# **Humanitarian aid networks: An exploration**

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# **Introduction**

International humanitarian aid is a contested discourse and difficult area to analyze mainly due to the data limitations, unclear motives from the donors’ side, and inconsistencies in reporting. However, it provides important insights into state relations and dependency. The main motive behind this research is to use the available data in international humanitarian aid to observe how humanitarian aid transactions establish networks with different topologies and investigate their robustness. In the light of this motive, the following research question was established:

* How to conceptualize and operationalize the robustness of the international humanitarian aid networks?

The data for analyses is gathered from **Financial Tracking Services (FTS) (UNOCHA)**. First, the dataset was partitioned according to the years between 2024 and 1999. Then, bipartite networks and Sankey diagrams are established according to each year. Finally, the **local** **clustering coefficients, degree distribution & edge weights, and PageRank** were analyzed to evaluate **network robustness** for the aggregation of the networks for each year that constitute the system of the international humanitarian aid network[[1]](#footnote-1).

# **Literature**

## International humanitarian aid

Humanitarian aid refers to the delivery of monetary, in-kind, or social assistance in emergency contexts triggered by (natural, anthropogenic, etc.) disasters, conflicts, epidemics, etc. The general motive behind humanitarian aid is to alleviate casualties and suffering in the short term. However, depending on foreign policy objectives, humanitarian aid can provide opportunities for donor states to exert hard or soft influence (Mert, 2021). There is a vast literature examining the behavior and motives of donor states. In a nutshell, donor states are self-interested. Even in the most dire situations, they would expect political returns such as positive change in public opinion regarding the donor state’s reputation (Andrabi, 2017) or influence on policy perspectives of the recipient states (Cheng & Minhas, 2021).

With the emergence of “humanitarian diplomacy” (De Lauri, 2018, p.2) in the early 2000s, international humanitarian aid has evolved into its own business pursued by countries who would like to improve their public image, collect favors, strengthen foreign engagement, and “diversify their economy” (De Lauri, 2018, p.3). For example, as an emerging and influential donor, the United Arab Emirates hosts one of the largest humanitarian aid logistics centers and the Dubai International Humanitarian Aid and Development Conference and Exhibition. Thus, attracting many corporations and for-profit organizations (De Lauri, 2018, p.3). That is why, new actors continue to emerge in the international humanitarian aid arena such as Qatar and UAE alongside prominent donors such as the United States, United Kingdom, Sweden, Norway, Switzerland, and Japan (De Lauri, 2018, p.3).

## International humanitarian aid network(s)

The political and economic motives behind humanitarian aid make it a vast, complex, and competitive area. The type of emergency and the degree of harm determine which actors are involved (e.g., states, UN agencies, NGOs, military organizations, corporations, individuals, etc.) in raising, mediating, or allocating resources. Seybolt regards these diverse humanitarian aid networks as a **system** that is not governed and coordinated by one or several central authorities. UN agencies such as the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) endeavor to identify and keep records of who, why, and how actors are involved in providing aid by publishing reports or managing databases such as the Financial Tracking Services (FTS). However, there are serious gaps in reporting which makes it extremely difficult to maintain transparency and investigate.

