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RESEARCH ARTICLE

Global renewable energy trade network: patterns and determinants

Lianyue Feng[1] · Bixia Chen[2] · Gang Wu[1] · Qi Zhang[3]

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Abstract

The renewable energy product trade is critically important to global economic prospects and its rapid development, making it a key issue in international economics of much interest to scholars. Previous studies have paid attention to bilateral trade, yet we still know little about the patterns of renewable energy product trade and its evolution from the whole industry perspective. Based on bilateral trade data, complex network, as well as ERGM and TERGM, we build global renewable energy trade networks (GRETNs) during 2000–2018 and explore the patterns and determinants. The results show that (1) the GRETNs expand during 2000–2018, characterized by a small-world, reciprocity, degree disassortative, and export volume heterogeneity. (2) The GRETNs form four communities, and the community patterns greatly fluctuate over time. (3) Economies in North America, Europe, and Asia play dominant roles, while the USA, Germany, and China are the cores of the GRETNs. (4) Endogenous structure of reciprocity, structural embeddedness, and out-degree popularity are essential parts of the evolving patterns of GRETNs. Most trade relationships are developed between economies located within the same continent, participating in APEC or WTO, or having similar areas. There is heterophily in GDP and per capita income, and Matthew effects in GDP, urbanization, and industrialization rate. Countries that share a common geographic border, language, religion, or currency, being former colonies of the same colonialists, and having signed regional trade agreements are more likely to trade in renewable energy products.

Keywords Renewable energy · Trade network · ERGM · TERGM

Introduction

Economic development is inseparable from the continuous supply of energy, of which conventional fossil energy (e.g., natural gas, coal, and oil) has been a predominant factor driving economic development in past centuries (Ellabban et al. 2014; Hu et al. 2018). However, the overexploitation and the prevalent utilization of fossil fuels have led to an energy crisis and serious environmental pollution, which is not conducive to the sustainability of economic development. In the meantime, renewable energy is gaining popularity since it can effectively promote economic development, optimize energy structure, harmonize supply–demand relationships, and preserve the environment (Xu et al. 2019). Recently, the proportion of renewable energy in global energy consumption has been increasing since many countries in the world regard renewable energy as a non-trivial component in their development strategies. According to Statistical Review of World Energy 2020, renewable energy comprised 11.4% of global energy consumption and its consumption grew by 41% in 2019, which is the fastest in all

Responsible Editor: Roula Inglesi-Lotz

✉ Gang Wu
wugang@swufe.edu.cn

Lianyue Feng
ivyfeng19@126.com

Bixia Chen
cchenbixia@163.com

Qi Zhang
qz@unc.edu

1 School of International Business, Southwestern University of Finance and Economics, Chengdu 611130, Sichuan, China

2 School of Economics and Trade, Hunan University, Changsha 410079, Hunan, China

3 Frederick S. Pardee Center for the Study of the Longer-Range Future, Boston University, Boston, MA 02215, USA

kinds of energy. However, the capacity of technology and equipment production in renewable energy is uneven among countries in the world with only a few having mastered producing renewable energy due originally to the spatially broken global value chains and the intensified international division of labor (Ezcurra and Rodriguez-Pose 2013). Trade in renewable energy products is playing a favorable role in balancing the uneven distribution of technology and equipment production capacity of renewable energy (Cantore and Cheng 2018; Kalirajan and Liu 2017), making the allocation of scarce resources more efficient and the products, services, and technologies of renewable energy more accessible (Barrat et al. 2004; Farah and Cima 2013 Ben Aissa et al. 2014). In fact, with the emphasis on energy conservation in many countries, the renewable energy product trade has experienced a dramatic increase. According to United Nations Comtrade (UNcomtrade) Database, the global trade in renewable energy products was \$167.93 million in 2001, and increased to a peak of \$641.14 million in 2011, maintaining an average growth rate of 13.9% during 2000–2018. Thus, a detailed examination of the evolving patterns and determinants is not only useful for characterizing the overall and regional trade features and capturing the changes of trade positions but also essential for policymakers to develop scientific strategies and policies for promoting sustainable development of the global renewable energy system.

