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Global E-waste Trade Network Analysis

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Abstract

In this paper, a study for Waste Electrical and Electronic Equipment (WEEE) trade is conducted by using graph theory. In specific, exports and imports for UN COMTRADE data code 854810 which corresponds to waste and scrap of prim cell are collected for 175 countries around the world, spanning the period from 2002 to 2014. WEEE trade networks are generated for each year and communities are produced applying spinglass community detection algorithm. Communities are compared with groups of countries produced by applying detection community algorithms on networks based on common currency, differences in CO_2 levels, geographical distances, common Language, colonial ties, and regional trade agreements (RTA). An estimation of the factors that affect key network metrics has also been conducted, using a random effect linear regression. The model assesses the effect that economic, environmental, geographical, and social, as well as intra-country commercial agreements have on degree of nodes, betweenness score, and clustering coefficient. The

results indicate that communities of WEEE trade network are very similar with groups produced by clustering countries regarding CO2 emissions and distance. Distance, contiguity, common currency, colonial ties, common language, and differences in CO_2 levels tend to affect significantly the degree of countries engaged in WEEE trade network. Betweenness score is affected only by common currency while clustering coefficient by common language and CO2 levels between countries. A statistical validation of WEEE network, with Erdos - Renyi, Small - World and Scale - Free networks, was conducted. The results reveal that in, cycle and middle clustering coefficients of Erdos - Renyi and Small - World networks were statistically equal to the corresponding of WEEE network for the period 2004 - 2008, while Scale - Free's out and clustering coefficients, coincided with WEEE's across all years.

Keywords: e-waste trade, Graph theory, Normalized Mutual Information, Mixed Effect Linear Models, Bootstrap.

1. Introduction

The importance of Waste Electrical and Electronic Equipment (WEEE) examination does not only lie on the environmental aspect, but it is also due to the fact that it contains a lot of materials with great financial value. However, attention should also be given on the flows of materials from one country to another, because these flows are not always based on inter or intra country agreements, but on other factors which have not been examined in detail, as for instance, employement generation, legislation, geographical location, differences between communities in income, etc. (Estrada-Ayub and Kahhat, 2014).

Lepawsky and McNabb (2010) were of the first to be engaged with the flows of e-waste trade, using data for exports and imports for many time periods. They

examined the assumption that rich countries are more likely to export rather than import WEEE and concluded that reality is more complex than that.

In this paper, WEEE trade flows between countries are considered as complex structures which, in the relative literature, are called graphs or networks. Under this hypothesis, that trade is a network, with flows of WEEE (edges) connecting countries (vertices), better insights are provided for the factors that affect countries' decisions to export or import such materials.

Although, this complex structure of trade interactions between countries has been examined in relative gravity model research articles, there is a limited amount of research focusing on the determinant factors that affect the segmentation of such networks into partitions, called communities. Furthermore, the majority of research papers examine the factors affecting the probability that countries either export or import trade quantities, while this paper focuses on the factors that affect some key network characteristics.

The structure of the rest of the paper is as follows: Section 2 summarizes the findings of literature review, while Section 3 provides the methodology followed in this study. The results are given in Section 4 and finally, conclusions and practical implications are concisely given in Section 5.

2. Literature Review

WEEE is a complex mixture of discarded equipment referring to about 900 electrical and electronic products in 58 different categories worldwide (Wang et al., 2012a). This type of waste, representing about 5% of the total solid waste, is one of the fastest growing and most hazardous waste streams in the world. In order to minimize the serious adverse effects of hazardous discarded electronic products, material recovering processes, and landfills, there is in progress a global trade of e-waste (although

WEEE and e-waste have a difference in their meaning, they are used interchangeably in this paper) collected mostly in North America and Europe and exported to developing countries. This practice is in contrast to the Basel Convention on the control of transboundary movements of hazardous wastes and their disposal (entered into force on 5 May 1992), which requires that participating countries will have to dispose of wastes as near to the source of production as possible (Wirth, 1998). But, as Robinson (2009) mentioned, exporting countries often violate international treaties concerning the transport of hazardous e-waste. Lepawsky (2015) pointed out that, estimating the volume of the international trade in e-waste is really a challenging issue since there is no single definition of e-waste as a trade category, as well as because there is a substantial traffic of e-waste in the so-called "zones of ambiguity", which is very difficult to be estimated. Awasthi and Li (2017) argued that China and India are the two countries which mostly suffer from illegal WEEE imports. The developed countries are shipping out their used EEE by labeling them as electronic goods (Huisman, 2008) or as donations to institutions in these countries (Puckett et al., 2002). Breivik et al. (2014) mentioned in their work that, it has been argued that the international trade of used EEE facilitates digital divide bridging, i.e. minimizing the disparity in the adoption of ICTs between developed and developing countries. Moreover, export of used EEE to less prosperous regions represents a reallocation of resources as raw materials, spare parts, valuable metals etc., which generate significant economic activity. According to Ibitz (2012), several Asian countries have allowed e-waste imports aiming to obtain raw materials for their domestic production of electronic goods. A technical approach that could create revenues with low environmental impacts for developing countries was proposed by Wang et al. (2012a) and Wang et al. (2012b). This paper introduced the 'Best-of-2-Worlds' philosophy, which could be a solution for sustainable e-waste treatment in developing countries.

This approach consists of pre-processing locally e-waste domestically produced by manual dismantling and forwarding critical output fractions to global state-of-the-art facilities. From the perspective of e-waste exporters, Tong and Wang (2004) examined the transboundary movement of e-waste and argued that it is driven by two forces: (i) the disassembly of discarded electronic products is labor-intensive with low value added, and (ii) compliance of exporting countries with the environmental regulations can increase the cost of disposal. Notwithstanding the potential economic benefits, there are tremendous risks to human and environmental health in the countries importing used EEE. In order to comprehend the magnitude of e-waste transport from developed to developing countries, Breivik et al. (2014) estimated that for 2005 the imports to the major recipients of e-waste globally (China, India, and five countries of West Africa) represented about 23% of the amounts of e-waste generated domestically in the OECD countries. In the context of addressing the lack of exact data on trade flows of e-waste, Kahhat and Williams (2012) followed a material flow analysis and estimated the percentage of exportation of used desktop and laptop computers from the USA in 2010, in the range of 6 to 29 %. Efthymiou et al. (2016) studied the factors that affect the choice of countries in which e-waste is illegally transported. They selected two kinds of factors: (i) macroeconomic, namely Gross Domestic Product (GDP) per capita and Open Markets Index (OMI), and (ii) social, namely Human Development Index (HDI) and Social Progress Index (SPI). Analyzing very briefly the above indicators, GDP per capita is one of the most known measures of a country's production divided by its population; OMI measures the openness of a county to trade; HDI is used to assess life expectancy, education, and a decent standard of living; lastly, SPI is calculated based on the categories of basic human needs, foundations of well-being, and opportunity. The results of the study of Efthymiou et al. (2016) indicate that both known and suspected ille-

gal flows take place from higher income to lower income countries; however, illegal e-waste trade is not only a matter of economic activity, meaning that other factors need to be taken into account, such as social development, legislation, and success of law enforcement. Lepawsky and McNabb (2010) also found that e-waste trade transactions tend to occur when the importer has a lower GDP per capita than the exporter. Expanding the previous work, Lepawsky (2015) found, that apart from the international trade of e-waste, there are highly regionalized patterns of trade within the Americas, Asia, and Europe. Based also on the forecast of Yu et al. (2010), that the amount of e-waste produced in developing countries will exceed a lot in the future the amount produced in developed countries, it can be inferred that e-waste flows are becoming complex and the flows from the developed to the developing world are not any more the most important. There are also many other studies which highlight that in some populous developing countries, such as India and Brazil, the amount of e-waste produced will surpass that amount in the most developed and developing counties (Sthiannopkao and Wong, 2013). In another work, Kusch and Hills (2017) examined the relationship between e-waste and GDP in the countries of the pan-European region and they found evidence of a strong linear relationship between economic development and e-waste generation. Kumar et al. (2017) also found that GDP of a country has a direct correlation with the amount of e-waste produced by that country; another correlation was found between e-waste generated by each inhabitant and their purchasing power. E-waste is characterized by high economic elasticity, implying that an increase of economic development will result in a corresponding increase of e-waste amounts. They proposed that GDP at purchasing power parity (GDP PPP) can be effectively used for forecasting future e-waste flows. Fan et al. (2005) compared the e-waste management system of five importing countries, namely China, Finland, Belgium, France, and USA, which handled,

in that period, more than 80% of the waste exported from Taiwan. China is the second largest e-waste generator following USA, as mentioned in Yu et al. (2017). Materials, which were considered as hazardous waste in Taiwan, were regarded as the seventh class of recyclable materials and accepted in China; in addition, a three-level review system was used concerning waste import and plant permission. In the three countries members of the EU, similar procedures were followed based upon the EU directives (e.g. all the documents associated with waste import and export required the approval of the governments of both countries). Lastly, in the USA, the procedures of hazardous waste import relied on bilateral agreements. Rochman et al. (2017) tried to understand the roles of formal and informal actors in the flows of e-waste in Yogyakarta, Indonesia. Their findings revealed that informal actors play an important role, inversely proportional to their profit margins, in the current e-waste system; thus, they should be incorporated into the new regulatory and management schemes of Indonesia. Bisschop (2012) also tried to determine the roles of the actors involved in an e-waste transport system. She identified three categories of factors that could assist in understanding how and why illegal transports of e-waste occur: (i) push factors, i.e. forces that drive illegal transports away from their source, (ii) pull factors, i.e. forces that draw illegal transports to their destination, and (iii) facilitating factors, i.e. whatever makes illegal transports possible. She concluded that transport actors walk on a thin line between legal and illegal, thus allowing illegal transports of e-waste to take place. According to Bisschop (2012), economic, cultural, political, and social motives and opportunities together determine the illegal e-waste flows. There are formal directives aiming to facilitate the design and production of electronic products that are safe and easy to dismantle and recycle, which will also have implications on the transboundary e-waste flows (Ilankoon et al., 2018); however, these apply only regionally and do not cover all the hazardous substances used

in electronics equipment (Ladou and Lovegrove, 2008). Evidence can be found in Li et al. (2015). Two of the most important directives intended to address the problem of the continuously increasing e-waste stream are the Restriction of Hazardous Substances (RoHS) Directive (European Commission, 2018a) and WEEE Directive (European Commission, 2018b). RoHS was established in the EU in 2002, aiming to restrict the use of six hazardous substances in electrical and electronic products. In 2011, the EU published RoHS 2, by which RoHS compliance is required for CE marking of products. Later, in 2015, RoHS 3 was published by the EU, adding four substances to the list of six restricted substances. Finally, the WEEE Directive was established in the EU in 2012 (inception in 2002), aiming to create a new management program that could have significant implications for the design and production of electronics equipment. The overall aim was for the EU to recycle at least 85% of e-waste, thus leading to a considerable decrease of the amounts of waste exported to developing countries.

