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Cross-country Environmental Inequality: Based on Nonlinear Indicators and Network Analysis

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Abstract: This study empirically examines the environmental inequality caused by international trade from 44 countries during 2005-2014, using the generalized method of multi-regional input-output and network analysis. On the measurement of inequality, we construct an indicator, taking into account the complexity of the environment and economic system simultaneously. Thus, the focal point of this paper is to develop a nonlinear index for environmental cost and benefits inequality and to create a series of networks through dimensional reduction. We calculate the overall topological structure properties, including degree and weight, cumulative distribution, community structure, and stability. The results suggest that the degree of inequality showed a gradual downward trend, which means that countries are gradually focusing on the coordinated development of environment and economy and, abandoning the mode that focus only on growth. Besides, the networks show typical heterogeneity and, the financial crisis is an important factor affecting the evolution of inequality in some high-income countries. In addition, although the number of communities has not changed much, the reorganization of countries in different communities displays a high instability.

Keywords: MRIO; Network analysis; Environmental inequality; Nonlinear indicator

1 Introduction

With the growth of economic data availability, input-output table has been increasingly analyzed using network analysis [1–3]. Network analysis has potential in understanding the structure of economy and offers new insights [4]. In the network of input-output, sectors or regions are usually considered as the nodes. The properties of the resulting networks have been extensively investigated, observing scale-free distribution and community structure, examples include studies by Ref. [5].

Carbon emissions can be considered as the environmental cost of energy production [6]. In the context of carbon emission transfer, countries that export carbon-intensive goods would arguably do so because they have managed to acquire a competitive advantage in the production of such goods [7]. Any change in the social-economic fields will have an impact on the environment, whether immediately or eventually, negatively or positively [8]. Previous studies have used the Environmental Kuznets Curve method to verify that environmental quality tends to decline as the economy grows. However, trade among regions not only allows the exchange of goods and services, associated economic benefits and pollution may be subject to environmental inequality.

The effect of trade on emissions has been investigated regionally. But a combined assessment of the environmental cost related to trade and the transport of benefit is lacking. In addition, with the development of heterogeneous firms and trade theories in recent years, the study of environmental transfer and benefit from a macro perspective has also become a new trend [9–11]. To evaluate unequal transfers of emissions and value added associated with trade, a regional environmental

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inequality index was done in Ref. [10], which provides effective references. However, the changes in network properties were never used to infer the properties of the system.

It is important to take multilayer features into account to improve our understanding of complex systems. Here we consider two-layer networks. In the first, the links represent emissions and the second the links represent benefit. Next, we construct a coupled network in which the links represent environmental costs-benefit inequality. Although the multi-layer network has a mature theoretical basis, the empirical researches in environmental area are limited. Therefore, this paper first proposes a non-linear index to measure environmental inequality. It is to study the two-layer network into one-layer through the idea of dimensional reduction and provides a new way for the empirical modelling of multi-layer networks.

The rest of this paper is organized as follows: Section 2 describes the methodology and data. Section 3 gives the results of environmental inequality network analysis. Section 4 is the conclusions.

2 Methology

2.1 Carbon emissions accounting

Using the multi-regional input-output (MRIO) model, the consumption-based national emissions inventories (NEI) can be calculated [12]. Carbon emissions associated with final demand, are calculated by multiplying the intensities of the production-based emissions (EF) with the Leontief inverse $(I-A)^{-1}$ and final demand matrix (Y):

$$CC = \widehat{EF}(I-A)^{-1}Y + \widehat{FNLC} \tag{1}$$

where $FNLC$ denotes direct emissions by final demand. The notation "$\widehat{\ }$" indicates the diagonalization of column vectors. In the matrix of CC, the element c^{rs} refers to the emissions of region r induced by the consumption of region s. Here, the net flows of emissions between region r and s is consider, as calculated by CC_{NET} with element cc^{rs}_{NET}. Thus, CC_{NET} is defined as the matrix with non-negative value with element of $\bar{c}^{rs}$. In order to ensure consistency with economic benefits, emission intensity is used.