Since the renewable energy trade is of critical importance to global economic prospects, many scholars have focused on how trade policy, environmental policy, and industrial policy impact the renewable energy product trade flows. For the trade policy, Steenblik (2006) examined the liberalizing trade in renewable energy in general and several representative fuels and technologies. Kalirajan and Liu (2017) studied constraints for energy product exporting in Asia and found that rigid rules, non-tariff actions in particular, are the main constraints, while the improved technical cooperations of the Regional Comprehensive Economic Partnership (RCEP) mooted by the ASEAN had a potential of removing the barriers. As for the environmental policy, previous literature such as Costantini and Mazzanti (2012), Groba (2014), Kuik et al. (2019), Costantini and Crespi (2008), and Miyamoto and Takeuchi (2018) analyzed the effects of environmental regulation on renewable energy products based on the Porter hypothesis (PH) (Porter and Cvd 1995). Some of them supported the PH and found that strict environmental regulations induce innovation, which is beneficial for countries as well as firms to build a comparative advantage and increase exports, while other studies (e.g., Ogura 2020) showed evidence against the PH. Besides, Lewis (2014), Kuik et al. (2019), Hughes and Meekling (2017), and Kim and Kim (2015) examined the interrelationship between domestic industrial policy and trade in solar and wind energy products, as well as the trade frictions in renewable energy. In addition, Jing et al. (2020) and Leng et al. (2020) measured the potential of renewable energy among countries involved in China's "Belt-and-Road" initiative. Although these studies are useful for understanding trade development in renewable energy products, there still exist some deficiencies as follows.

First, most of the previous researches has paid attention to bilateral trade relations, yet our understanding of the evolution patterns is still very poor from the perspective of the renewable energy industry as a whole. A complex network has the unique advantage to evaluate the structure of a system including its direct and indirect flows, which provides a scientifically comprehensive method for analyzing the evolutionary patterns from the multilateral trade relations and the whole perspective (Benedictis et al. 2009; Schweitzer et al. 2009; Barigozzi et al. 2011). With the mature of complex network theory, a growing number of researchers have adopted complex networks to analyze international energy trade issues such as coal (He and Wang 2014; Wang et al. 2019), petroleum (An et al. 2014; Du et al. 2017; Kitamura and Managi 2017), natural gas (Geng et al. 2014; Ma and Xu 2017), and fossil energy (Zhong et al. 2016, 2017). However, only a few have focused on the renewable energy trade by considering the trading system as a network. Fu et al. (2017) examined the geographic characteristics of solar and hydro energy trade and explored their evolutions based on complex networks. Yang et al. (2017) analyzed the spatial patterns and mobility of global solar energy trade in Asian countries from 1990 to 2013 based on network analysis. Considering most of them focus only on specific renewable energy products (e.g., solar, wind, or hydro products), there is a paucity that examines the global trade patterns of renewable energy encompassing all renewable energy products. More importantly, these researches only used corresponding network analysis indicators, such as density, clustering coefficient, and node centrality indicators, to investigate network characteristics of renewable energy product trade, without fully examining the driving factors. The study periods were also limited to 1988–2013; thus, little is known about the patterns of renewable energy trade after 2013.

Second, one major assumption of most previous studies is that countries involved in trade are independent of each other. In fact, with the deepening of global value chain and international division of labor, the trade dependence between countries has been strengthened (Zhu et al. 2015). In other studies, although mutual dependence is acknowledged, it is only controlled by incorporating the multilateral resistance term in traditional economic models, which requires further validation more rigorously. At the same time, the method of adding multilateral resistance terms can only eliminate the impact of trade interdependence on the results, but it cannot identify the endogenous dependence mechanism that affects trade and trade potentials (Almog et al. 2015). Unlike

Table 1 Comparative analysis of existing literature

Topics	Trade policy/frictions	Environmental policy	Industrial policy
Representative documents	Kalirajan and Liu (2017)	Costantini and Mazzanti (2012), Groba (2014), Kuik et al. (2019), Miyamoto and Takeuchi (2018)	Lewis (2014), Kuik et al. (2019), Hughes and Meekling (2017), Kim and Kim (2015)
Research perspectives	Macroscopic/microcosmic	Macroscopic	Macroscopic
Research objects	Bilateral trade relations	Bilateral trade relations/domestic development	Intra-industry development
Research methods	Causal inference	Policy analysis/causal inference	Statistical analysis/causal inference
Research hypotheses	Independent participants	Independent participants	Independent participants