3. Methodology

3.1. Data collection

Following the work of Lepawsky (2015), in order to examine in deep the network based on e-waste trade between various countries around the globe, we collected data for $N = 175$ countries concerning exports and imports' trade values (measured in US dollars), of HS 2002 code 854810 from UN COMTRADE online database (Comtrade, 2015). The combined result is the construction of a database which counts 11,640 points and spans from 2002 to 2014 ($T = 13$ years). As mentioned in Lepawsky, (Lepawsky, 2015) the choice of collecting data for code 854810, instead of searching in national customs or national statistical agencies, ensures not only that data are

reliable due to the fact that they are not produced by estimation techniques (Grant and Oteng-Ababio, 2012) or concern only a territory, but also they are publicly available and easily accessed (Duan et al., 2013), making research findings reproducible. However, collecting data for 854810 HS 2002 code, which includes waste and scrap of primary batteries and electrical accumulators, does not ensure that the majority of e-waste categories have been covered. Kahhat and Williams (2012) have raised issues regarding how well this category reflects solely a group of e-waste products. This argument, although true, does not reduce the reliability of the collected data neither provides a solution to a well known problem, which is the construction of a database reporting exports and imports between countries for each e-waste category. Such attempt has been done by Eurostat, however countries included and years spanning are rather limited.

In order to investigate whether the decision of some countries to export e-waste is randomly taken or it is based on several exogenous variables, data for explanatory variables were collected from various databases. In specific, variables which concern the geographical traits of countries are distances (Estrada-Ayub and Kahhat, 2014), common language, colonial ties, and contiguity between countries. Data for those variables have been extracted from GeoDist CEPII database (Mayer and Zignago, 2011). Distance, d_{ij}, is measured in kilometers, while common language, colonial ties, and contiguity are dummy variables.

The second set of exogenous variables concerns differences in economic situations between countries which are engaged in trade and it includes Regional Trade Agreements and existence of common currency. Data concerning regional trade agreements, $RTA_{ij,t}$ between countries i and j concerning HS 2002 code 854810 and spanning from 2002 to 2014 have been retrieved from World Trade Organization database (Bartels and Ortino, 2006). The existence of common currency between countries i

and j is a dummy variable receiving values, 1 if countries use the same currency and 0 otherwise. Lastly, we operationalize both industrial activity and environmental "burden" by using the level of CO_2 emissions measured in kg per 2010 US dollar of GDP.

GDP was not used in the present study as independent variable, due to the fact that GDP is a hidden (explanatory) variable for nodes degree which is a power law, hence high degrees are connected with low degrees. This is always true independently of the sector/level of aggregation, according to Garlaschelli and Loffredo (2004).

3.2. Network construction and measures of similarity

Trade between countries is depicted using graph theory analysis as a network. Due to the fact that, the trade intensity from country i to country j is not always the same as the trade intensity from country j to i, we construct a weighted and directed network based on trade values of exports and imports of e-waste between several countries. Let $\mathbf{M}$ be a square adjacency matrix, whose entries, $m_{ij,t}$, are trade value transactions between countries i and j at year t. Rows of $\mathbf{M}$ present the exporting country while columns the importing country. Let G be a graph, with N nodes and E vertices established between nodes, namely $G(N, E)$ depicting interactions of trade between countries.

Afterwards, countries are classified into communities, using a community detection algorithm. Communities are groups of nodes, which in the case of this research are countries, whose interactions between them are so intense within community, rather than with every other country outside of it (Newman and Girvan, 2004). Construction of communities is implemented using a technique which maximizes modularity, a quantity which measures whether the produced community is a good partition of the network (Arenas et al., 2007). Modularity is given as follows:

$$Q = \frac{1}{M} * \sum (m_{ij} - \frac{m_j^{in} * m_i^{out}}{M}) * \delta(c_i, c_j) \tag{1}$$

where, m_{ij} is the weight of the link between countries i and j, $M = \sum_i \sum_j m_{ij}$ is the total trade volume, $m_j^{in} = \sum i m_{ij}$ while $m_i^{out} = \sum j m_{ij}$ denote output and input strengths of nodes i and j. Lastly, $\delta(c_i, c_j)$ is a dummy variable, which is 1 whenever i and j belong to the same community and 0 otherwise.

Communities of countries were not constructed only for e-waste trade network, but also for networks based on geopolitical traits, which are distance, contiguity, common language, regional trade agreements, common currency, colonial ties and differences in CO_2 levels between countries.

Except for the communities produced by applying the detection algorithm, the group of countries which have common characteristics were also constructed.

In specific, undirected and weighted networks are constructed for all explanatory exogenous variables, in which entries of adjacency square matrix $\mathbf{W}$ are $w_{ij,t} = w_{ji,t}$. Community detection algorithms were applied to group of countries according to their geographical distance, which is modeled as $D_{ij} = \frac{1}{\sqrt{d_{ij}}}$, as well as number of regional trade agreements between them. In case of binary variables, such as contiguity between countries, existence of common official language, colonial ties, and common currency, the produced network is undirected, yet unweighted, due to the fact that weights are either 0 absence of common characteristic or 1 presence of common characteristic.

Networks for differences of CO2 were based on the inverse of the absolute difference of CO_2 for each combination of countries and time, $\Delta CO_{2ij,t} = \frac{1}{|CO_{2i,t} - CO_{2j,t}|}$. Produced graphs were assumed to be weighted and undirected (Barigozzi et al., 2011). At a final stage, community detection algorithms were implemented networks

based on inverse difference of CO_2 levels between exporting and importing countries engaged in e-waste trade network.

Lastly, we compare communities produced from e-waste trade network with the corresponding produced from networks constructed based on distance, contiguity, common language, colonial ties, common currency, RTA and CO_2 (Barigozzi et al., 2011), by applying modularity maximization detection algorithm, using *normalized mutual information* index, *NMI*. This measure defines the degree by which two groups are similar and is defined as Danon et al. (2005):

$$NMI(P_A, P_B) = \frac{-2 * \sum_{i=1}^{C_A} \sum_{j=1}^{C_B} log(\frac{N_{i.} * N_{.j}}{N})}{\sum_{i=1}^{C_A} N_{i.} log(\frac{N_{i.}}{N}) + \sum_{i=1}^{C_B} N_{.j} log(\frac{N_{.j}}{N})} \tag{2}$$

where N_i denotes the number of nodes of community i which belong to partition P_A and also belong to community j of the partition P_B. Values of *NMI* fall in the range from 0, which indicates that partitions P_A and P_B are dissimilar, to 1 which implies complete identity of compared partitions.

3.3. Network measures

Having constructed the network based on net export flows, we compute important network metrics which characterize the complex structure between countries. These key network characteristics are: i) total degree of nodes, ii) the betweenness score, and iii) the transitivity of nodes.

Total degree of a node is defined as the quantity of edges that a node possesses, namely how many other nodes a specific node is linked to. In the frame of this research, high degree of a node is interpreted as that the specific country is either exporting to many other countries, or importing from other countries of the world. In both cases, countries (nodes), which either heavily export or import, are influencers to the overall network structure. Usually, nodes that are characterized by high

degree value, seem to be too rich, that are exporting or too poor countries, that are importing e-waste from other countries. Total degree of nodes is defined as the sum of in and out degree, namely $k_{it}^{total} = k_{it}^{in} + k_{it}^{out}$.

Betweenness is a measure that describes the centrality score of a network. It is defined as the sum of all minimum routes from vertex A to vertex B that pass through a middle vertex C. Countries that serve as middle points in a network structure, namely they receive and simultaneously send large amount of e-waste, tend to have high value of betweenness centrality score and are called *hubs*. Mathematical formulation of betweenness centrality index is given below:

$$g(u) = \sum_{s \neq u \neq t} \frac{\sigma_{st}(u)}{\sigma_{st}} \tag{3}$$

In equation 3, $\sigma_{st}(u)$ denote the amount of shortest paths, which pass through node u, while σ_{st} is the number of all shortest paths.

Last but not least, transitivity between 3 nodes is defined as the number of triads that exist in a network. Let nodes i, j, and h, then they would be characterized as transitive if there would be a connection between i and j, as well as j and h, and between h and i. Networks that demonstrate high values of transitivity are characterized as *clustered* and in the frame of the present research this can be seen if countries form cliques between them. In the present study, due to the fact that e-waste trade networks are weighted, the total clustering coefficient index was used (Fagiolo, 2007):

$$\tilde{C}_i(W) = \frac{[W^{1/3} + (W^T)^{1/3}]^3_{ii}}{2[k_i^{tot}(k_i^{tot} - 1) - 2k_i^{\leftrightarrow}]} \tag{4}$$

The global clustering coefficient is defined as the ratio of the triangles and the connected triples in the graph, namely:

$$CC_{Global} = \frac{\lambda_G(u)}{\tau_G(u)} \tag{5}$$

where $\lambda_G(u)$ is the number of triangles on $u \in V(G)$, while $\tau_G(u)$ is the number of triples on $u \in G$.

