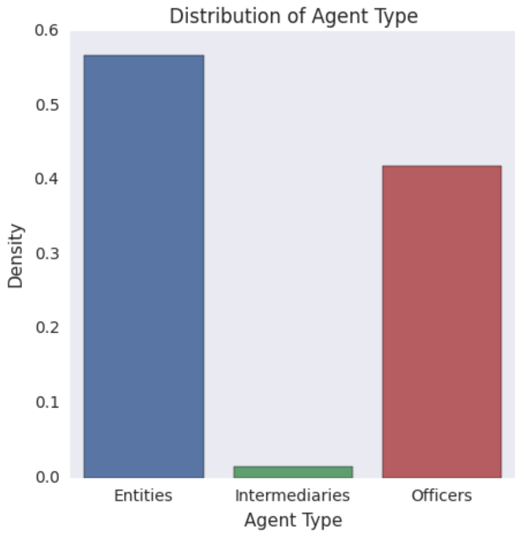

Figure 3: Distribution of Agent Type for nodes in the canonical network.

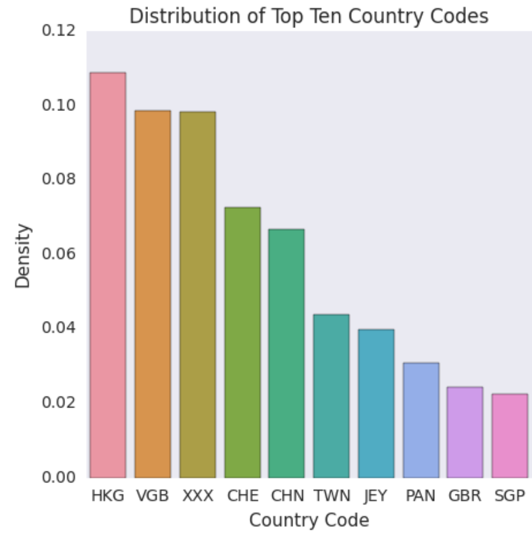

Figure 4: Top Ten Country Codes for nodes in our canonical network. These codes include both countries and territories of certain countries. The country code "XXX" represents a not identified country code.

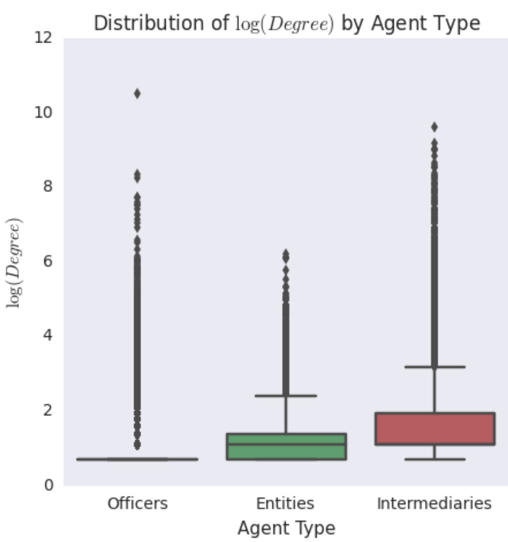

Figure 5: Distribution of $\log(Degree)$ by Agent Type in the canonical network.

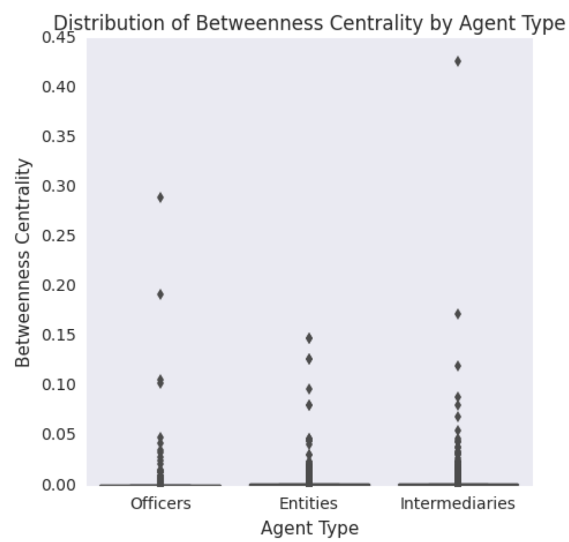

Figure 6: Distribution of betweenness centrality by Agent Type in the canonical network.

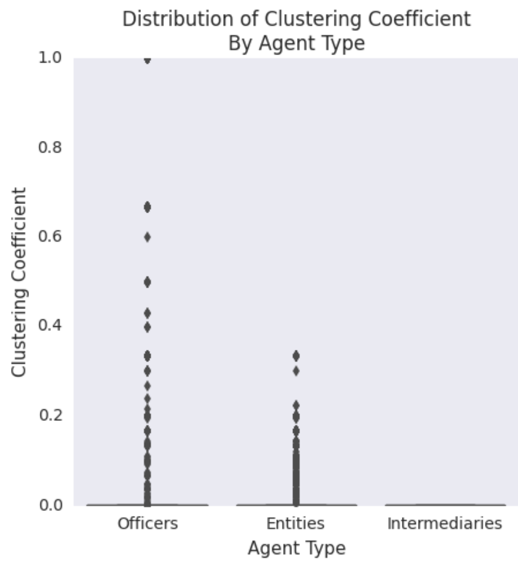

Figure 7: Distribution of clustering coefficient by Agent Type in the canonical network.