2.2 Calculate the trade-induced value-added

Similarly, define V as a direct value-added coefficient vector. Then, we can define the total value-added coefficient matrix $VB = \widehat{V}(I-A)^{-1}$. Because all value-added must be either domestic or foreign, the sum along each column is unity. The estimates of sector and country sources of value-added in each country's final goods production can be written as $VA = \widehat{V}(I-A)^{-1}\widehat{Y}$. Let $\bar{v}^{sr}$ and $\bar{v}^{rs}$ represent the value-added of region $r(s, s \neq r)$ induced by the consumption of region $s(r, r \neq s)$. That is, trade-induced value-added flow from region $s(r)$ to $r(s)$. Then, the net flows of value-added between regions r and s can be calculated.

2.3 Environmental inequality (EI) index

We follow and develop Ref. [10] in the definition of "regional environmental inequality index". Thus, we can obtain the matrix of EI index, whose element e^{rs} can be calculated by formula (2). Note that higher EI value indicate a higher level of inequality.

There are three types of relationship between region r and region s: (a) When $\bar{c}^{rs} > 0$ and $\bar{v}^{rs} > 0$, both environmental cost and benefit outsourcing occur from region r to region s, and the elements in matrix $\frac{\bar{c}^{rs}}{\bar{v}^{rs}}$ are normalized to range between 0 and 1. (b) When $\bar{c}^{rs} > 0$ and $\bar{v}^{rs} < 0$, region r transfers environmental cost to region s and receives benefit from region s. Obviously, region r not only receives emissions but also has a negative balance of economic gains, so we normalize both $\bar{c}^{rs}$ and $|\bar{v}^{rs}|$ to between 0 and 1 and add them up to reflect both inequalities. To reflect the difference between $|\bar{v}^{rs}| \leqslant \bar{c}^{rs}$ and $\bar{c}^{rs} < |\bar{v}^{rs}|$, we multiply a value $(1 - \frac{|\bar{v}^{rs}|}{\bar{c}^{rs}})$ less than 1. Moreover, we add 1 to distinguish results from situation (a). (c) To reflect the difference between $|\bar{v}^{rs}| \leqslant \bar{c}^{rs}$ and $\bar{c}^{rs} < |\bar{v}^{rs}|$, we multiply a value $(1 + \frac{|\bar{v}^{rs}|}{\bar{c}^{rs}})$ larger than 1. Moreover, we add 1 to distinguish result from above two situations.

$$e^{rs} = \begin{cases} f(\frac{\bar{c}^{rs}}{\bar{v}^{rs}}) & \text{if } \bar{c}^{rs} > 0 \text{ and } \bar{c}^{rs} > 0 \\ [f(\bar{c}^{rs}) + f(|\bar{v}^{rs}|)](1 - \frac{|\bar{v}^{rs}|}{\bar{c}^{rs}}) + 1 & \text{if } \bar{v}^{rs} < 0 \text{ and } |\bar{v}^{rs}| \leqslant \bar{c}^{rs} \\ [f(\bar{c}^{rs}) + f(|\bar{v}^{rs}|)](1 + \frac{|\bar{v}^{rs}|}{\bar{c}^{rs}}) + 1 & \text{if } \bar{v}^{rs} < 0 \text{ and } 0 < \bar{c}^{rs} < |\bar{v}^{rs}| \end{cases} \tag{2}$$

2.4 Network construction and measures

We use the following metrics to show the global structure of environmental inequality network (EIN).

• Degree centrality. Centrality is a board concept applied for identifying the most important actors [13]. Degree refers to the extent to which two nodes are graphically adjacent to one another and hence serves as a local point-based centrality measure. In order to assign weights to each directed link, the weighted degree is represented as node strength (s_i), which can be further divided into in-strength and out-strength.