On the most general perspective, Seybolt defines this system in six dimensions. The first one is the “size” (Seybolt, 2009, p.1033), which defines the number of actors involved in a humanitarian aid network. The second one is “complexity” (Seybolt, 2009, p.1033), which refers to the amount of funding and services provided by actors. The third one is “differentiation” (Seybolt, 2009, p.1033), which refers to the degree of diversity of actors who provide these resources. The fourth one is “stability” (Seybolt, 2009, p.1033), which refers to the consistency in active engagement and provision of resources. The fifth one is “connectivity” (Seybolt, 2009, p.1033), which refers to the existence and strength of communication channels between donor and recipient actors. The sixth one is “centrality” (Seybolt, 2009, p.1033), which defines to what extent communication channels or resources flow through a few actors. According to this frame, the increasing number of actors responding to emergencies around the world increases the complexity of humanitarian aid networks along with their diversity in responding to different needs. In these networks, however, the degree of differentiation and the capacity of actors to respond is not stable, meaning that some networks depend on the resources and capabilities of a few actors. This can jeopardize the effectiveness of certain networks where the big actors are removed or function as effectively (Seybolt, 2009, p.1033-1034). So, Seybolt’s conceptualization of humanitarian aid networks provides an important schema about the arrangement of international humanitarian aid networks as well as how effective and resilient they are. With this framing, Seybolt concludes that international humanitarian aid networks are inefficient because they are “unstable, highly complex, and large, with a low level of differentiation between many of the constituent organizations” (Seybolt, 2009, p.1046) alongside dependency on donor states with stronger capacities, richer resources, and more ambitious political motives (Seybolt, 2009, p.1046).

The complexity and non-regulation of international humanitarian aid networks create asymmetrical relations. This means that resource-gathering and allocation networks are highly dependent on several states (mainly the United States as a ‘universal’ donor) and organizations (UN agencies such as UNICEF or other prominent international NGOs such as Save the Children, Oxfam, etc.) for funding, mediation, and distribution (Seybolt, 2009, p.1032). Seybolt coined the term the “oligopoly of donors” (Seybolt, 2009, p.1032) to attract attention to the dependency relations in humanitarian aid networks and argues that inadequate regulation and accountability make these networks fail in providing and sustaining relief while making them vulnerable to shocks. For example, if the United States were to experience a serious economic shock what would happen to the local NGOs as well as other organizations or countries that depend on the economic and human resources that flow from it?

Not many articles in the literature ask this question. Most of the articles focus on the developmental aspect of aid. Mainly they focus on the political and economic reasoning behind donor states’ aid allocation decisions (Cheng & Minhas, 2021), inferring budget allocation decisions and simulating possible aid networks based on them (Scattergood & Bishop, 2023), the effect governance systems’ of recipient states’ on the extent of aid they receive (Alesina & Weder, 2024), and the effectiveness of foreign aid (Bearce & Tirone, 2010).

Alongside motives behind aid allocation, the articles that focus specifically on humanitarian aid investigate local-level cooperation and effectiveness (Urrea et al., 2016), the role of NGOs in mediating aid (Olsen et al., 2003), the importance of connectedness among local actors and between international actors (Curtis, 2018), conceptualizing and modeling cooperation among actors to improve success and efficiency of humanitarian logistics (Anaya-Arenas et al., 2014) (Tacheva & Simpson, 2019), and designing bottom-up relief networks by analyzing the behavior of groups and organizations (Xu et al., 2024). Within the literature, Clark’s (2020) research directly investigates the resilience and robustness of international humanitarian aid networks considering their centrality and dependence on asymmetric relationships on a broader scale. Clark approaches this situation from the perspective of “cascading failure” (Clark, 2020, p.14), which denotes the serial collapse of humanitarian aid networks when the central node is disconnected from the network. Clark also utilizes the FTS dataset, but the focus is on forced migration-related emergencies (Clark, 2020).

While building the discussions regarding the effectiveness and robustness of aid networks, this research presents a larger investigation by using all the aid flows between 2024 and 1999 that are gathered via FTS API. The novelty of this research comes from the analysis of robustness in a long time frame and with all the data gathered from the FTS.

# **Data and methods**

## Data

Data is gathered from the Financial Tracking Services (FTS) database managed by the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) via an extensive API call. The API call involves finding endpoints in the API documentation, creating dictionaries to incorporate country codes (iso\_3 codes), creating a function to send endpoint requests, and then adding the data to a data frame, applying random spot checks to assess the safety of the data gathered from FTS. After gathering the data, cleaning and filtering were conducted to ease analyses.