Usually, this is obvious between countries that do not pose any restrictions on exports or imports from other countries, and indicative examples of this are the European Union (EU), NAFTA, and other regional or international trade organizations.

3.4. Statistical Validation of e-waste Networks

In order to statistically validate the results produced by the procedure explained above, we use three well - known graphs as null models.

The first one is the Erdős and Rényi (1960) graph model, which produces a random network. A $G(N, p)$ random graph model, indicates that the N nodes' probability of connection is equal to $p^M * (1-p)^{\binom{N}{2}-2}$, where M describes the amount of edges in the network and p defines probability for drawing an edge between two arbitrary vertices. Erdos - Renyi's degree distribution is binomial and is given as follows:

$$P(deg(u) = k) = \binom{N-1}{k} * p^k * (1-p)^{N-1-k} \tag{6}$$

where $P(deg(u) = k)$ is defined as the probability that node u will receive overall k edges incident to it.

The second graph, that served as a null model in order to statistically validate our results, is the Watts and Strogatz (1998) model, which provides the ability of producing from regular networks (lattices) to fully random ones. In specific, for the case of a regular network consisting of k edges, the rewiring probability p is equal

to 0, while for fully random graphs, the probability of connecting any two random nodes (p) is equal to 1. When probability of rewiring, lies between 0 and 1, namely $0 < p < 1$, it produces a semi - regular, semi - random network, which in the relative literature is called after "Small - World". When a network is completely regular, namely the rewiring probability p is equal to 0, average path length's value (L) is equal to $\frac{N}{2*k}$ and clustering coefficient's value (C) is approximately equal to $\frac{3}{4}$. On the other hand, when rewiring probability is equal to 1, average path length is equal to $\frac{ln(N)}{ln(k)}$ while clustering coefficient is given as $\frac{k}{N}$.

The last graph which was used as null model, is the scale - free network Barabási and Albert (1999). According to this model, the degree distribution follows a power - law distribution:

$$P(k) = k^{-\gamma} \tag{7}$$

where γ is the degree exponent. Several studies, investigated the potential similarity of networks produced by scale - free procedure with well - known graphs such as the World Wide Web (WWW), actors' collaboration, social media network structure, and many others.

The statistical validation procedure was conducted as follows:

Step 1: Let $\mathbf{W}$ be the matrix of weights in network, based on exports and imports of e-waste among countries. We re-sample those weights, by columns, using bootstrap technique and create a new matrix of weights,$\tilde{\mathbf{W}}$.

Step 2: The new weighted, directed adjacency matrix of strengths, ($\tilde{\mathbf{S}}$) results from the element - wise multiplication of bootstrapped weight matrix ($\tilde{\mathbf{W}}$) by the matrix obtained from applying null models ($\tilde{\mathbf{A}}$), namely $\tilde{\mathbf{S}} = \tilde{\mathbf{A}} * \tilde{\mathbf{W}}$, under the constraint that density should be approximately the same as the real networks.

Step 3: We conduct for each of the three null models described above, $\mathbf{B} =$ 5,000 replications, calculating in each step the following network metrics proposed by Squartini et al. (2011):

$$\begin{aligned}
\tilde{c}_i^{in} &\equiv \frac{\sum_{j\neq i}\sum_{k\neq i,j}(\tilde{w}_{ki}\tilde{w}_{ji}\tilde{w}_{jk})^{1/3}}{k_i^{in} * (k_i^{in}-1)} \\
\tilde{c}_i^{out} &\equiv \frac{\sum_{j\neq i}\sum_{k\neq i,j}(\tilde{w}_{ik}\tilde{w}_{jk}\tilde{w}_{ij})^{1/3}}{k_i^{out} * (k_i^{out}-1)} \\
\tilde{c}_i^{cyc} &\equiv \frac{\sum_{j\neq i}\sum_{k\neq i,j}(\tilde{w}_{ij}\tilde{w}_{jk}\tilde{w}_{ki})^{1/3}}{k_i^{in} * k_i^{out} - k_i^{\leftrightarrow}} \\
\tilde{c}_i^{mid} &\equiv \frac{\sum_{j\neq i}\sum_{k\neq i,j}(\tilde{w}_{ik}\tilde{w}_{ji}\tilde{w}_{jk})^{1/3}}{k_i^{in} * k_i^{out} - k_i^{\leftrightarrow}}
\end{aligned} \tag{8}$$

as well as normalized degree distribution ($\tilde{k}_i^{tot}$) for each simulated directed, weighted network.

Step 4: We validate the similarity of simulated null models with real networks per year, using empirical formulation of p - value, which is $\frac{\sum_{i=1}^{B} t_{it} > t_{obs,t}}{B}$, or $\frac{\sum_{i=1}^{B} t_{it} - t_{obs,t} > 0}{B}$ where $t_{it} = \frac{\overline{y_{null,t}} - \mu_t}{\frac{\sigma_{null,t}}{\sqrt{N_t}}}$, $\overline{y_{null}}$ is the mean value of network metrics assessed in each null model employed, μ is the corresponding value in real networks, σ_{null} is the standard deviation of network metrics assessed in each null model and N is the number of nodes in null model. In order to validate the similarity of normalized total degree distribution between null models and real networks for each year, Kolmogorov-Smirnov statistic was used.

In order to statistically validate the similarity of communities produced from networks formed in terms of a) Distance, b) Contiguity, c) RTA, d) Common Language, e) Common Currency, and f) differences in CO_2 levels between countries, we followed the same approach that was described earlier. We simulated $\mathbf{B} =$ 5,000 times each e-waste network and produced communities based on spinglass community detection

algorithm.

Then, we compared each community produced by applying detection community algorithm on undirected and weighted networks based on distance, contiguity, RTA, colonial ties, common currency, common language and differences in CO_2 levels between exporting and importing countries ($\Delta CO_{2,ijt}$), with e-waste networks' communities.

At the final stage, we calculate 97.5% confidence intervals, in order to provide with a limited range of values that NMI may receive, when comparing spinglass communities from e-waste trade network with communities produced based on the independent variables which were described earlier. Confidence intervals for bootstrapped method are given as follows:

$$\overline{NMI} - D_{2.5\%} * \frac{s_{NMI}}{\sqrt{B}} \leq \mu \leq \overline{NMI} + D_{97.5\%} * \frac{s_{NMI}}{\sqrt{B}} \tag{9}$$

In 9, $D_{2.5\%}$ and $D_{97.5\%}$ describe the 2.5% and 97.5% points correspondingly of the empirical distribution of NMI values and s_{NMI} is the sample standard deviation.

3.5. Linear mixed effect model

In order to evaluate the effect that independent variables have on network metrics described above, a mixed effect model was deployed. The use of mixed effect over a standard linear regression is preferred due to the fact that data structure is too complicated and therefore there would be no possibility to examine the specific traits that independent variables over time have on network measures. Let $\mathbf{y}$ be the response which is measured over the various e-waste networks produced by the procedure described above and $\mathbf{X}$ the matrix of independent variables, whose entries are distance between countries, d_{ij}, contiguity between countries i and j, $contig_{ij}$, existence of common official language between countries i and j,

$commonlang_{ij}$, existence of regional trade agreement between countries i and j at time t, RTA_{ijt} and difference in environmental deficit between countries i and j at time t, $\Delta CO_{2,ijt} =\mid CO_{2,it} - CO_{2,jt} \mid$. The linear mixed effect model can be formulated as follows:

$$\begin{aligned}
&\mathbf{y} = \mathbf{bX} + \mathbf{Zu} + \mathbf{e} \\
&\mathbf{X} = log(d_{ij}) \oplus Contig_{ij} \oplus RTA_{ijt} \oplus Colties_{ij} \oplus ComCur_{ij} \oplus Commonlang_{ij} \oplus \Delta CO_{2,ijt} \\
&\mathbf{e} \sim \boldsymbol{N}(\mathbf{0}, \mathbf{S})
\end{aligned} \tag{10}$$

In equation 10, $\mathbf{X}$ is the design matrix, $\mathbf{b}$ represents the vector of coefficients to be estimated using Restricted Maximum Likelihood (REML) procedure, $\mathbf{Z}$ is the design matrix for the random effects included in the model, while $\mathbf{u}$ is the vector of random effects used and $\mathbf{e}$ is the vector of residuals which are assumed to be normally distributed with mean 0 and variance - covariance matrix equal to $\mathbf{S}$.

In case where dependent variable, describes the difference of countries engaged in e-waste trade network total degree of (Model 1), then we record the value across each country and time period from $2002 - 2014$, namely $\mathbf{y} =\mid k_{it}^{total} - k_{jt}^{total} \mid$.

Likewise, in case where we investigate the effect of independent variables on differences of betweeness score (Model 2), then the dependent variable is $\mathbf{y} =\mid g(u)_{it} - g(u)_{jt} \mid$.

For the case of linear model, which assesses the impact of independent variables on differences of transitivity scores (Model 3), dependent variable is $\mathbf{y} =\mid C(W)_{it} - C(W)_{jt} \mid$.

Assuming that the majority of the independent variables do not change over time but over different countries, random effect is included only in the intercept

term. Estimation of linear mixed effect model was conducted in R (CRAN) by using the lme4 package (De Boeck et al., 2011).