• Cumulative distribution. The cumulative distribution is used to describe the distributing characteristic of weighted edges. The function is described $CP(w) = \sum_{W \geqslant w} p(W)$, where $CP(w)$ is the cumulative distribution of links whose value is larger than w; $p(W) = \frac{N_w}{N}$ is defined to be the fraction of links in the network with weight W; and N_w is the total inequality of links with weight W; N is the total weight of links.

• Gini coefficient [14]. The Gini coefficient is defined as follows:

$$Gini = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j| = \frac{1}{n^2\mu}\sum_{i=1}^{n}(2i-n-1)x_i \tag{3}$$

where n is the number of samples; μ epresents the average value; and x_i is the weight of edge i. In formula (3), $Gini \in [0, 1]$, where 0 indicates perfect equality and 1 indicates perfect inequality.

• Community structure [15]. The relationships between nodes in the same community are usually stronger than those between nodes of different communities. While it is possible to visually obtain regional neighborhood patterns from centrality measures, the community structure is better quantified based on the notion of modularity. Up to a multiplicative constant, modularity Q refers to the number of edges falling within a group minus the expected number in an equivalent network with edges placed at random. For directed networks, Q is expressed as follows:

$$Q = \frac{1}{m}\sum_i\sum_j[w_{ij} - \frac{k_i^{in}k_i^{out}}{m}]\delta(c_i, c_j) \tag{4}$$

• NMI index [16]. To study the stability of the partition, a measure to quantify the statistical information shared between two distributions is introduced here, named the Normalized Mutual Information (NMI). Given two community partitions P_t and P_{t+1}, the confusion matrix N is defined as a matrix whose N_{ij}-th element is the number of nodes in the community i of the partition P_t that appear in the community of the partition P_{t+1}. The algorithm below evaluates the MNI between two neighboring years:

$$NMI_{(P_t,P_{t+1})} = \frac{-2\sum_{i=1}^{C_A}\sum_{j=1}^{C_B}N_{ij}\log(\frac{N_{ij}N}{N_jN_i})}{\sum_{i=1}^{C_A}N_i\log(N_i/N) + \sum_{j=1}^{C_B}N_j\log(N_j/N)} \tag{5}$$

2.5 Data

This study uses the multi-regional input-output tables from 2005 to 2014 download from the World Input-Output Database (WIOD). This database provides information for 44 countries (including the Rest of the World) and 56 industries by country. Data for carbon emissions embodied in trade is taken from the Organization for Economic Co-operation and Development database (OECD) and BP, covering the period from 2005 to 2014. GDP data come from the World Bank and the TRADINGECONOMICS.

3 Empirical results

In order to intuitively understand the overall structure of environmental inequality, we Measured the density. A network's density is a measure of the number of relationships and the complexity of the network. The definition of a network's density is given by $2L/N(N-1)$. The density of the constructed networks decreased obviously from 2005 and onwards. This finding indicated that the environmental inequality relationship in the global networks is weakening. Next, some other indicators are selected to describe the structural characteristics of the network from the aspects of structural characteristics, centrality and stability.

3.1 Link centrality analysis

In order to have a clearer insight into the role that specific countries or links between countries can play in the evolution of EI, we show the evolution of the inequality indicators by countries and links. The centrality is used to quantify the power of the actors in the network, i.e., the ability to control and influence others. The distribution analysis provides powerful demonstration of the fact that only a few links dominate and control the world's environmental inequalities (Fig. 1). The results for Figure 1 show that the central positions of hubs may also understood combined with the percentage index in Table 1.

