

Network Analysis of Bilateral Trade Data Under Asymmetry

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Abstract—Trade statistics is a vivid example of bilateral data with asymmetry. Exporter and importer report their own versions of a flow between them, that frequently differ in dozens of times. In order to construct a network of trade relations we need to choose only one value for each weighted edge. We propose new methodology that aims to deal with the problem of mirror statistics. Our approach includes outliers detection step, the analysis of National Compilation and Reporting Practices survey and the construction of coherence metric of trade. We apply the proposed approach to real global trade data and compare several network statistics with corresponding statistics of networks that are constructed on export and import data. The key advantage of our methodology is that it does not depend on commodity selection and can be applied to trade networks on various levels.

Keywords—trade network, asymmetry, mirror data, export/import relations.

I. INTRODUCTION

Data accuracy and completeness are one of the main factors of the research quality. However, a researcher frequently faces the problem of data misrepresentation as well as gaps in initial statistics. Another point is the inconsistency of various data sources. The main sets of data in network analysis are nodes, edges, directions and weights of connections between nodes and the lack of information in any of these sets may lead to erroneous results. In this work we investigate the problem of bilateral data in network analysis in the context of trade between countries.

In the analysis of trade between countries we assume that there exists some good or service that one country sells to its partner. It means that there exists a money flow between exchanging parties, which, in a perfect world, should be equal for both sides. However, in most real cases exporter and importer statistics are inconsistent as each partner reports its own version of a flow between them. On the one hand, both reported values may be reliable for each partner. On the other hand, it is required to determine a single value for each flow in order to construct a network model of a commodity trade.

With the growing amount of information we need more accurate and precise tools of data pre-processing in order to obtain structured and clear data sets. There is no unique method that can help us to choose a correct value of a flow between two countries. It might be reasonable to choose an exporter or importer statistics exclusively; however, this can lead to the loss of information as not all countries report their data. Thus, our main goal is to show the difference in reported statistics by exporter and importer and the sensitivity of key network metrics to inconsistency in trading data. We also propose new approach that helps to choose one value of a flow between two trading countries in order to construct a network model of a trade. Our approach is based on official open source UN inquiries as well as on a pure statistical analysis of countries trade with their partners.

The paper is organized as follows. In Section 2, we describe the main trade data source, the reasons of

inconsistencies in trade data and current methods that address to this problem. In Section 3, we provide with the description of our approach that allows to choose a unique value of a flow. In Section 4, we apply new approach to real trade network. In Section 5, we present the results and make a conclusion.

II. Background and Data Description

World Integrated Trade Solution (WITS) database is one of the largest and the most extensive databases for the analysis of trade flows between countries [1]. WITS is compiled from several sources including UN Comtrade database, which provides to WITS detailed trade export and import statistics by commodities [1].

The main advantages to use WITS for the analysis of trade statistics are that it is free access, collects data since 1962, covers more than 170 countries and territories, contains various commodities, is regularly updated and converts all reported values into one unit (US dollars) using relevant exchange rates [2].

WITS (with UN Comtrade) also provides data in various classifications [3]. There are two main systems that are used in international trade statistics: the Harmonised System (HS) and the Standard International Trade Classification (SITC). There are no recommendations on the usage of specific classifications. The only recommendation is to use SITC if a researcher wants to analyze time series as it provides data from 1962, and to use HS if a researcher wants to consider more detailed goods categories. The first survey of the National Compilation and Reporting Practices (NCRP) that was conducted between 1992 and 1995 shows that among 148 countries 77% of respondents use HS classification, while 65% use SITC classification (53% of them use both classifications) [4].

WITS Comtrade provides with bilateral trade data, where both partners are expected to report the values of a particular flow between them. However, for a huge number of flows only one partner reports its statistics and we do not have the mirror value. Another problem that arises here is that for the rest of the flows where both partners (exporter and importer) report their versions of a flow value we obtain two different reported statistics that may differ significantly.

There are several explanations to such discrepancies [5]. For instance, countries may report their statistics in different trade systems or reported values may be received with some time lag. Moreover, export and import values usually include transportation and insurance costs: FOB (Free On Board) values for export and CIF (Cost, Insurance and Freight) for import. FOB and CIF values may represent some difference (10% - 20%), and CIF values are usually higher than FOB values, but numerous flows differ is more than 20%.