The dataset contains 227473 rows. It involves *“flow\_id, organization, country\_iso3, description, boundary, organization type, organization sub-type, organization level, amount ($), contribution type, method, date, and status”* as variables. The short description of all the variables is as follows[[2]](#footnote-2):

* **Flow\_id:** Defines an identification tag for each flow.
* **Organization**: Involves donors who are states, international NGOs (e.g. International Federation of Red Cross and Red Crescent Societies), UN agencies, supranational institutions (e.g. European Commission's Humanitarian Aid and Civil Protection Department), private actors (e.g. Private (individuals & organizations), etc.
* **Country\_iso3**: Involves recipient countries’ International Organization for Standardization (ISO) codes (e.g. TUR for Türkiye).
* **Description**: Involves the description of the type (e.g. Girls Education South Sudan II (GESS 2)) of aid provided
* **Boundary**: Involves the direction of flow (e.g. incoming).
* **Organization type**: Indicates the type of donors (e.g. NGO, Multilateral Organizations, Governments, Private Organizations, etc.).
* **Organization** **sub-type**: Gives details about the organization types. For example, it indicates whether private organizations are international or local/national.
* **Organization level**: Indicates the governance level to which the organizations belong (e.g. international, national, sub-national, and local) and whether they are national or non-national actors.
* **Amount ($)**: Indicates the total amount that the donors allocated. The database translates every type of donation (e.g. financial or in-kind) to monetary value and converts every currency to $.
* **Contribution type**: Indicates whether the donation is financial or in-kind.
* **Method**: Indicates the ways donations were allocated (e.g. cash transfer or traditional).
* **Date**: Indicates the date of the donation arrivals to the recipient country.
* **Status**: Indicates whether the donations are paid or in the commitment phase.

**Organization, country\_iso3, amount ($), and date** are the variables of interest within the scope of this study.

## Methods

This study builds and replicates Seybolt’s arguments (2009) and Clark’s analyses (2020) to investigate the robustness of networks.

Robustness refers to the ability to sustain functionality and performance against challenges, disruptions, or failures. Robustness can be conceptualized and operationalized by analyzing the particular nodes that create dependency on its distribution and number of resources, which can be indicated by analyzing the weighted degree distribution (out) and local clustering coefficients. It can also be conceptualized and operationalized by analyzing how important a node is via PageRank (Clark, 2020, p. 29). Page rank can be used to understand node importance while accounting for the weight and direction of flows.

Clark defines approaches robustness from the perspective of “cascading failures” (Clark, 2020, p. 42), which means that networks that heavily depend on one or few nodes for resources are more susceptible to experiencing shocks and an eventual collapse once the dependency-generating nodes are removed from the system or experience losses that disrupt their aid flows.

Within the scope of this study, degree distribution & edge weights, local clustering coefficient, and PageRank were analyzed. The analyses were conducted after cleaning the dataset (e.g. removing empty values in the amount donated), defining countries as the unit of analysis, removing self-loops in the aid flows, aggregating a country’s flows for the same year, and aggregating the aid flows between 2024 and 1991.

* **Degree distribution and edge weights** are used to gather information regarding which donor countries generate dependency on their resources. It can be inferred by the number of connections each donor country makes, allowing us to see countries that are more active in making donations.
* **Local clustering coefficients (LCC)** of donor countries, measured strictly based on outgoing edges from countries that have received aid from each country, help to see if there are any hubs of aid flow. Therefore, in a less robust network, we would expect lower LCCs in countries that delivered the most aid as this indicates sparse connections and independent aid flows. Within the scope of this study, LCCs were used to apply the ***Shapiro-Wilkis test*** to examine how far the aid flow distribution in a certain year is distant from the normal distribution.
* **PageRank** centrality measures the overall impact of all nodes using the centrality of both the nodes themselves and their neighbors using the directionality and weight of each edge. Here, PageRank values of donor countries based on their outgoing edges and incoming edges of their neighbors were used to measure the dominance of each donor country within the humanitarian aid network system.

To analyze robustness via these metrics, we used statistical and qualitative analyses to make causal connections between metrics and our literature knowledge. The main aim here is to incorporate a large body of data into the research of aid network robustness using statistical analysis. For additional clarification on limitations or abnormalities, we provided qualitative explanations.