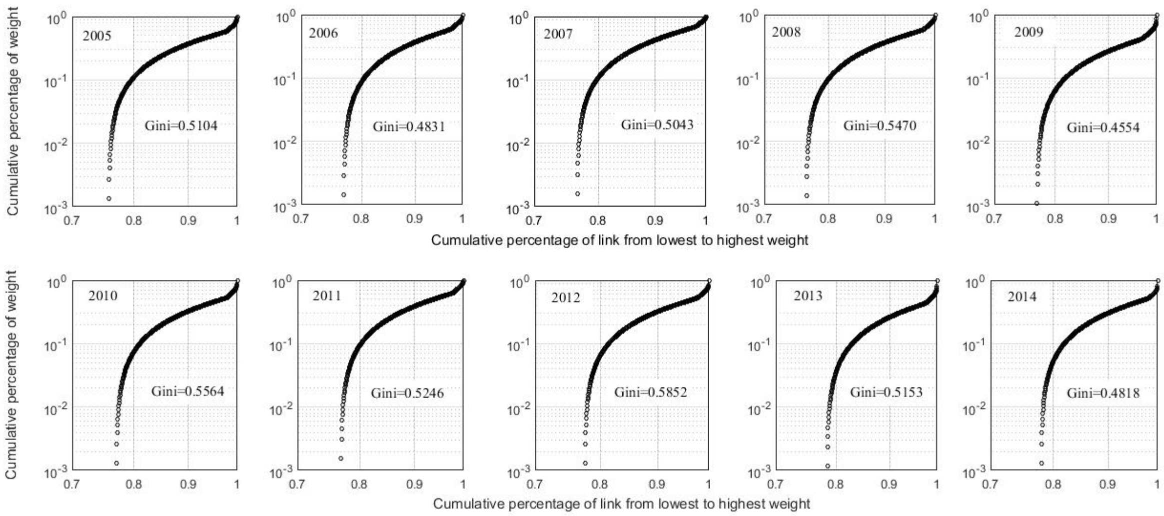

Figure 1: Weighted edge distribution of links and Gini coefficient.

Table 1: Top 10 links based on weighted edge in the EIN.

	2005			2014		
Rank	Edge	Weight	Precent	Edge	Weight	Precent
1	Slovenia → Luxembourg	46.83	6.24%	Romania → Malta	150.55	19.36%
2	Bulgaria → Malta	25.78	3.44%	Malta → Luxembourg	41.76	5.37%
3	Bulgaria → Netherlands	25.24	3.36%	Bulgaria → Estonia	22.74	2.92%
4	Romania → Slovak Republic	20.77	2.77%	Spain → Latvia	16.72	2.15%
5	Greece → Lithuania	11.22	1.50%	Slovenia → Lithuania	10.61	1.36%
6	Australia → Lithuania	9.78	1.30%	Mexico → Slovenia	8.46	1.09%
7	Poland → Korea	9.76	1.30%	Slovenia → Latvia	6.68	0.86%
8	Slovenia → Cyprus	8.71	1.16%	Canada → Latvia	5.87	0.75%
9	Croatia → Netherlands	7.71	1.03%	Australia → Germany	5.52	0.71%
10	Hungary → Netherlands	7.67	1.02%	Finland → Germany	5.32	0.68%
Total		173.37	23.12%		274.23	35.25%

Table 1 reports the top 10 links with the sources and targets. The sources obtained low benefits with higher environmental costs, while the targets gained high benefits. So, the sources are sufferers with disadvantages. Besides, the rankings of the ten largest links were inconsistent in the two years of 2005 and 2014. The top 10 made up 23.12% and 35.25% of all links, respectively. It can be described by heterogeneity, which is consistent with the Gini coefficient in Fig. 1. For the top sources, including Slovenia, Brazil and Romania, sector 35 (electricity, gas, steam and air conditioning supply) accounts for a large proportion. This suggest that, for these three high income countries, additions in sector 35'trade will result in higher inequality levels of environmental transfer. In other words, environmental inequality is affected by industrial factors. The contribution rate for the largest link increase with time going on. It shows that although the global environmental equality is decreasing, the share of some countries is deteriorating.