One of the easiest solutions to the raised problem is to follow exporters statistics or importer statistics exclusively. The main advantage of this approach is that one does not mix CIF and FOB values that are in different dimensions.

However, in this solution we miss a vast number of flows as not all countries report their statistics. In order to keep information about all mentioned flows we need more accurate approach to this problem.

Number of studies investigate a problem of CIF/FOB correspondence, which is an important stage in the process of understanding discrepancies in trade data. The assessment of CIF/FOB ratio allows us to reduce trade data to one dimension. The Direction of Trade Statistics of International Monetary Fund (DOTS IMF) database [6] provides with estimated trade statistics, that imputes missed values in trade data. Previously, DOTS IMF used a fixed percent of CIF/FOB factor for the conversion of export and import values, and currently they apply the splicing approach based on prior data [7]. In [8] it is analyzed whether the matched partner CIF/FOB ratios from DOTS IMF are applicable for the assessment of transportation costs. Authors compared the estimated CIF/FOB ratios with real values of transportation costs for the US and New Zealand and concluded that IMF CIF/FOB ratios are not useful for this purpose but might be helpful as intermediate value.

There also exist other world trade databases that provide with detailed statistics as WTO [9], OECD [10], BACI [11], etc. Despite the fact that most of these databases propose their own methodologies that overcome the problem of missing values in data or asymmetries in bilateral statistics they also have many limitations. For instance, OECD proposes an approach to the problem of asymmetries in international merchandise trade statistics [12]. However, the balanced data is available only for 121 countries from 2007 to 2016 and for particular commodities. Additionally, most of the databases are based on the initial UN Comtrade bilateral statistics. Other approaches that deal with asymmetries in trade data are discussed in [13].

In our work we propose new approach that can be applied to any time period and commodity in UN Comtrade statistics. We believe that our methodology might be helpful and practical for the trade analysis as well as be employed as complementary factor for other approaches that deal with the problem of asymmetries in trade data.

III. UN Comtrade Trade Data Processing

In this work we analyze gross exports between countries according to HS1996 nomenclature. We mainly focus on year 2018 but other time periods have been analyzed as well. As the main goal of the work is a network analysis of trading relations between countries we eliminate all special territories from the data such as Free Zones, Bunkers, Neutral Zone, areas not elsewhere specified, unspecified territories and special categories [14]. After this elimination 235 territories and 30 875 bilateral flows are left in data for the further analysis.

On the first stage we can reduce export and import statistics to unified scale (for example, FOB values) according to any appropriate methodology [13]. We consider data as given. Next, we discuss the process of network construction from the obtained trade data.

All flows between countries are in one of the two states: both partners suggest their own versions of the flow between them or only one partner suggests its own version of a flow between them. For global trade in 2018 there are 13 631 flows reported by exported countries, 24 362 flows reported by imported countries. 6 513 flows are reported by exported countries exclusively and 17 244 flows are reported by imported countries exclusively. Hence, 7 118 flows are reported by both partners.

In case when only one partner reports a value of a flow we use the represented statistics as the weight on the corresponding directed edge in a trade network. The only exception are outliers in data (see Subsection III.A). For global trade data in 2018 when only one partner reports its value we use export statistics 3 452 times and import statistics 8 295 times, which covers 38% of all flows.

For the rest of flows where both partners report their statistics we need to choose one value of the weighted edge between them. Ideally, both partners should report relatively equal values. However, if we look at the initial data for 2018 only 17% of all bilateral values differs in less than 20% (relatively to minimal of the reported values) while the maximal difference between reported statistics differ by the factor of 699 457. Such huge discrepancies occur due to the fact that one of the partners reports extremely small value that is close to 0, which usually refers to some error in reporting statistics. Hence, our first goal is to detect such outliers in our data. Fig.1 represents the distribution of the fraction of the maximal reported flow value to the minimal reported flow value. We can see the huge diversity in reported statistics and the number of inconsistent flows. In green we represent flows that differ in less than twice and in red we represent flows that differ in more than twice. The vertical blue line indicates the threshold of 20% divergence.