4. Results and discussion

4.1. Data descriptive statistics

In this section, an overview analysis of the dataset used is presented. In Fig. 1, the violinplot presents the distribution of distance and CO_2 based on Regional Trade Agreements (RTA). It can be seen that the median of the distance of each country for all periods, is slightly higher among the countries without any RTA comparing to the ones with RTA. This finding suggests, that countries which are distant one another, are less probable to sign trade agreements, compared to those whose geographical distance is small.

Regarding the CO_2, it can be seen that the median for all countries and periods is approximately the same among the countries without any RTA comparing to the ones with RTA. However, exporting countries, or else reporters, which tend to have a large value of CO_2 levels, are less probable to sign regional trade agreements with countries, with low levels of environmental burden (low levels of CO_2).

As it is implied in Fig. 2, continuous scale variables correlation is low and lies in the range of -0.042 up to 0.11. In addition, none of the pairwise correlations is statistically significant, at 5% level of significance. Interesting is the fact that the net exporting amount of e-waste flows, namely $\mid Exports_{it} - Imports_{jt} \mid$, is not related to either the distance between countries, or the difference in CO_2 levels. Therefore, there might be other socio-economic features which affect the decision of countries to export, or import, e-waste. This suggests that variables are independent and a potential inclusion in the random effect linear model, would not cause multicollinearity, leading to inconsistent estimations.

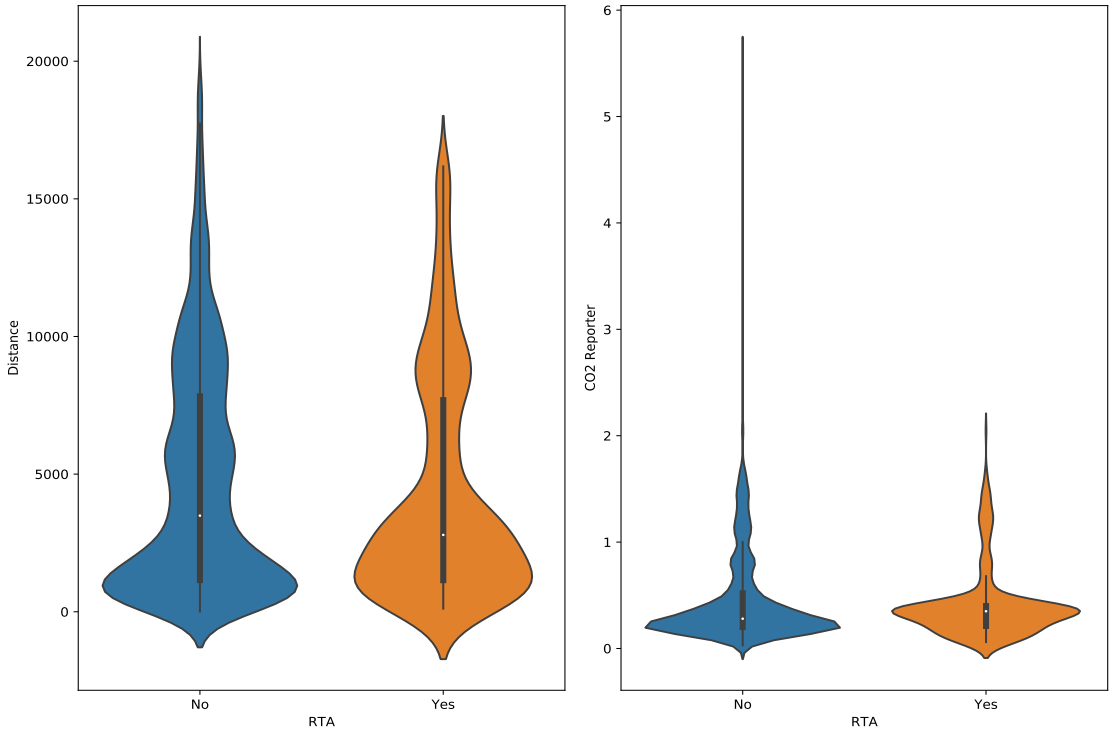

Figure 1: Violin plots for distance and CO_2 Reporter variables based on RTA

4.2. Network descriptive statistics

The evolution of preliminary network metrics is reported in Table 1. For each year, the density of the graph, namely the percentage of connected countries, number of communities, transitivity, and the country with the maximum out degree are reported.

From 2002 to 2014, on average, 3.5% of the countries are engaged in trade of e-waste quantities. This implies that trade flows of e-waste quantities are predetermined from one country to another. Furthermore, the number of produced communities spans from 10 (minimum) to 16 (maximum). This fact implies that on average each community includes 13 to 17 countries engaged in e-waste trade. For this reason, the network could be characterized as preferential as some countries export to

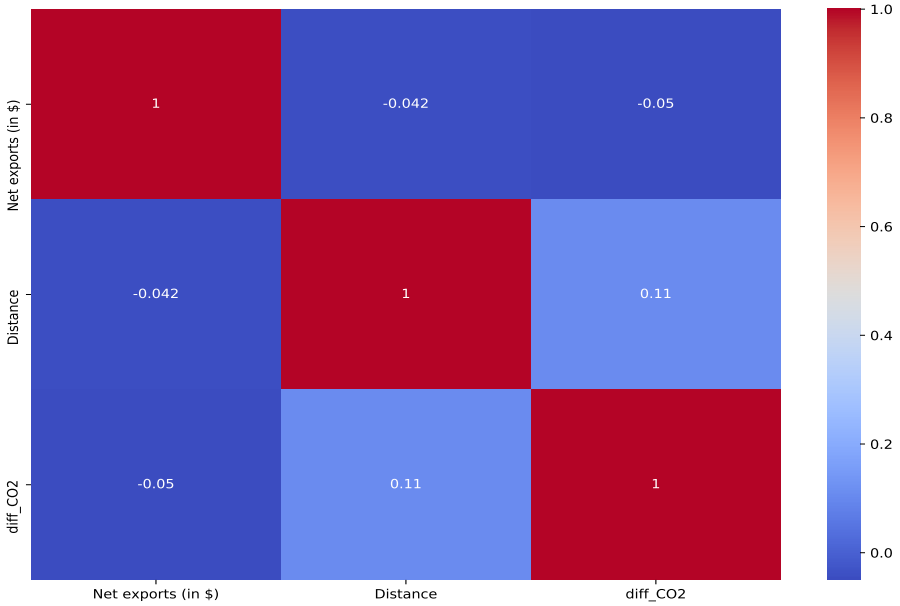

Figure 2: Heatmap plot of correlation of variables Net exports in $, Distance and CO_2 difference

specific ones, either directly or through others.

Transitivity (global clustering coefficient) score shows that e-waste trade networks are less clustered before 2010, while after that year it exceeds 30%. From this, it can be deducted that countries choose to form close connection in e-waste trade flows between other countries rather than engage in trade with others using middle countries as hubs.

As expected, USA remains in the first place for the time period examined in terms of maximum out - degree score, while Great Britain seems to outperform USA in 2003 and 2004. Both countries exhibit the largest out - degree score which means that they are intensively exporting, and that makes sense since both countries rank in first places in the production of innovative products.

Concerning the maximum in - degree, USA seems to rank first in the majority of time periods between 2002 and 2014. Germany seems to outperform USA during 2002 and 2003, while China exhibits the largest in degree score during 2006, 2007 and 2010.

Table 1: e-waste Network Descriptive Statistics

Year	Density	No Communities	Global CC	Max Out Degree Country	Max In Degree Country
2002	3.67%	10	27.7 %	USA	USA
2003	2.87%	10	26.9 %	Great Britain	Germany
2004	3.34%	14	29.9 %	Great Britain	Germany
2005	3.32%	16	28.9 %	USA	USA
2006	3.26%	15	28.1 %	USA	USA
2007	3.27%	15	27.6 %	USA	China
2008	3.33%	14	28.9 %	USA	China
2009	2.92%	15	27.6 %	USA	USA
2010	3.05%	13	29 %	USA	China
2011	3.11%	14	30.1 %	USA	USA
2012	3.21%	15	30.4 %	USA	USA
2013	3.34%	16	30.3 %	USA	USA
2014	3.24%	12	30.7 %	USA	USA

4.3. Produced communities

In Fig. 3, the produced communities from employing spinglass community detection algorithm are presented for each e-waste trade network.

e-waste trade network's communities of countries for 2002, demonstrate that there is a large amount of countries that constitute a homogeneous group of America which expands to other countries (mostly) being located in Central and East Asia. Furthermore, meaningful communities have been formed in countries of East Mediterranean and Northern Africa, as well as Northern Balkan enhancing the assumption that trade is encouraged when countries are close. In addition, a large cluster of countries, which are located in Central Eurorean and former USSR countries, along with

countries located in Oceania, has been created. In grey colour, countries which do not participate in e-waste trade are presented.

On the other hand, in 2014, more countries are engaged in e-waste trade network, yet, communities formed by application of spinglass detection algorithm, are somehow confusing. The major and meaningful clusters that were formed are those which consist of countries located in North and Latin America, Scandinavia, Oceania and partially some European countries. Countries mostly located in Africa and Asia, tend to join either the community of European countries, either the community which includes the Oceania countries.

Communities produced from the aggregated network (across all years) and communities of e-waste trade network in 2014, are, by a simple visual inspection, quite similar. Similarity refers to the degree of overlapping, between communities of countries based on e-waste trade network and the corresponding at $t = 2014$. Northern and Latin American, Scandinavian, Oceanian East-Asian and partially Central European, as well as former USSR clusters remain the same. African states tend to either join Central European or Central Asian countries.

The formation of communities may not solely depend on network characteristics, rather than other geographical and/or economic conditions. A comparison of e-waste trade network spinglass, with clusters formed based on distance proximity, contiguity between countries, existence of common official language or common currency, existence of colonial ties and regional trade agreements has been conducted, in order to investigate whether the formed communities are linked to the previously mentioned variables, or are just artifacts.