# **Results**

## Data collection

The data collected from the FTS was converted into a data frame, which incorporated aid flows from countries and organizations to countries. We aggregated a country’s flows for the same year, aggregated the networks between 2024 and 1999, eliminated self-loops in aid flows, and defined countries as the main unit of analysis. Thus, we generated the following (cleaned) weighted and directional network of the humanitarian aid flow system.



Figure 1: The cleaned graph of the entire network.

To analyze the entirety of the networks for each year, please refer to our GitHub page. To analyze the Sankey diagrams regarding the entirety of the aid flows between countries please refer to our code as they are interactive.

## Local clustering coefficients

The local clustering coefficients (LCC) of each donor country were calculated for each year. Then, these values were used to apply the **Shapiro-Wilk distribution analysis** to investigate the distribution of LCCs for each year. Thus, according to the p-values generated, the null hypotheses of the normal distribution of LCCs for each year were rejected except in 1999. We attribute this situation to the low amount of data that was available that year.

The uneven distribution of LCCs shows that aid recipient countries did not form sufficiently complete aid networks to make the networks robust.

The **W-statistics** illustrated in the table below show how close to a normal distribution each year was, while the p-value acts as a test of statistical significance. With the average W-statistic being 0.17, we can see that some years with extreme events that called for international aid flows mostly had higher than average W-statistics which means the distribution of these aid networks were closer to normal and relatively balanced.

|  |  |  |
| --- | --- | --- |
| **Year** | **W** | **p-value** |
| 2020 | 0.171319 | 3.225218e-28 |
| 2022 | 0.241838 | 3.008923e-27 |
| 2024 | 0.073883 | 1.866832e-29 |
| 2012 | 0.045854 | 8.598678e-30 |
| 2002 | 0.132380 | 1.001863e-28 |
| 2013 | 0.086344 | 2.650987e-29 |
| 2001 | 0.189927 | 5.726940e-28 |
| 2011 | 0.273920 | 8.778064e-27 |
| 2014 | 0.056642 | 1.156296e-29 |
| 2003 | 0.127516 | 8.683041e-29 |
| 2000 | 0.045854 | 8.598678e-30 |
| 2015 | 0.056093 | 1.138911e-29 |
| 2016 | 0.182557 | 4.556482e-28 |
| 2017 | 0.127352 | 8.641278e-29 |
| 2018 | 0.054667 | 1.095065e-29 |
| 2019 | 0.047331 | 8.953226e-30 |
| 2004 | 0.054911 | 1.102421e-29 |
| 2005 | 0.298339 | 2.033884e-26 |
| 2021 | 0.088283 | 2.800613e-29 |
| 2010 | 0.346255 | 1.133438e-25 |
| 2023 | 0.166441 | 2.779281e-28 |
| 2006 | 0.123856 | 7.799978e-29 |
| 2007 | 0.098192 | 3.713268e-29 |
| 2008 | 0.269121 | 7.461556e-27 |
| 2009 | 0.088284 | 2.800703e-29 |
| 1999 | 1.000000 | 1.000000e+00 |

Figure 2: Results of the Shapiro-Wilk distribution analysis by year.

For example, the W-statistics is the highest for 2010 (0.35). This is because 2010 was the year of the Haiti earthquake which required a large international effort and resources for rescue and recovery. In this context, a high W-score indicates that a disaster this catastrophic prompted a lot of countries to provide significant resources rather than a few designated donors such as the USA.

The Boxing Day Tsunami of 2004, which happened at the end of 2004, affected the W-statistic of 2005 which is the second highest in the table (0.30). The earthquake and the subsequent tsunami were felt across Southeast Asia and East Africa, prompting an international response. The Great Tohoku Earthquake of 2011 is another disaster that prompted large and diverse aid flows. This resulted in the W-statistic of 0.27, which is the third highest in the table.