traditional econometric models, exponential random graph model (ERGM) is a statistical inference model based on relational data, the premise of relational interdependence, and the local structure to analyze the formation of the overall network structure (Cranmer et al. 2012, 2017; Silk et al. 2017). Its modeling idea is to regard the formation of the overall network structure as the emergence of local network structures, and to test the process evidence that contributes to the formation of network structure by incorporating multiple network configurations into the model (Robins et al. 2007). The stochastic graph model of time index further considers the dynamic changes caused by time factors. Due to the above attributes, the exponential random graph model (ERGM) and temporal ERGM (TERGM) test the evidence of network structure formation based on network simulation, and have become effective tools for the analysis of cross-countries trade (Monge and Contractor 2003; Contractor et al. 2006). They can comprehensively examine the impact of various endogenous structural relations, exogenous economic attributes, and external dualistic relations within network patterns (Robins et al. 2007; Lusher et al. 2012). Thurner et al. (2019), Smith et al. (2019), and Feng et al. (2020) have applied ERGM or TERGM to test the determinants of trade patterns and demonstrated their effectiveness in the examination.

Table 1 more succinctly summarizes the comparison between research topics, perspectives, objects, methods, and hypotheses in previous relevant studies, as well as presents representative literatures to point out research gaps more directly and clearly. To fill in the gaps in previous research, we construct the global renewable energy trade networks (GRETNs) during 2000–2018 based on the complex network method and the bilateral trade data from the UNcomtrade Database covering 213 countries. The evolutionary patterns of GRETNs at different levels of macrooverall, medium-community, micronode, and triadic motifs, and the determinants are empirically tested using the ERGM and TERGM. Moreover, we provide scientific evidence and policy advice on how to promote stable and sustainable development of the global renewable energy system. The marginal contributions of this research can be as follows. Firstly, in terms of research perspective, this paper captures the complex trade network characteristics of global renewable energy trade; we construct the GRETNs in 2000–2018 from the whole industry perspective based on the analytical method of complex networks for the first time and systematically analyze its evolutionary patterns of multi-levels and triadic motifs. Secondly, different from the existing studies which focus on analyzing the influence of relevant trade and industrial policies, not only the national economic attributes but also the internal network structure and embedding effects of external relations are incorporated to systematically test the influencing factors of the GRETNs' formation and evolution. Finally, as for research methods, the ERGM and TERGM are both used to analyze the factors influencing the formation and evolution of GRETNs from the aspects of cross-sectional networks and longitudinal networks based on the research assumption of the essential attributes of the interrelation between GRETNs' entities, further enriching the application research of ERGM and TERGM.

Remaining sections are arranged as follows: "Methodology" section explains the data source, the construction of GRETNs, and network methodology. "The patterns of GRETNs" section presents the evolutionary patterns of GRETNs. "Determinants of the GRETNs" section explores the determinants of the GRETNs with ERGM and TERGM. "Conclusions and discussion" section gives conclusions and policy implications.

Methodology

GRETNs construction

According to the definition of renewable energy by Statistical Review of World Energy, five types of products are relevant to renewable energy trades, including solar energy, wind energy, hydro energy, bioenergy, geothermal energy, and marine energy. Referring to Jing et al. (2020), solar energy and hydro energy contain 17 products, wind energy 19 products, bioenergy 18 products, geothermal energy 8 products, and marine energy 2 products. For a list of the renewable energy products