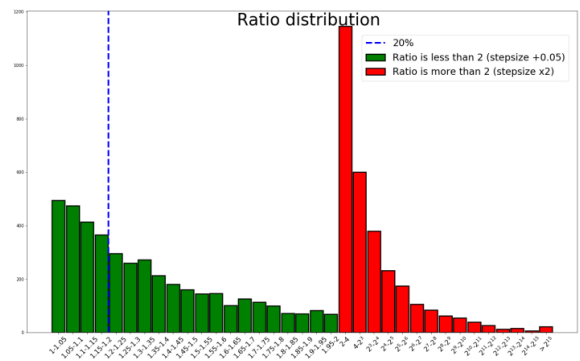


Fig. 1. Distribution of max value / min value.

A. Outliers Detection

Outliers are isolated instances of extraordinary large or small values. For the outliers detection we use flow distributions among all reported values for export and import statistics separately. In order to detect outliers limits, we firstly exclude tails from the distributions in order to make the following calculations unbiased. In other words, for both export and import samples we keep values that are between the k -th and K -th percentiles, where k and K are tuning parameters. Next, for the truncated sample we calculate trimmed mean value of a flow (mean export and import values). We denote by $M_{exp}(k, K)$ a trimmed mean export value and by $M_{imp}(k, K)$ a trimmed mean import value, where both variables depend on parameters k and K . Both $M_{exp}(k, K)$ and $M_{imp}(k, K)$ are stable in relation to outliers, which means that these variables determine mean volume of trade more precisely than mean values calculated for the whole samples.

Finally, we consider a reported statistics of export (import) as an «extremely small» if its value is less than $q\%$ of a trimmed mean value $M_{exp}(k, K)$ ($M_{imp}(k, K)$ correspondingly), where q is also a tuning parameter. Hence, all values higher than this measure are considered as consistent. Further, we consider a problem of data cleaning for «extremely small» values as this problem for «extremely large» values can be solved in a similar way.

For our data of global trade in 2018 $M_{exp}(5,95) = \$ 83\,050\,460$ and $M_{imp}(5,95) = \$ 97\,100\,139$ and we if we take $q = 1\%$ it means that we consider a reported export value as «extremely small» if it is less than $\$ 830\,504$ and import value as «extremely small» if it is less than $\$ 971\,001$. Other values we denote as consistent. In our analysis we do not detect «extremely large» values.

As the result, if one of the partner reports «extremely small» statistics with respect to the obtained values while the other partner reports a consistent statistics then we take a consistent data as the weight on the corresponding directed edge in a trade network (*for global trade in 2018 this occurs in 753 cases*). In case when both countries report “extremely small” values or one of the partner does not report any statistics while the other partner reports an “extremely small” value we eliminate this flow from consideration (*for global trade in 2018 this occurs in 14 212 cases*). Despite the fact that we eliminate such a huge number of flows, the sum of eliminated flows is equal to 0.008% of the total sum of global trade both for export and import statistics. The last step helps to reduce the density of a network almost by the factor of two, which significantly declines the complexity of calculations but does not affect the quality of the results.

The rest mirror data are left for the further analysis of the unique value determination.

B. National Compilation and Reporting Practices

The second type of difference in data occurs when both countries report consistent values and we need to decide whose data we should take as a unique flow value.

Similar values for the same flow are reported rarely. It is acceptable when flow statistics differs within 10-20% as export and import values take into account different factors besides selling and buying of a product itself [5]. However, a huge amount of data differs significantly due to external factors and errors. Official sources, that provide trade data, do not give recommendations about the choice of a unique value. WITS WorldBank suggests to choose a value of a partner for which a researcher believes statistics is the most accurate [5]. The opinion of a researcher about the accuracy of countries statistics is usually very subjective. Hence, the need of an objective method of mirror data processing arises.

In this work we consider data that are collected by UN Statistical Division for WITS Worldbank. Thus, we believe that it is reasonable to address to UN sources regarding the quality of represented data. As we already mentioned above, UN conducts a regular survey among different countries about the practices of a statistics reporting [4]. The first survey was conducted in 1996 and the second one (and currently the last one) was conducted in 2006, which was released in 2008. 132 countries participated in the last survey and they were asked to answer 173 questions about reporting practices. All questions require absolute answer (yes/no) and for some of the questions a respondent may leave comments. The questions are divided into 13 sections, where each section is responsible for a particular area. Some of the questions rely to the inclusion and exclusion of different factors that form a flow value, another block of questions refers to trading systems, it is also asked about means of transportation, etc. The main feature of this survey is that UN gives answer recommendation for 107 questions, i.e. it indicates which answers are correct if the statistics is reported in accordance with international standards. Hence, UN gives recommendations about reporting practices and the results of a survey show how each country follows these recommendations.