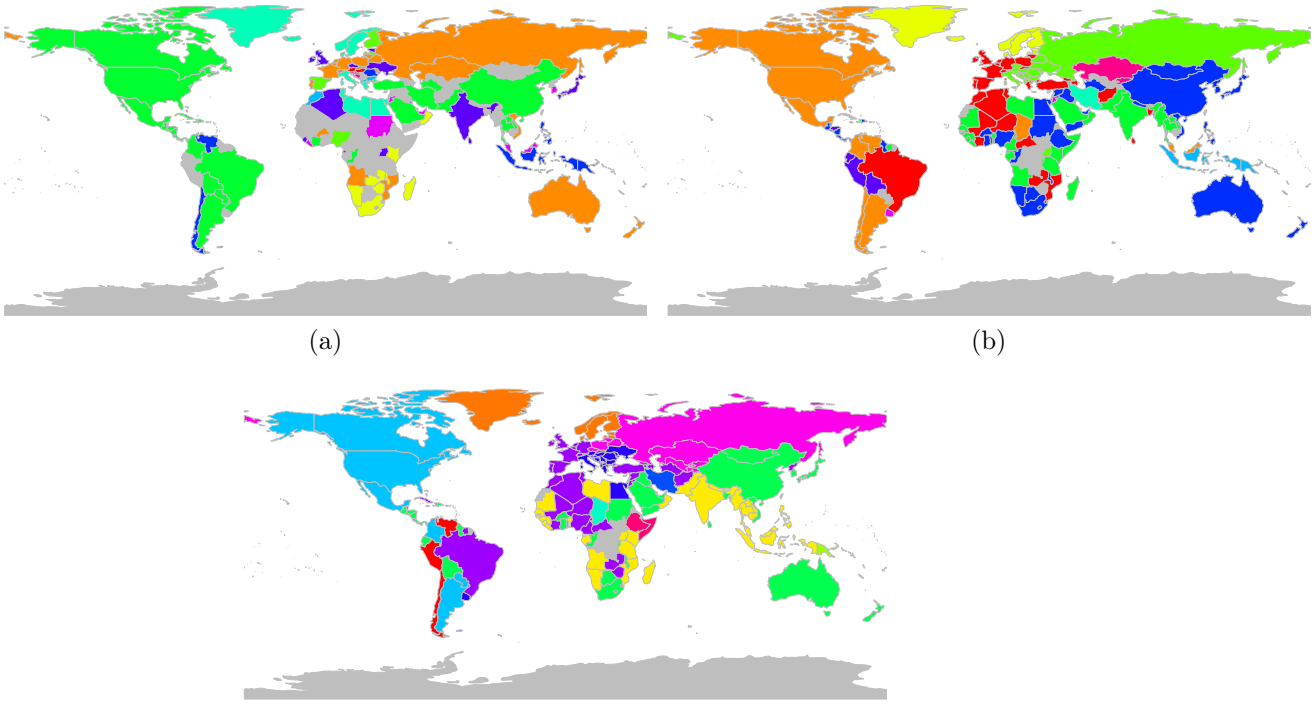

Figure 3: Communities produced by implementation of spinglass detection algorithm for e-waste trade networks : a) in 2002, b) in 2014 c) across all years

4.4. Statistical Validation

In Table 2, the results of NMI are presented, after bootstrapping e-waste networks for $B = 5,000$ times and compared the produced e-waste trade network spinglass communities with those produced by networks based on independent variables of this study.

Regarding the similarity measure (NMI) for e-waste trade network spinglass communities with communities produced from the network based on differences in CO_2 levels between countries, average values exceed 50% across all time periods from 2002 until 2014. The maximum mean value of NMI is reported in 2009, reaching 62.71%. However, this trend seems to be decreasing, as time passes by. Across all years, the

similarity index, NMI, between communities of differences in CO_2 levels and e-waste trade network, on average exceeds 60%.

Communities of networks, which were constructed based on existence of colonial ties between countries, exhibit on average lower similarity score with e-waste trade network communities, compared to communities based on differences of CO_2 levels between countries. In specific, average value of NMI, from 2002 until 2014 reaches 39.80%. The highest mean value of NMI, was reported in 2005. Likewise, NMI values for differences in CO_2 levels between countries, NMI values for colonial ties, tend to decrease over time. On average, for all years, NMI between communities of networks based on common language and e-waste trade network, tend to be approximately 40% similar.

NMI values for comparison of common language networks with communities of e-waste trade network, present a steady decline over time. Specifically, in 2002 NMI was nearly 47% ($CI_{2.5\%} = 46.89\%, CI_{97.5\%} = 47.06\%$), while in 2013 and 2014 the corresponding values barely exceed 35% (32.78% in 2013 and 34.67% in 2014). This suggests, that in the beginning, countries were more probable to engage in trade with others, which they share common official language, while as time passes, this faded and other traits played an important role. The average value of NMI, for the period from 2002 until 2014, between communities of networks based on common language and e - trade network, reached approximately 40%.

Regarding geographical proximity,it is expressed in two ways; using the actual distance between countries in kilometers and using a binary variable (contiguity) which is 1 whenever countries are neighboring and 0 otherwise, we assessed the similarity of networks' communities based on these variables with communities based on e-waste trade network. NMI values are quite close to each other, but in different scale. NMI values of contiguity network communities and e-waste trade network,

are close to 50% during the period from 2002 until 2007, while NMI values for distance network communities and e-waste trade network, are following the same trend; however, they are 5 to 7% lower. In both cases, we can observe that there seems to be a decline in NMI values over the years, which suggests that countries which are engaged in trade network, do not choose to export or import to other countries based on distance. On average, across all years, NMI values for comparison of contiguity and distance communities with the corresponding of e-waste trade network are 45.94% and 46.06%, respectively.

Communities based on common currency networks and e-waste trade communities are on average 25.32% similar across all years. In 2008, NMI similarity index receives its higher value ($Mean = 34.20\%, CI_{2.5\%} = 34.12\%, CI_{97.5\%} = 34.27\%$), while in 2014 its lower value ($Mean = 18.71\%, CI_{2.5\%} = 18.66\%, CI_{97.5\%} = 18.76\%$). This finding suggests that countries' decision to participate in e-waste trade, is not based on the existence of common currency between engaged parts.

Concerning the similarity index of e-waste trade network communities, with those of RTA network, we observe that from 2002 until 2014, NMI values span from minimum 22.89% reported in 2007 to maximum 37.25% reported in 2002. The trend of NMI values is decreasing and statistically significant, which means that countries either do not sign regional trade agreements so as to export or import e-waste or even if those agreements are signed, they are not an important factor for decision of countries to engage in trade.

In addition to the statistical validation of communities comparison, proximity of real against null model networks' characteristics was conducted.

In Fig. 4, values for clustering coefficient cycle of real against null models are presented. It seems that values for cycle clustering coefficient of e-waste networks (hereafter real networks) from 2004 until 2008 coincide with the corresponding values

of all simulated null model networks, namely Erdos - Renyi (hereafter random), Small - World (hereafter SW) and scale - free (hereafter SF). However, if we use as threshold $\alpha = 1\%$ instead of $\alpha = 5\%$ level of confidence, then SW's cycle clustering coefficient value coincides with real network's corresponding measure, from 2002 until 2009 and 2011. In 2010 and from 2012 until 2014, none of the null models employed, present cycle clustering coefficient which is close to real network value, at $\alpha = 1\%$.

Concerning middleman clustering coefficient (Fig. 5), SF simulated networks tend to be closer to real networks, compared to other null models. In specific, SF value of middleman clustering coefficient is statistically equal to real network's corresponding value from 2002 until 2009, while from 2004 until 2008 SW's middleman clustering coefficient values tend to statistically coincide with real network's metric. SF's and real network's middleman clustering coefficient are statistically different from 2010 until 2014, although, boostraped p -values are higher than corresponding of SW and random network.

Comparison of real networks' in clustering coefficient with the corresponding of random, SW and SF network models, is presented in Fig. 6. From 2004 until 2007, random and SW networks' in clustering coefficient coincides with real network's, while SF tends to produce statistically indifferent values for the whole period (2002 - 2014). However, comparison of clustering coefficient out, for real network and SF depicts a proximity for almost all years (Fig. 7). From 2004 until 2007, all three null models' value for clustering coefficient out, is statistically equal to the corresponding of real network. Only, SF's clustering coefficient out values are statistically equal to the real networks' one, across all years.

Regarding the total clustering coefficient, in Fig. 8, all three null models' values tend to coincide with the real network's one. However, SF's total clustering coefficient is statistically equal to real network's corresponding mean value, and loosening the

error threshold from $\alpha = 1\%$ to $\alpha = 5\%$, SF's values coincide with those of real network from 2002 until 2013. SW's and random network's mean values for total clustering coefficient are statistically equal to real network's for the period from 2004 until 2008.

Surprisingly, Kolmogorov-Smirnov's p - value which concerns comparison of null models' degree distribution (in, out, and total) with the corresponding of real network, across all years, exhibited statistically inadequate fit, namely, none of random's, SW's or SF's degree distribution (in, out or total) matched the degree distribution produced by real network, from 2002 - 2014. Even if in some cases, SF's degree distribution approached real network's, still Kolmogorov - Smirnov's p - value was much lower than $\alpha = 1\%$, indicating that statistically the null hypothesis cannot be accepted.