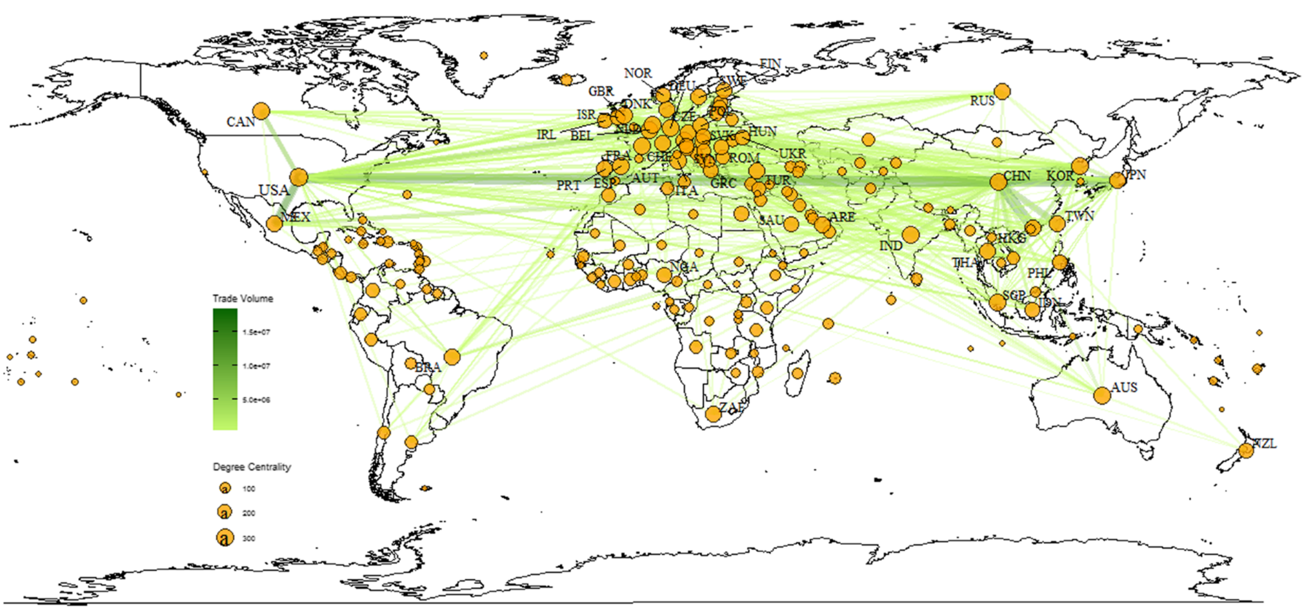


Fig. 1 The global renewable energy trade network in 2018

with their 6digit harmonized system codes, please see Table 7 in the Appendix 1. We take the average of the total value of exports and imports reported by the respective economies to overcome the bilateral inconsistency in the UNcomtrade trade data, which is caused by different statistical caliber, time lag, and omissions (Javorsek et al. 2016).

Based on this bilateral renewable energy trade data, we construct the GRETNs in 2000–2018, covering 213 economies. Following the complex network theory, we take the renewable energy product exporting economies as the starting nodes represented by the vector$\boldsymbol{V}_i = (v_1, v_2, ..., v_n)$, the importing economies as the destination nodes represented by the vector$\boldsymbol{V}_j = (v_1, v_2, ..., v_n)$, and applying a weight matrix $\boldsymbol{W} = [w_{ij}](i \in \boldsymbol{V}_i, j \in \boldsymbol{V}_j, i \neq j)$ to represent the weighted edge between $\boldsymbol{V}_i$ and$\boldsymbol{V}_j$. There is a weighted edge from country i to j if$w_{ij} > 0$, and the weight is the renewable energy product trade volume from country i to$j$. Thus,$\boldsymbol{V}_i$,$\boldsymbol{V}_j$, and $\boldsymbol{W}$ constitute the directed weighted GRETNs, recorded as$\boldsymbol{G}(\boldsymbol{V}_i, \boldsymbol{V}_j, \boldsymbol{W})$. The GRETN in 2018 showing only the trade with a volume of more than 100,000 dollars is mapped in Fig. 1 (see the list of countries in Table 8 in the Appendix 1). We can see that the 2018 GRETN is complex, involving most economies in the world, and the trade volume between China and the USA is the largest, while many European economies maintain a large number of trade partners.

Network pattern measurements

Macrooverall measurements

Macro-level measurements show the overall topological properties of the network. *Nv* measures the number of trading economies, and *Ne* measures the quantity of bilateral renewable energy trade relationships. Density (ρ) ranges from 0 to 1 (Wasserman and Faust 1994) and can depict the tightness of the connection between economies. Average degree (AD) and average strength (AS) represent, respectively, the average number of trading partners and average trade volume of each country. These measurements reflect the size of a network at different dimensions.

The average clustering coefficient ($\overline{C}$) is the average of all individual clustering coefficients, which is measured by the ratio of the actual number of triangles containing node i to the total number of possible triangles containing node i. $\overline{C}$ reflects the tightness between economies that are connected with the same trading system. Its range is [0, 1], and a larger value indicates a stronger agglomeration. The maximum distance along the shortest path between nodes is called diameter (Dia), and the average number of sides of the corresponding pair of nodes along the shortest path is called average path length (APL), measuring the effectiveness between economies. The smaller the value, the higher the trade efficiency, and vice versa. The reciprocity (R) is an important measure for characterizing the significance of symmetric relationships in networks. Assortativity (A) describes the tendency of direct connections among high-degree nodes, as well as low-degree nodes (Barabási and Albert 1999). The GRETNs are assortative if $A \geq 0$; it is disassortative if $A < 0$.