Since countries follow UN recommendations differently we need to define quality factor of reporting practices. In this work we define the set of countries whose reports meet UN standards at most in the following way. We choose countries whose answers correlate with recommendations on more than $x\%$ while the proportion of not coincident answers is less than $y\%$, where x and y are tuning parameters. Additionally, several countries do not answer some of the questions due to the fact that they are not relevant for these countries or otherwise. This is why both parameters x and y are essential as $x + y \neq 100\%$. We also assume that countries answer the questions fairly as the source of the survey is reliable and there is no opportunity to check the inaccuracy of countries. As the result, we can define the set of countries that properly report their trade statistics and follow recommendations at most. We call this set of countries as Sustainable Group (SG), i.e. this is the set of countries whose answers coincide with recommendations on more than $x\%$ and differ on less than $y\%$.

In current work we consider all questions that have recommendations and take $x = 70\%$ and $y = 20\%$. As the result, 40 countries occur in set SG .

C. Coherence of Reported Statistics

In general, not all countries occur in SG . Moreover, some of the countries did not take part in the NCRP survey and we cannot claim without objective reasons that such countries are not reliable. Hence, we need to assess how the statistics of these countries differ from the statistics reported by countries from SG . In other words, we propose a metric that reflects the statistics coherence of countries that do not belong to SG with countries from SG . We analyze each country as an exporter and as an importer of goods separately.

Consider two trading countries A and B . We denote by $A \rightarrow_A B$ a flow from A to B according to the statistics of country A (export value) and by $A \rightarrow_B B$ a flow from A to B according to the statistics of country B (import value). We assume that both countries agree that there is a flow between them that is equal to $\min(A \rightarrow_A B, A \rightarrow_B B)$, i.e. this value is reported by both countries and in addition one of the countries reports beyond. This measure indicates the consistency of a flow between countries A and B .

As the result, for each exporter $A \notin SG$ and all importing countries from SG , where A exports to, we can calculate the total amount of consistent flows and, consequently, the metric of coherence for exporter A is calculated as the ratio of consistent flows. More precisely,

$$C_{exp}(A) = \frac{2 \times \sum_{B \in SG} \min(A \rightarrow_A B, A \rightarrow_B B)}{\sum_{B \in SG} A \rightarrow_A B + \sum_{B \in SG} A \rightarrow_B B}. \quad (1)$$

Denominator in (1) is the sum of the total export from country A to countries B by the version of country A and total export from country A to countries B by the version of countries B . Accumulation factor 2 in a numerator normalize the metrics over the range $(0; 1]$ and $C_{exp}(A) = 1$ when the statistics of country A completely coincide with the statistics of its partners from SG . In a similar manner we also determine $C_{imp}(A)$.

Interestingly that most of the export coherence values belong to $[0.5; 1]$ while import coherence values are more in $(0; 0.5]$, which means that export statistics is more accurate than import statistics.

D. Choice of the Unique Value

As a consequence, we use two factors in order to define weights on corresponding directed edges in a trade network: the appearance of one of the partners in *SG* and coherence metric of trading with countries from *SG*. Below, we consider all possible alternatives of divergence in data and determination of a unique value in each case. For each option we also provide the number of cases (in brackets) for global trade data in 2018.