3.2 Country centrality analysis

In addition, we analyzed the role of each country based on in-strength and out-strength. Figure 2 displays the distribution of in-strength and out-strength for countries in three years. Countries below the diagonal reflect that it gains lower benefits compared with its environmental cost. That is, the country has paid a higher environmental cost in exports. Besides, a different ranking was found. Belgium, Australia, and Malta stand out with higher in-strength, and are also main contributors to out-strength in the year of 2005. The results show that many countries have dual identities, namely they are both sufferers and drivers for environmental inequality.

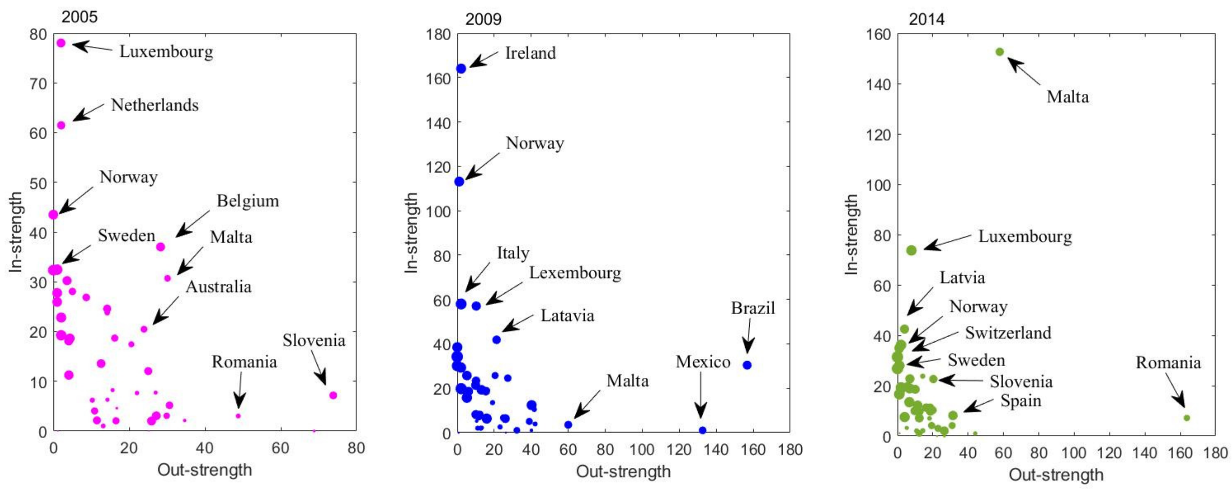

Figure 2: Distribution of countries by in-strength and out-strength.

Seen from the long-term trend (Fig. 3(A) and Fig. 3(B)), the evolution of node strength for Korea, Turkey, India and Canada are increasing which indicates that EI in these countries has worsened. By contract, there is a decline trend for Bulgaria, Portugal, Poland, and Chinese Taipei which suggests that EI issues in these countries has got an improvement. Fig. 3 (C) shows that the evolution of node strength for Denmark, Australia, Brazil, Slovak Republic, Mexico, Malta and Romania. We can find a stability period before 2008, followed by a marked sudden shift in which the inequality index reaches the boom threshold. It is worth noting that this finding is consistent with the idea that inequalities expand in times of crisis. Countries represented by Brazil and Mexico are vulnerable to financial crisis. After the crisis, some countries can recover their competitiveness, that is, followed by a long period of tepid growth, while other countries, such as Mexico, has lost his advantages. EI for countries represented by Bulgaria has been ameliorated. Contrastively, other countries include Turkey and India are becoming more and more disadvantaged according to their increased environmental inequality level.