Table 2: Bootstraped confidence intervals for NMI values

	$\Delta CO2$			Colonial Ties			Common Language			Contiguity		
Year	Lower 2.5%	Mean	Upper 97.5%	Lower 2.5%	Mean	Upper 97.5%	Lower 2.5%	Mean	Upper 97.5%	Lower 2.5%	Mean	Upper 97.5%
2002	60.96%	61.02%	61.09%	41.69%	41.78%	41.86%	46.89%	46.98%	47.06%	45.52%	45.60%	45.68%
2003	58.82%	58.89%	58.96%	38.52%	38.60%	38.68%	34.70%	34.77%	34.83%	53.22%	53.31%	53.41%
2004	60.88%	60.95%	61.02%	41.51%	41.60%	41.68%	43.32%	43.40%	43.48%	48.46%	48.53%	48.60%
2005	62.12%	62.21%	62.29%	46.14%	46.21%	46.29%	44.83%	44.91%	44.98%	49.15%	49.23%	49.31%
2006	63.42%	63.48%	63.53%	45.13%	45.20%	45.28%	39.63%	39.70%	39.77%	49.62%	49.69%	49.76%
2007	61.18%	61.26%	61.34%	39.00%	39.08%	39.15%	35.67%	35.74%	35.81%	48.61%	48.68%	48.76%
2008	62.48%	62.54%	62.59%	39.16%	39.22%	39.29%	38.68%	38.75%	38.82%	45.82%	45.89%	45.95%
2009	63.65%	63.71%	63.76%	41.24%	41.31%	41.38%	36.34%	36.41%	36.47%	44.85%	44.91%	44.98%
2010	60.36%	60.42%	60.48%	39.04%	39.11%	39.19%	36.42%	36.49%	36.56%	42.37%	42.43%	42.50%
2011	59.79%	59.86%	59.92%	40.88%	40.95%	41.02%	39.86%	39.94%	40.01%	43.84%	43.90%	43.97%
2012	59.50%	59.56%	59.62%	33.95%	34.01%	34.07%	36.71%	36.78%	36.85%	43.36%	43.43%	43.49%
2013	58.40%	58.45%	58.51%	36.26%	36.33%	36.41%	32.72%	32.78%	32.85%	42.50%	42.57%	42.64%
2014	56.77%	56.84%	56.91%	34.02%	34.08%	34.14%	34.61%	34.67%	34.74%	39.10%	39.16%	39.22%

	Currency			Distance			RTA		
Year	Lower 2.5%	Mean	Upper 97.5%	Lower 2.5%	Mean	Upper 97.5%	Lower 2.5%	Mean	Upper 97.5%
2002	25.24%	25.32%	25.39%	51.45%	51.55%	51.64%	37.06%	37.15%	37.25%
2003	29.69%	29.78%	29.86%	55.32%	55.43%	55.53%	30.81%	30.91%	31.01%
2004	22.25%	22.32%	22.38%	50.80%	50.90%	51.01%	36.62%	36.70%	36.78%
2005	31.95%	32.03%	32.11%	45.89%	45.98%	46.08%	28.30%	28.37%	28.44%
2006	25.44%	25.50%	25.57%	46.35%	46.44%	46.53%	25.66%	25.73%	25.81%
2007	25.64%	25.71%	25.77%	41.98%	42.07%	42.16%	22.76%	22.82%	22.89%
2008	34.12%	34.20%	34.27%	41.57%	41.68%	41.78%	28.36%	28.43%	28.50%
2009	28.71%	28.79%	28.86%	45.66%	45.75%	45.83%	28.40%	28.47%	28.54%
2010	21.40%	21.46%	21.53%	45.12%	45.20%	45.29%	35.14%	35.22%	35.29%
2011	23.52%	23.59%	23.65%	44.63%	44.72%	44.80%	31.75%	31.82%	31.89%
2012	19.19%	19.24%	19.29%	44.21%	44.29%	44.37%	27.60%	27.66%	27.72%
2013	22.44%	22.49%	22.55%	46.13%	46.20%	46.28%	26.10%	26.15%	26.21%
2014	18.66%	18.71%	18.76%	38.51%	38.59%	38.67%	29.55%	29.60%	29.66%

4.5. Linear mixed effect model results

Three different models have been estimated so as to assess the effect of several exploratory variables on key network characteristics. Model 1 assumes that geopolitical traits, as well as difference in CO_2 levels between countries, affect the degree of nodes, namely the number of links. In addition, model 2 assumes that the same independent variables have an effect on the betweenness score, while model 3 on the transitivity score. In all the above models, a random effect drawn from normal distribution has been added to each exporting country and in Table 3 the estimation results from all the models are presented.

Model 1 has been estimated in a set of 11,640 observations, for the period from 2002 until 2014. Geographical proximity (distance) tends to affect positively and

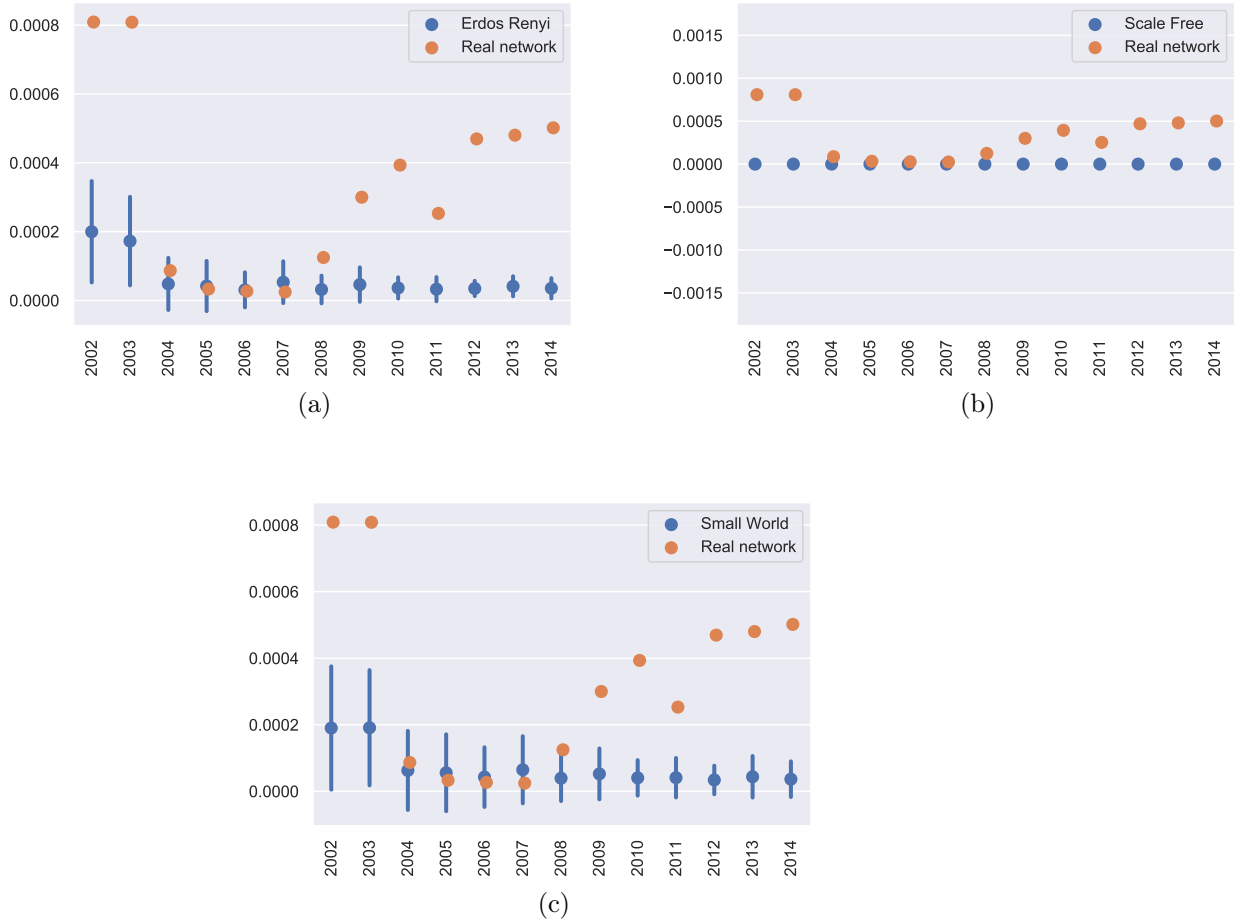

Figure 4: Comparison of Clustering Coefficient Cycle of: a) Erdos - Renyi, b) Scale Free and c) Small World network types with the proposed network

statistically significantly the degree of nodes ($\beta = 0.649, p < 0.01$). This means, that countries which are distant one another, are more probable to connect, not only with each other, but with other countries, as well. This finding is confirmed by the negative sign of contiguity, whose parameter is statistically significant at 1% level of significance ($\beta = -0.510, p < 0.01$). Countries, which are adjacent, are less probable to obtain new connections. Furthermore, less probable to be connected are countries,