Strength entropy (E_S) describes the heterogeneity of a node's trading volume, and can be divided into out-strength entropy (E_S^{out}) and in-strength entropy (E_S^{in}) in the directed-weighted network, which are used to characterize the heterogeneity of export and import trade volume respectively. The larger the E, the more different the economies are in trading volume, and the greater the heterogeneity. E_S^{out} and E_S^{in} are defined as:

$$E_S^{out} = -\sum_{i=1}^{N} I_i^{out} lnI_i^{out}, E_S^{in} = -\sum_{i=1}^{N} I_i^{in} lnI_i^{in} \tag{1}$$

Here, $I_i^{out} = \frac{S_i^{out}}{\sum_i^N \sum_j^N w_{ij}}$, $I_i^{in} = \frac{S_i^{in}}{\sum_i^N \sum_j^N w_{ij}}$, and w_{ij} is the renewable energy trade volume between economies i and j.

Mediumcommunity measurements

The measurement of mediumcommunity patterns is the normalized mutual information (NMI). NMI aims to compare community members across time to reflect the stability of a network. The range of NMI is [0, 1], and a large NMI value represents a more stable network community pattern. It is defined as follows:

$$\mathrm{NMI}_{(t,t+1)} = \frac{\sum_{s=1}^{k^t} \sum_{l=1}^{k^{t+1}} n_{s,l} log\left(\frac{n.n_{s,l}}{n_s^t n_l^{t+1}}\right)}{\sqrt{\left(\sum_{s=1}^{k^t} n_s^t log\frac{n_s^t}{n}\right)\left(\sum_{l=1}^{k^{t+1}} n_l^{t+1} log\frac{n_l^{t+1}}{n}\right)}} \tag{2}$$

where n_s^t is the number of economies in the community s at t, $n_{s,l}$ is the number of economies moving from the community s at t to community l at $t+1$, and n is the number of nodes at t.

Micronode measurements

The measurements of micronode patterns describe the status of the node in the network. D describes the role which each country plays according to the number of direct renewable energy trade partners in GRETNs, and a larger D value indicates that the country has more trading partners and plays a more important role in the GRETNs. Out-degree and in-degree centrality (D^{out}, D^{in}) are subdivisions of D in the directed GRETNs and their formula are (Freeman 1978):

$$D_i^{out} = \sum_{j=1}^{N} a_{ij}, D_i^{in} = \sum_{j=1}^{N} a_{ji} \tag{3}$$

where a_{ij} is binary; $a_{ij} = 1$ means there is a network relationship between country i and county j, otherwise $a_{ij} = 0$.

Strength centrality (S) depicts the role of economies in the network in terms of their total trade in GRETNs (Opsahl et al. 2010), and the larger the S of a country, the more trade volume and the more important role the country has. Out-strength and in-strength centrality (S^{out}, S^{in}) are subdivisions of S in the directed GRETNs and are calculated as:

$$S_i^{out} = \sum_{j=1}^{N} w_{ij}, S_i^{in} = \sum_{j=1}^{N} w_{ji} \tag{4}$$

where w_{ij} is the renewable energy trade volume between countries i and j in the GRETNs.

Triadic motif measurements

Generally composed of a few nodes, the motif shows the basic connection pattern between nodes, which is called the "element" of the network (Milo et al. 2002). Among them, triadic motifs are the most widely used measures to explore basic units in various empirical networks, reflecting different interconnections among three nodes (Guan et al. 2020). In directed networks, there are theoretically 13 different types of triadic motifs (Milo et al. 2002; Squartini and Garlaschelli 2012). In GRETNs, triadic motifs can reflect the trade patterns among economies from a local configuration perspective. The principle is to judge the importance of triadic motifs in GRETNs according to whether the frequency of triadic motifs in GRETNs is much higher than that in a random network, given the same number of nodes and edges. The importance of a triadic motif can be measured by the Z score. The higher the Z score, the more important the motif. It is calculated as:

$$Z = (F_{\mathrm{real}} - F_{\mathrm{random-mean}})/\sigma_{\mathrm{random}} \tag{5}$$

where F_{real} is the frequency of triadic motifs in real networks, $F_{\mathrm{random-mean}}$ is the mean frequency of triadic motifs in random networks, an σ_{random} is the standard deviation of the random network.