Russia’s military offensive in Ukraine in 2022 was an extreme event that caused an outpouring of aid from all around the world to not just Ukraine but also its neighbors so that they could provide essential support for people affected by war whether they have been displaced (internally or externally) or not. The W-statistic for 2022 is 0.24, which is the fourth highest.

The 2023 earthquake in Türkiye and Syria prompted a desperate campaign to find as many survivors as possible and provide support for the millions of people who were suddenly left without a home. The situation in Syria was more dire due to the ongoing civil war and the sanctions imposed on the Syrian regime, therefore a larger-than-average aid network had to be built to support Syria’s earthquake survivors. The W-statistic for 2023 is 0.16, which is an outlier compared to other extreme event years. We attribute this to the scale of help needed for a small number of countries, resulting in the aid dominance of a few states.

## Degree distribution and edge weights

Within the scope of this study, degree and edge weight distributions were analyzed in two ways. The first way was to sum up all donations made by each donor country to see which countries were the most dominant. The second way was to make a heatmap of all donations between country pairs to see which countries depended on given countries the most for aid. Then, interpretations were made based on these results.

We argue that the domination of certain countries in this area makes aid networks less robust. We used total outgoing edge weights to observe which countries generate dependency on their resources via the number of resources they provide. If nodes that represent these countries were to fail in the network, catastrophic losses would occur. We use heatmaps that display the rates of each donor’s share in recipient countries’ networks to come to this conclusion.

A graph of a number of people

Description automatically generated with medium confidence

Figure 3: Total outgoing donations per country.

## As can be seen from Figure 3, the USA provided a total of USD63,237,828,354.00 which corresponds to 40.51% of all donations. The UK, Germany, Japan, Saudi Arabia, Norway, Canada, the UAE, Sweden, and the Netherlands follow the USA in the top 10. These countries contributed USD236,889,166,083.67 to the aid flow, which is %86,7 of total aid within the database. This makes the system of the international humanitarian network highly dependent on the resource allocation of a few countries. While wealth is distributed across countries unequally and different states have different levels of willingness to pay for other countries’ disaster recovery, the (almost) entirety of the global aid network being dependent on 10 countries makes it extremely vulnerable.

The make-up of the top donor list is also worthy of attention. 7 out of 10 top donors are NATO members. The rest are either strategic allies of the US and/or wealthy petro-states that derive a significant portion of their domestic product from hydrocarbon products. This composition of the aid network means that it is open for strategic use by dominant countries.

The distribution of outgoing aid means the global aid network has many cracks in it, which is made apparent in the heatmap in Figure 4.

A screenshot of a computer screen

Description automatically generated

Figure 4: Heatmap of the share of aid given by individual donors within the incoming aid networks of recipient countries. For legibility only the top 20 donors and 50 recipients are being shown.

In the heatmap network in Figure 4, the USA is the top donor for all recipients, except Sierra Leone, the Philippines, Egypt, and India. While many cells originating from the USA are shaded in blue or dark blue, it is easy to see cells that are shaded yellow or white from other countries of aid origin.

The most robust networks would have a more even color distribution across donors, or multiple donors shaded in darker colors. While there are no fully robust examples, India, Yemen, Libya, Philippines, and Myanmar draw attention for having multiple donors shaded in green or teal. This means these countries rely on similar amounts of aid coming from multiple donors instead of one big donor, therefore increasing robustness.

## PageRank centrality

The PageRank centralities of all donor countries were calculated based on their outgoing edges and the incoming edges of recipient countries. PageRank is an important metric for evaluating the importance of a node by considering the direction and weight of each of its connections.

A graph of a number of donor countries/regions

Description automatically generated

Figure 5: PageRank centralities of donor countries, based on outgoing donations of individual countries.