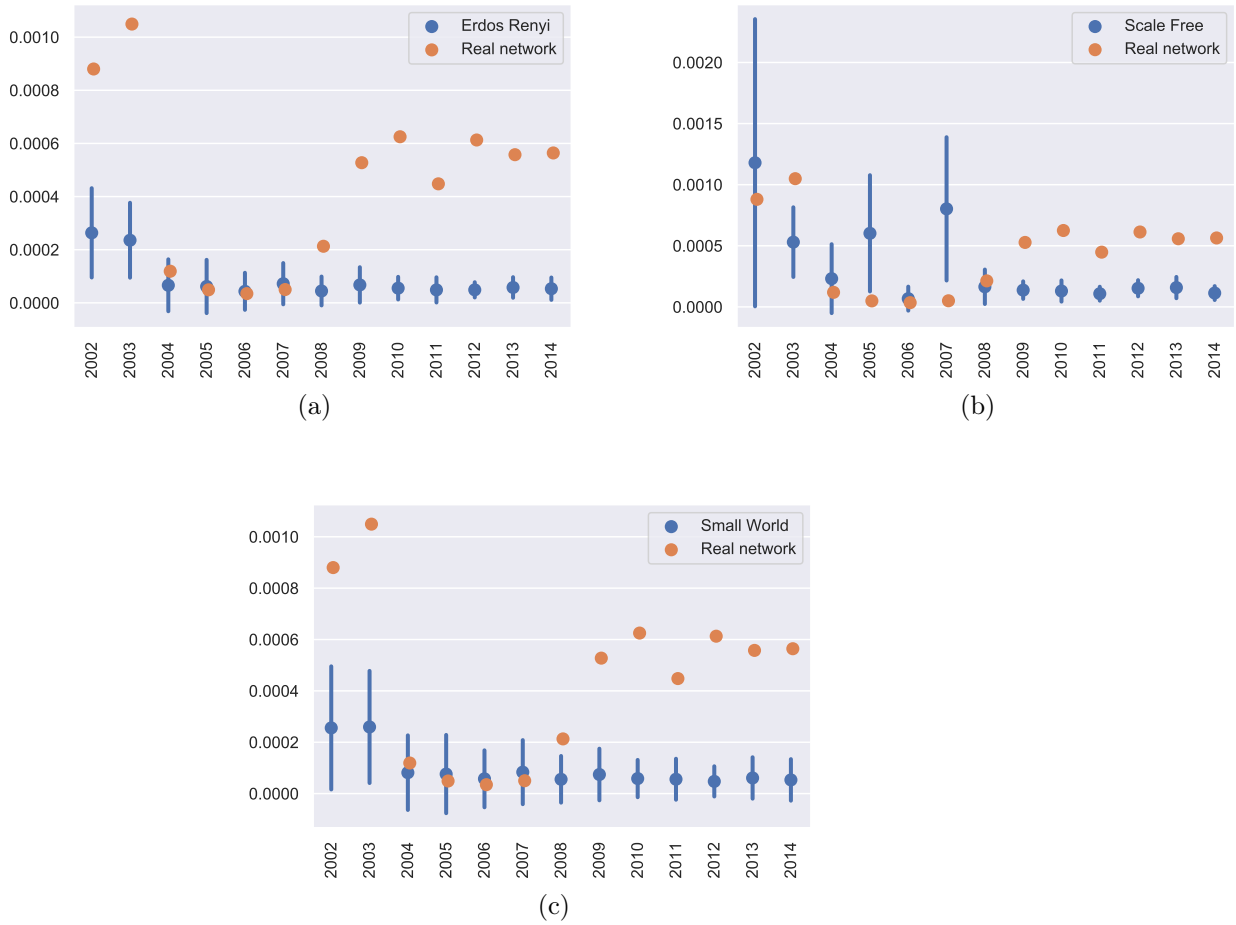

Figure 5: Comparison of Clustering Coefficient Middleman of: a) Erdos - Renyi, b) Scale Free and c) Small World network types with the proposed network

which retain ties with former colonies ($\beta = -0.898, p < 0.01$) and share the same common currency ($\beta = -1.186, p < 0.01$). On the other hand, countries which share common official language, are more probable to be connected with other countries which are engaged in e-waste trade network ($\beta = 0.568, p < 0.05$). Lastly, differences in CO_2 levels between countries, tend to decrease total degree score ($\beta = -0.473, p < 0.05$). That means that, the more environmental deficit a pair of countries has, it

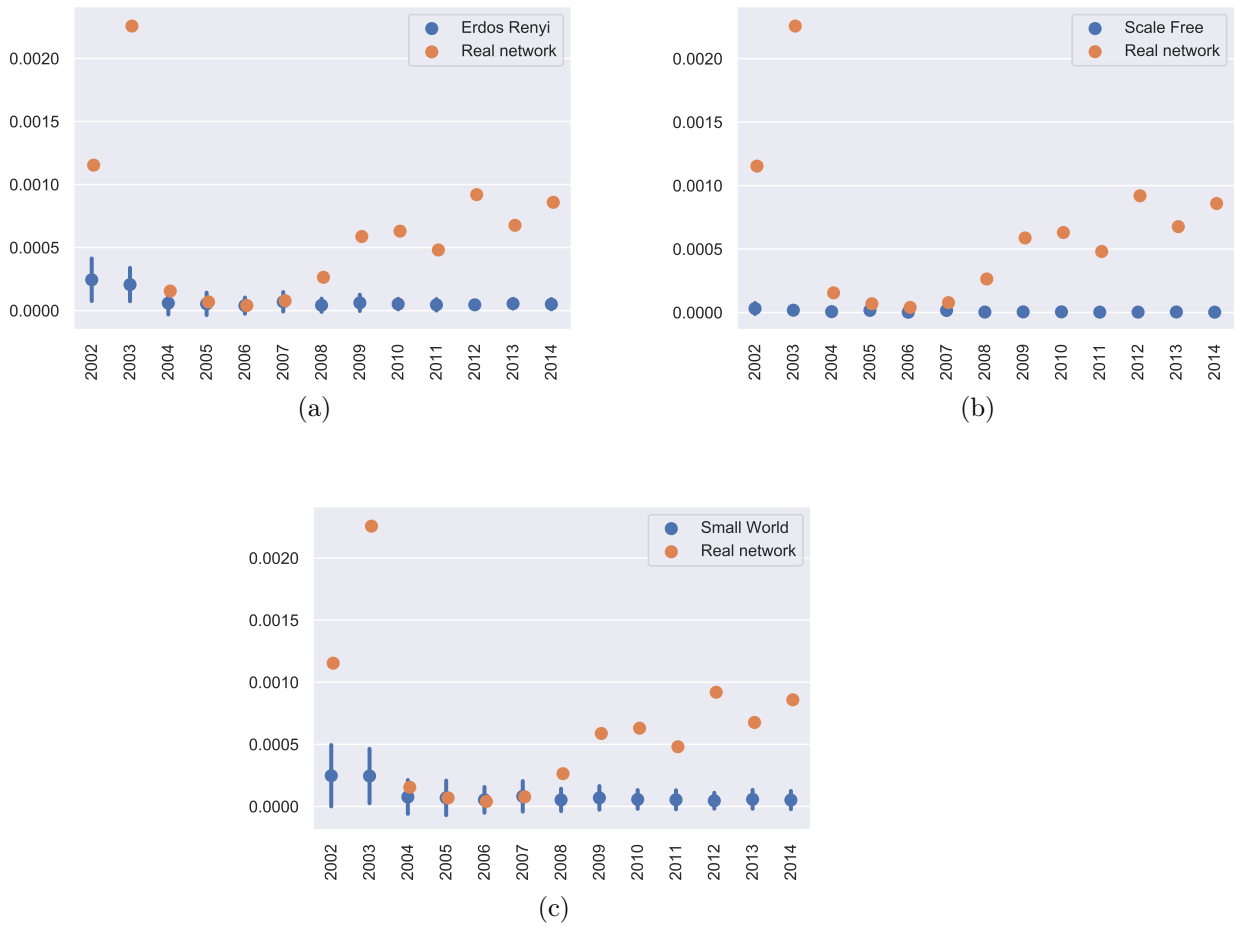

Figure 6: Comparison of Clustering Coefficient In of: a) Erdos - Renyi, b) Scale Free and c) Small World network types with the proposed network

is less probable a connection between them to be established. Model 1 exhibits a considerably high R^2 index, which is equal to 77.67% and this suggests very good fit to the observations used.

Betweenness, on the other hand, seems to be affected negatively only by common currency. In specific, countries which share the same currency do not exhibit high betweenness score. This means that countries which do not share the same currency,