- 1) In case when both partners belong to *SG* we take the statistics of a more reliable country, i.e. a country that gives more correlated answers with UN recommendations (*we take export data in 196 cases, import data in 283 cases*). If the number of coincident answers is the same for both partners then we took the statistics of a country that gives less not coincident answers (*we take export data in 9 cases, import data in 9 cases*). Otherwise, in case of equal numbers of coincident and not coincident answers for both partners a researcher may choose the statistics of any partner or calculate and compare the coherence metric for both partners (*no cases*). One can also use coherence metric in this part.
- 2) Secondly, if one of the partners belongs to *SG* while the other one does not belong to we choose the statistics of a country from *SG* (*we take export data in 1 158 cases, import data in 992 cases*).
- 3) In case when both partners do not belong to *SG* we compare their coherence metrics of trading with countries from *SG* (*we take export data in 1 562 cases, import data in 707 cases*). There is little likelihood that the values of both countries are equal. In this case a researcher may choose a statistics of any partner or compare their answers to NCRP survey with relaxed parameters x and y (*no cases*).
- 4) There also exist a possibility that both partners did not participate is the NCRP survey and they do not trade with countries from *SG*. This means that it is impossible to calculate the coherence metric. In this case a researcher may choose a statistics of any partner (*no cases*).

The final distribution of estimated flows is represented in Fig. 2 along with initial export and import distributions. As we can see, we eliminated left tail from consideration while the represented distribution remains the same (in terms of shape) as for export and import values.

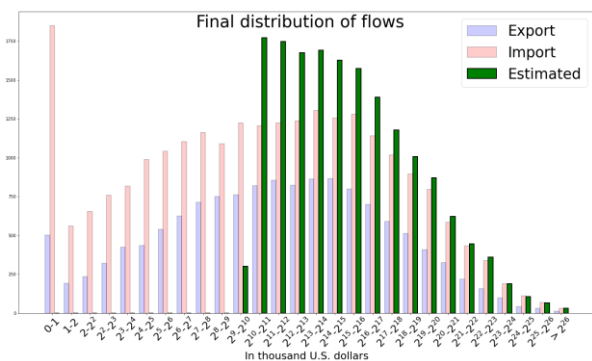


Fig. 2. Estimated flows distribution for 2018.

As the result, some values are derived from export statistics and other values are derived from import statistics. Presiesly, the final estimated data consist of 38% export statistics and 62% import statistics (including one side data). If we consider all flows where both values are given then we use export data in 59% and import data in 41%.

IV. Network Analysis of Global Trade

In this Section we provide with the basic network statistics of global trade data that is obtained above. We

compare the results with two networks constructed on export and import statistics exclusively.

The key network statistics (the number of edges, density, strongly and weakly connected components (SCC and WCC), weight of a network and maximal weight) are represented in Table 1. The number of nodes is equal to 235 for all three networks.

TABLE I. KEY NETWORKS MEASURES (GLOBAL TRADE NETWORK 2018)

Measure	Export	Import	Estimated
# edges	13 629 ^a	24 356 ^a	16 662
Density	0,25	0,44	0,30
# SCC	96	95	9
# nodes in giant SCC	140	141	227
# WCC	3	1	4
# nodes in giant WCC	233	235	232
Max. weight	\$ 563 bln.	\$ 314 bln.	\$ 563 bln.
Sum. weight	\$ 8,4 tln.	\$ 18,3 tln.	\$ 18,7 tln.

^a Flows with 0 weight implies the absence of the edge.

According to Table 1 we can see that estimated trade network has more connections that export network (as we use mirror data in estimated network) and less connections that import network (as we eliminate edges with small weights). However, the aggregated weight of a network is larger for estimated case that for export and import ones. Another important point is that our approach allows to considerably reduce the number of strongly connected components and as the result we obtain one giant component that is vastly larger than in export and import networks. On the other hand, in estimated network we obtain more weakly connected components. The reason is that after the elimination of edges with small weights we get three isolated nodes (these are Br. Antr. Terr, Heard Island and McDonald Islands and Pitcairn).

The key difference between estimated and export/import networks is that estimated network does not contain weak edges. For instance, in-degree (Fig. 3) distribution shows that the edges with small weights (from 0 to \$ 1 000) stand out from the main distribution and may be considered as errors in data. Such results demonstrate the consistency of outliers detection step.

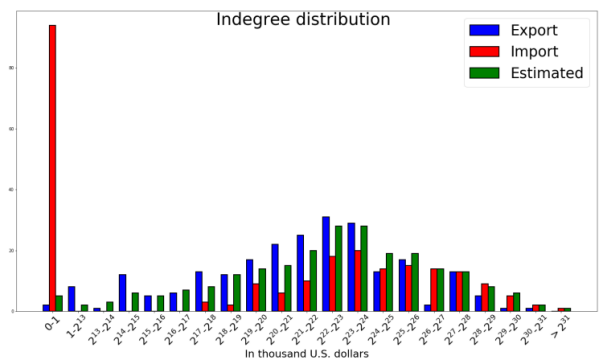


Fig. 3. Indegree distribution for global trade network in 2018.