ERGM and TERGM

ERGM is a statistical model for analyzing the formation of networks based on relational data, local configuration, and interdependence (Feng et al. 2020). The idea is that the probability of the occurrence of a network relationship depends on whether other relationships appear (Cranmer et al. 2012, 2017; Silk et al. 2017). According to Feng et al. (2020), the ERGM is specified as:

$$pr(Y = y|\theta) = \frac{1}{\kappa} exp\{\theta_\alpha^T g_\alpha(y) + \theta_\beta^T g_\beta(y, x) + \theta_\gamma^T g_\gamma(y, g)\} \tag{6}$$

Table 2 Pattern evolution characteristics of GRETNs in 2000–2018

Year	N_v	N_e	ρ	AD	AS	$\overline{C}$	APL	Dia	R	A	E^{out}	E^{in}
2000	201	9292	0.231	92.5	18,243.7	0.563	1.801	4	0.471	−0.394	0.567	0.666
2001	201	9497	0.236	94.5	17,115.7	0.570	1.788	3	0.468	−0.387	0.583	0.678
2002	201	9881	0.246	98.3	16,772.5	0.581	1.774	3	0.472	−0.377	0.589	0.684
2003	201	10,244	0.255	101.9	19,379.4	0.590	1.774	4	0.476	−0.366	0.591	0.688
2004	201	10,601	0.264	105.5	23,581.2	0.591	1.747	3	0.491	−0.376	0.588	0.689
2005	202	11,046	0.272	109.4	25,862.3	0.601	1.742	3	0.490	−0.373	0.591	0.688
2006	203	11,473	0.280	113.0	30,302.3	0.610	1.738	4	0.505	−0.379	0.596	0.692
2007	203	11,930	0.291	117.5	35,800.2	0.618	1.720	3	0.496	−0.364	0.599	0.699
2008	203	12,203	0.298	120.2	41,935.5	0.624	1.715	3	0.508	−0.361	0.601	0.710
2009	203	12,194	0.297	120.1	35,127.1	0.627	1.726	3	0.511	−0.362	0.600	0.711
2010	203	12,492	0.305	123.1	43,816.3	0.637	1.716	4	0.504	−0.351	0.579	0.687
2011	203	12,483	0.304	123.0	49,965.2	0.638	1.708	3	0.508	−0.361	0.583	0.688
2012	203	12,524	0.305	123.4	45,120.4	0.639	1.711	4	0.505	−0.372	0.588	0.703
2013	203	12,816	0.313	126.3	43,627.8	0.645	1.700	3	0.504	−0.361	0.591	0.706
2014	203	12,742	0.311	125.5	43,393.0	0.641	1.706	3	0.509	−0.375	0.596	0.709
2015	203	12,835	0.313	126.5	39,591.5	0.644	1.697	3	0.503	−0.365	0.588	0.705
2016	203	12,781	0.312	125.9	38,747.0	0.641	1.697	3	0.511	−0.380	0.595	0.703
2017	203	13,147	0.321	129.5	44,411.6	0.650	1.686	3	0.514	−0.373	0.592	0.703
2018	204	12,836	0.310	125.8	48,602.4	0.634	1.696	3	0.526	−0.411	0.595	0.702

N_v and N_e are the number of economies and edge of the GRETNs. ρ is the density, AD is average degree, AS is average strength degree, $\overline{C}$ is average clustering coefficient, APL is average path length. R is reciprocity, Dia is diameter, R is reciprocity coefficient, A is assortativity. E^{out} and E^{in} are out-strength and in-strength entropy, respectively. What calls for special attention is that E^{out} and E^{in} are normalized for the comparability of results, and the range of them is [0, 1].

where κ is a normalizing quantity which ensures that Eq. (6) is a proper probability distribution (Wasserman and Pattison 1996). Y is all possible networks, which have the same number of nodes with the observed y, namely the GRETNs. Moreover, $g_\alpha(y)$, $g_\beta(y,x)$, and $g_\gamma(y,g)$ are endogenous structural variables (Snijders 2002), economies attribute variables (Wang et al. 2016), and external relationship embeddedness variables (Pattison and Wasserman 1999). The θ_α^T, θ_β^T, and θ_γ^T are the parameters corresponding to these three types of variables.