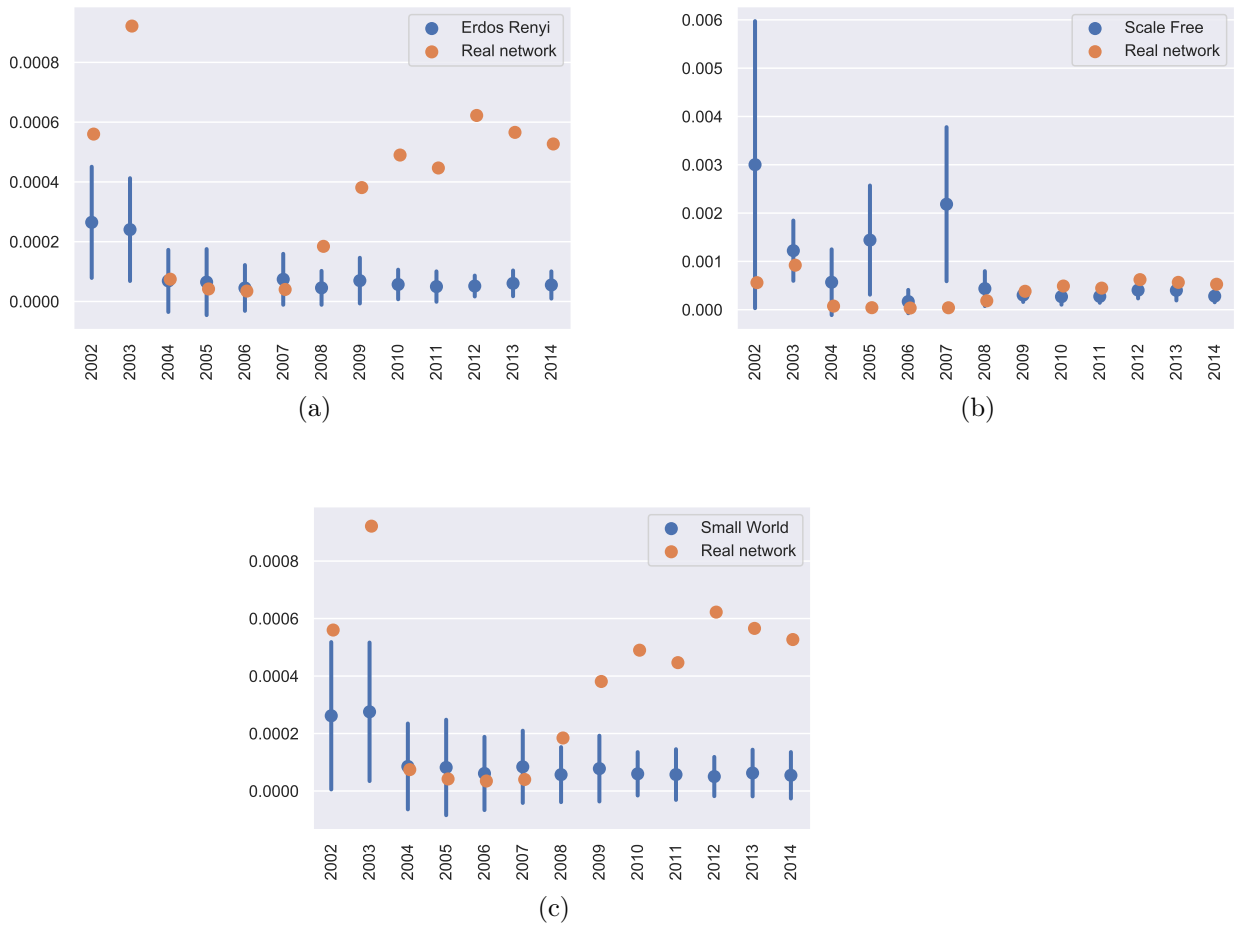

Figure 7: Comparison of Clustering Coefficient Out of: a) Erdos - Renyi, b) Scale Free and c) Small World network types with the proposed network

do not serve as middles through which e-waste trade is facilitated. All other independent variables do not affect the betweenness score. Coefficient of determination exceeds 65%, which indicates a decent fit of the model to the observations used.

Clustering coefficient is negatively, yet marginally statistically significantly, affected by the existence of colonial ties between countries ($\beta = -1.024, p < 0.1$). This means that countries which retain ties with their former colonies, tend to be more

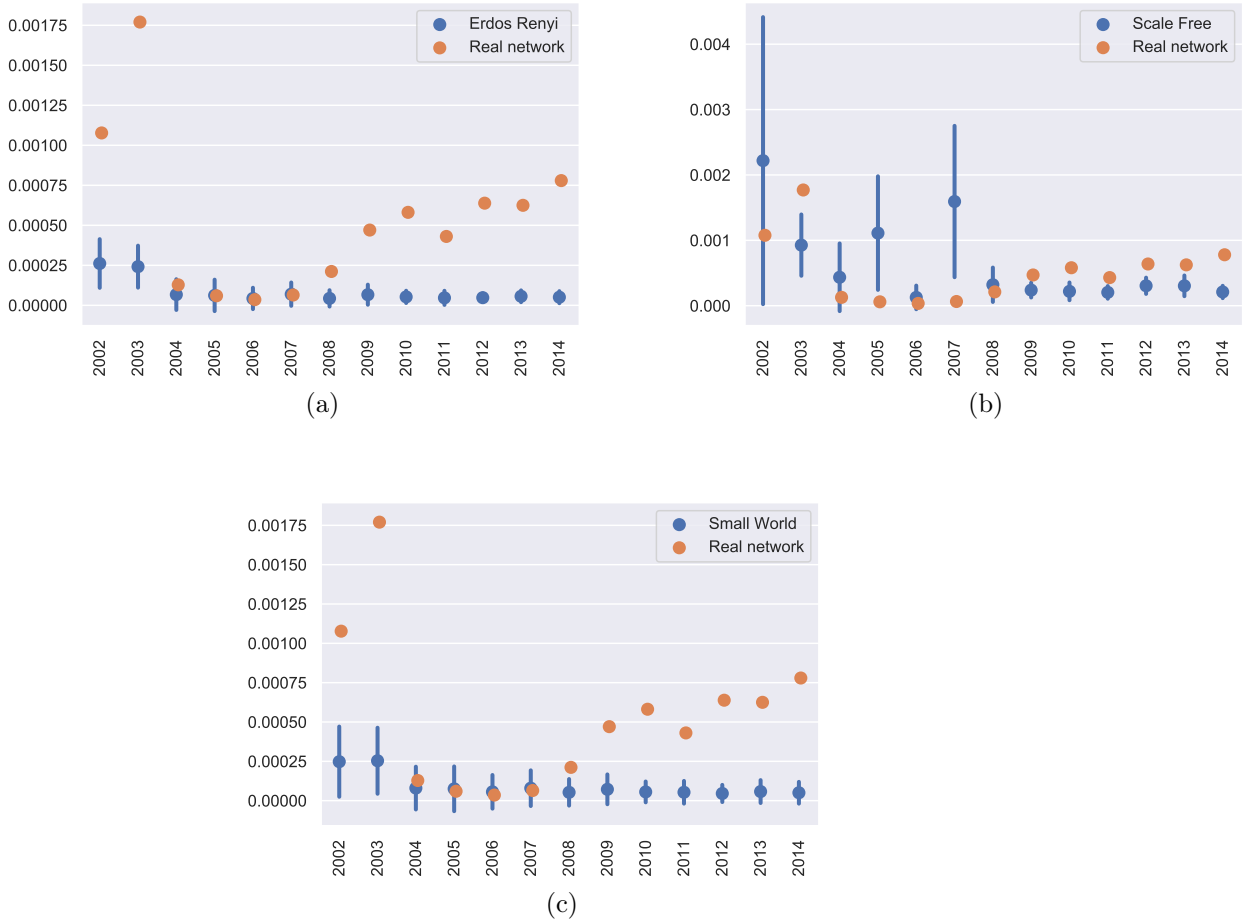

Figure 8: Comparison of Clustering Coefficient Total of: a) Erdos - Renyi, b) Scale Free and c) Small World network types with the proposed network

clustered than countries which do not retain ties with their former colonies. The same effect on clustering coefficient has the existence of common language between countries. There is a negative effect of the existence of common official language between countries ($\beta = -0.506, p < 0.05$). Lastly, differences in CO_2 levels between countries, tend to decrease clustering coefficient score. Countries which have a large environmental burden, tend to be more clustered.

5. Conclusions and implications

In the present study, considerable findings were extracted, which have practical implications upon e-waste trade. First, communities of WEEE trade network, which are produced by applying spinglass community detection algorithm and communities produced by networks based on geographical distance and dissimilarity in differences of CO_2 levels, are in terms of Normalized Mutual Information index, very close, compared to communities of networks which were structured based on contiguity, common language, common currency, existence of colonial ties and Regional Trade Agreements (RTA). This suggests, that the formation of spinglass communities may, partly, depend on geographical distance and differences in environmental burden between countries.

Using as null models, Erdos - Renyi, Small - World, and Power - Law directed and weighted networks, we concluded that Power - Law is statistically closer to e-waste trade network in terms of total and out clustering coefficient values, while Small - World and Erdos - Renyi's clustering coefficients cycle, middleman and in are statistically equal to the corresponding of e-waste trade network, especially for the period from 2004 to 2008. None of null models' degree distribution, emitted statistical proximity with e-waste network's degree distribution.

It is believed that this study has significant practical implications; these are for the governments of countries participating in the e-waste trade, international environmental organizations, competent legislative bodies, as well as for businesses. As it was found, e-waste trade flows are based, among other factors, on the differences in terms of geographical distance and environmental deficit.

It is a fact that poor countries with limited industrial development are usually the recipients of e-waste flows. Taking these flows for granted, actions must be taken

so that the appropriate infrastructure should be developed in the countries receiving e-waste products: dismantling and processing facilities, recycling centers, landfills for the safe disposal of e-waste components and materials, etc.

If e-waste flows continue to dramatically increase in the future, as it is expected, and if the appropriate infrastructure will not be developed, the environmental and health risks, particularly for the developing world, will be tremendous. Another way to minimize the confirmed, through our study, e-waste flows is that the governments should provide motives for manufacturers to design and produce electronic goods with low carbon footprint (e.g. green and super green products); also, motives for people and businesses to collect discarded electronic products and return to producers and retailers.

Manufacturers should adopt the extended producer responsibility, which makes them responsible for all the stages of their products' life cycle. Appropriate recycling centers should be constructed and new recycling technology should be invented. If the governments of developed countries have the will to reduce the confirmed e-waste flows, financial disincentives should be voted and applied. All of us should bear in mind that e-waste represents one of the most serious threats for the global economy and the environment.

We report a limitation of our study, which lies in the procedure by which communities are extracted. Spinglass community detection algorithm may produce more meaningful results compared to other community detection algorithms; however, due to its stochastic nature, it may deliver remarkably different results along time.

Table 3: Estimation of linear mixed model effect regression

	Model 1			**Model 2**			**Model 3**		
Variable	β	std	t	β	std	t	β	std	t
$log(Distance)$	0.649	0.106	6.134***	0.579	0.714	1.233	-0.106	0.091	-1.163
Contiguity	-0.510	0.319	-1.598***	-0.127	1.310	-0.096	-0.006	0.276	-0.022
RTA	-0.174	0.354	-0.492	0.039	1.452	0.028	-0.154	0.305	-0.506
Colonial ties	-0.898	0.341	-2.637***	-1.431	1.397	-1.024	0.421	0.295	1.429*
Common Currency	-1.186	0.341	-3.475***	-1.013	0.404	-2.507***	0.076	0.295	0.259
Common language	0.568	0.351	1.615**	0.111	1.442	0.077	-0.506	0.304	-1.665**
$\Delta CO2$	-0.473	0.252	-1.874**	0.116	0.104	0.112	-0.281	0.390	-1.389*
Obs	11640			11640			11640		
Log Likelihood	-41989.96			-58279.54			-40241.49		
AIC	83999.92			116579.1			80502.99		
R^2	77.67%			67.21%			64.53%		

Note: $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$

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