In order to statistically compare all three networks we also estimated the edge correlation between them and obtain the following results. For global trade network 2018 Pearson correlation of weighted edges between export and estimated networks is equal to 0.48 while the correlation between import and estimated networks is equal to 0.997. Such results confirm the fact that our network is closely related to import network. We also analyze global trade networks for other years (from 1996 to 2018) and obtain identical results (Person correlation coefficient for import and estimated networks varies between 0.995 to 0.998). Such high correlations confirm the state that imports are usually recorded with more accuracy [5] and our choice is justified.

Despite such a high similarity of estimated and import networks there are still a lot of statistical and structural

differences. In order to justify this fact we also analyzed connections within each continent separately. For instance, weighted edges between African countries in 1999 correlates with import subgraph at the rate of 0.49 while correlation with export subgraph reaches 0.91. Despite the fact that the total weight of all edges within African continent covers 0.15% of the total trade we believe that detailed analysis of mirror data is essential for all levels of interactions.

V. Conclusion

This work aims to analyze the problem of asymmetrical trade data. In order to construct a network of trade relations between countries we need to define a unique value on each edge. However, in initial trade statistics both partners report their own versions of a flow between them, that are frequently differs several hundred-fold.

We propose an approach that allows to define the most plausible value for each existing trading flow between countries and territories. Our methodology consists of several steps. The first step includes outliers detection, i.e. such values of export and import statistics that we consider as “extremely” small. At this stage we analyze export and import distributions and select a threshold that defines the values of outliers. As real data have shown, this step allows to considerably reduce the number of edges and make our network more sparse.

Next, we address to the official UN NCRP survey. It shows the accuracy of countries in the matter of reporting export and import data. The key advantage of using this source is that UN gives recommendations to 107 out of 173 questions. In other words, we can range countries with respect to the number of correctly given answers. At this stage we form a set of countries that we call as Sustainable Group.

As not all countries participate in NCRP survey and only few of them are included in Sustainable Group we propose additional approach of detecting the most accurate countries in terms of reporting export and import data. Precisely, we construct coherence metric that separately analyze exporters and importers. This metric indicates the level of coincident reported values of a country with trading partners.

Finally, we choose a unique value using the obtained information about countries reported data.

The proposed approach is applied to real data of global trade from 1996 to 2018. We analyze the obtained estimated networks and calculate key network statistics. The estimated networks are compared with networks constructed on export and import data exclusively. The key difference between the estimated network and export/import networks is that estimated network does not contain unimportant flows with small values while export and import networks contain these flows in large numbers. Another distinction refers to the number of strongly connected components that is lower in estimated network. Hence, we can conclude that estimated network is more sparse in terms of weak connections but it also contains more strong linkages as the number of strongly connected components significantly decline.

We also calculate correlations of weighted edges between estimated network and export/import networks. The results show that estimated network of global trade is almost identical with import network and correlation coefficient lies between 0.995 to 0.998 for networks from 1996 to 2018. Such results confirm the fact that import statistics is more accurate than export statistics. One can argue that we can analyze trading relations based on import data exclusively and do not analyze flows from the point of their consistency.

However, we believe that detailed analysis of mirror data is sufficient. We analyze the correlation of estimated and export/import relations among different subgraphs (based on territorial allegiance) and conclude that for some of the considered subgraphs the rate of correlation is much higher between estimated and export relations than import relations.

At this point we also note that detailed analysis of different commodities is also essential. Global trade network does not distinguish between different goods and services while partition among commodities may cause additional errors in data. The preliminary analysis shows that estimated networks of particular commodities trade is less correlated with corresponding import network than in the case of global trade network.

One of the advantages of the proposed methodology is that it does not depend on product type. Thus, in further research, we are to apply our approach to different commodity statistics and study the obtained networks in more details. Moreover, some stages of our approach can be applied to other data with asymmetrical statistics.

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