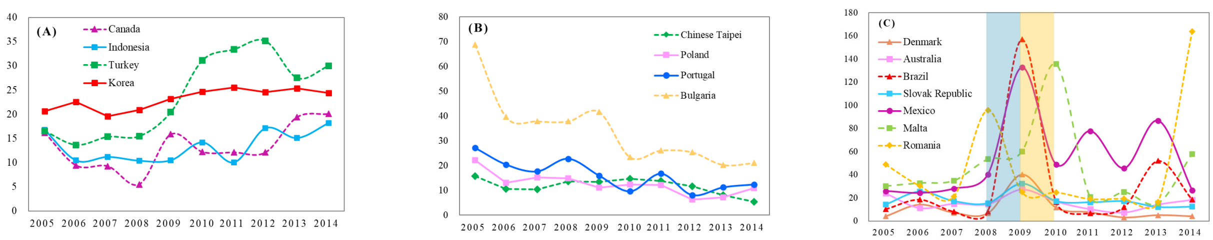

Figure 3: Environmental inequality evolution for some countries.

3.3 Community and stability

Combined with the community detection algorithm, we used Gephi to divide communities based on the 10 networks from 2005 to 2014. Networks with high modularity have dense connections between the nodes within same community but sparse connections between nodes in different communities. Fig. 4 (A) shows the obtained communities. Modularity measures the quality of the partition of the communities. We recorded the values of modularity while detecting communities in Fig. 4 (B). besides, the NMI is also calculated and pictured in Fig.4 (C). In all, the partition of the networks is unstable, which means the relationship between countries is unstable even though the number of clusters remains the same.

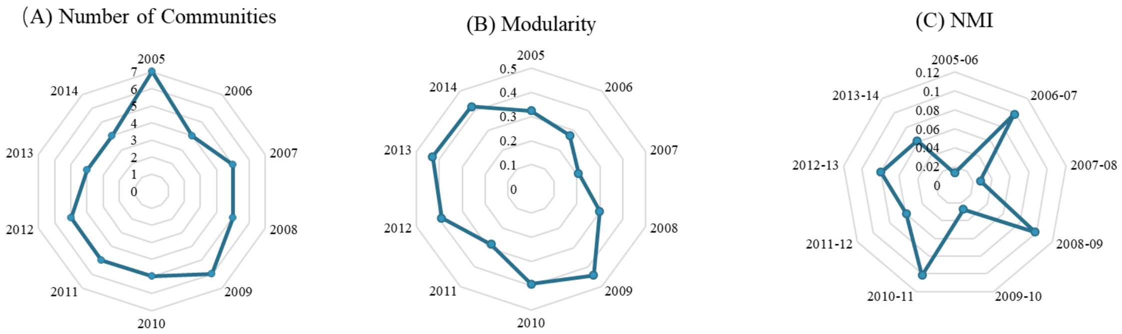

Figure 4: The results of community division.

4 Conclusions

The wide scale adoption of inequality indicators into environmental development and analysis continues to be an uphill task. This paper provides a new approach for the investigation of the relationship between two different systems. Methodologically, we have applied two analytical tools, inequality index and social network analysis, in order to gain a better understanding of the relationships between export-induced carbon emissions and economic benefits. We propose a nonlinear piece-wise function here that will simplify consideration of any inequality and disparity into environmental transformation analysis. Then, the inequality networks were created using the input-output network method, and properties of the networks were measured based on density, degree, cumulative distribution, community structure, and stability criteria.

The findings presented here have significant policy implications in terms of designing systems that are efficient and resilient. The results of network's density showed that the degree of inequality showed a gradual downward trend. It shows that environmental inequality is affected by non-human-controlled market forces. Core drivers are more having high-income while core sufferers covering lower-income, and upper-middle-income countries. Besides, we found that there is one turning point where the value of environmental inequality fluctuated to a higher level. The environmental inequality evolution for some countries, such as Denmark, Australia, Brazil will change due to changes in factors such as financial crisis. During the period of financial crisis, the overall level of environmental inequality is inversely related to the pattern of environmental costs and economic benefits transformation. The study findings show that environmental inequalities may be related to other socioeconomic factors such as financial crisis, industrial structure and the globalization of trade level. Clarifying the complexity and evolution of environmental inequality among countries can provide reference for achieving sustainable development and keeping long-term stability relationships.

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