As can be seen, the USA is the most dominant node in the system defined by the aggregation of the international humanitarian aid networks. This means that its connections had the most impact, as the way we calculated this centrality measure considers both the weight of the connections the donor had and the weight of other connections the recipients made. Therefore, it is possible to argue that the flows prompted by the USA were the most impactful. Japan, Germany, Switzerland, Norway, Canada, The UAE, Sweden, France, and the UK followed the USA in the top 10. These results confirm the domination we observed in the combined edge weight distributions and LCCs. 7 out of the top 10 are NATO members, while Switzerland, Japan, and the UAE also appear on the list as high-income economies. The presence of Switzerland and France may be noticed, which are absent from the top 10 donors list, alongside a great number of European countries in the top 20 list. It may be possible to attribute this situation to the resource richness and effectiveness of European countries’ humanitarian aid allocation. Their high PageRank centralities imply a greater level of cooperation compared to the rest of the world, making European aid networks more robust. Despite this situation, there still exists a system of international humanitarian aid flow that depends heavily on a handful of countries, especially the US, to deliver essential help during extreme events.

Our results perpetuate Clark’s and Seybolt’s arguments regarding the “oligopoly of donors” (Seybolt, 2009, p.1032) in the humanitarian aid system and the general vulnerability of the networks against sudden shocks or removals.

# **Conclusion**

This study both replicated and built upon the literature on international humanitarian aid by conceptualizing and operationalizing robustness on the entirety of the Financial Tracking Services dataset as the proxy of the international humanitarian aid system.

As both the literature and this study revealed, humanitarian aid networks are complicated to analyze mainly due to the limitations in the gathering and processing of data. Consequently, this situation affects the definition and measurement of robustness.

The conceptualization and operationalization of robustness were mainly based on Clarke’s analyses. Before settling on this decision, there were multiple failed attempts in the analysis. In the earlier steps, we decided to use degree distribution, average path length, clustering coefficient, and global efficiency to enhance Clark’s analyses. However, attempts with average path length and global efficiency generated uninterpretable results. Moreover, we steered our path from analyzing the networks generated in every year. Rather we decided to focus on the entirety of the flows by aggregating all the flows between 2024 and 1999. Thus, we based our analyses and interpretations on this entirety as the system of international humanitarian aid (as defined by Seybolt).

With our results, we were able to replicate Clark’s analyses and confirm the arguments regarding the overall vulnerability of humanitarian aid networks as they are heavily dependent on the resources and connections provided by a few nodes, which can cause disruptions in aid delivery in the event of shocks and decrease in their efficiency in aid allocation.

# **Limitations and future directions**

As discussed in the previous sections, there are significant limitations with the dataset, methods, and results generated.

Limitations with the dataset:

* Among donors, some organizations are both donors and recipients. Therefore, countries were selected as the main unit of analysis.
* Donations with both paid and commitment status were included in the analyses to avoid losing a significant portion of the data.
* For recipients, the countries are coded in iso3 codes. However, for donors, not every country was labeled with their respective iso3 codes. We used Python codes to translate non-coded donor countries. Therefore, there may be few unlabeled donor countries.

Limitations with the methods:

* Degree distribution (out), edge weights, LCCs, and page rank may not be the best or sufficient metrics to measure robustness. However, trial and error showed that they are the most appropriate metrics for the task.
* Due to time constraints, we were not able to simulate possible failure or collapse scenarios when dependency-generating nodes are removed.

Limitations with the results:

* As the literature and analysis results show, the definition and measurement of robustness are not standard. Therefore, the results generated by this study cannot be generalized to the topology and behavior of all the humanitarian aid networks considering the limitations of the dataset and methods.

As a future direction, this research needs to address its limitations, augment the dataset, and use advanced methods the simulate robustness.

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1. Please refer to our [GitHub](https://github.com/aybike-s/Network-Analysis-Financial-Tracking-Services) page for our codes and graphs. [↑](#footnote-ref-1)
2. To see the entirety of the dataset, please refer [here](https://docs.google.com/spreadsheets/d/1LSV97-vfYW_-VlGPm68pLuewM-AIEGw2/edit?usp=sharing&ouid=109903149128153538285&rtpof=true&sd=true). [↑](#footnote-ref-2)