To capture temporal dependence of the observed y, the ERGM in Eq. (6) for network y at time t (y^t) can be modified to include dependencies on some number of previously observed networks by introducing lagged networks into $g(y)$, $g(y,x)$, and $g(y,g)$, and it is called temporal ERGM (TERGM). According to Leifeld et al. (2018, 2017) and Wu et al. (2020), for network y^t, the TERGM can be set as:

$$Pr(y^t|y^{t-K},...,y^{t-1},\theta) = \frac{exp\{\theta_\alpha^T g(y^t,y^{t-1},...,y^{t-K}) + \theta_\beta^T g(y^t,y^{t-1},...,y^{t-K}|x_t) + \theta_\gamma^T g(y^t,y^{t-1},...,y^{t-K}|g_t)\}}{\kappa(\theta,y^{t-K},...,y^{t-1})} \quad (7)$$

To specify a TERGM for several networks at different time points, we model the joint probability of observing the networks between times $K+1$ and T by taking the product of the probabilities of the individual networks conditional on the others (Cranmer et al. 2014; Hanneke et al. 2010):

$$Pr(y^{K+1},...,y^T|y^1,...,y^K,\theta) = \prod_{t=K+1}^{T} Pr(y^t|y^{t-K},...,y^{t-1},\theta) \quad (8)$$

The Akaike informative criterion (AIC) and Bayesian information criterion (BIC) in the results of ERGM can be used to judge whether a model is good or bad for the formation of a GRETN, and the smaller the AIC and BIC, the better the results of ERGM.

The patterns of GRETNs

Macro-overall patterns

To describe the patterns of GRETNs at the macro-level, relevant network indicators of the GRETNs are shown in Table 2.

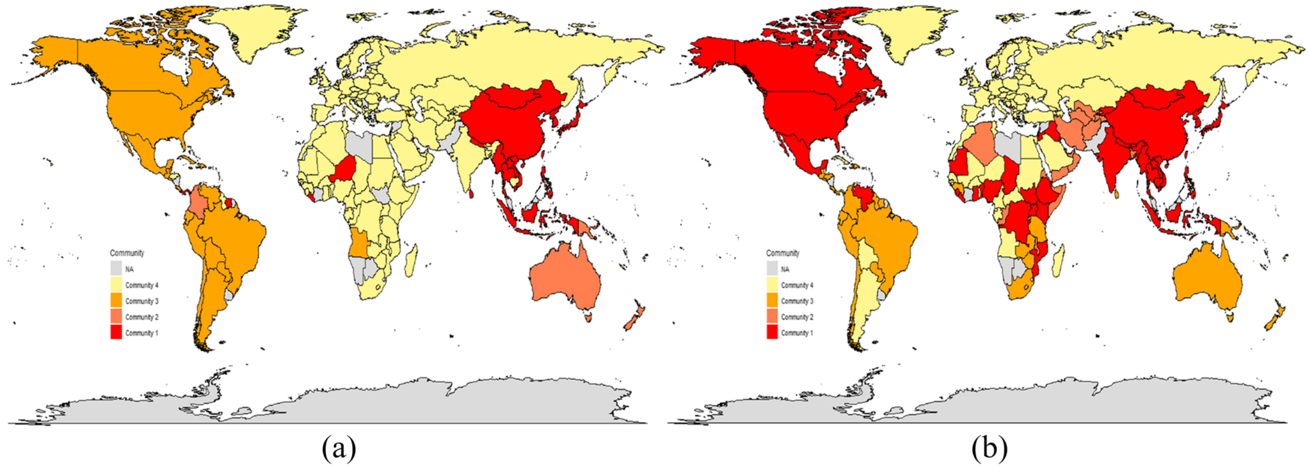


Fig. 2 The community pattern of GRETNs in 2000 and 2018

First, the scale of the GRETNs expands over years. The number of economies (N_v) remain between 201 and 204, reflecting that more than 87% of the economies in the world participate in the renewable energy trade. The number of edges (N_e) increases from 9292 in 2000 to the peak values of 13,147 in 2017 and density (ρ) from 0.231 to 0.321, respectively. This means that trade in renewable energy products between economies has become more frequent, reflecting that more economies increase demand and competition for green energy as the complementary energy source to fossil fuels under globalization and industrialization. Moreover, the average degree (AD) increases from 92.5 to 129.5 during 2000–2017, and average strength (AS) shows a generally growing trend, from 16,772.5 in 2002 to the peak value of 49,965.2 in 2011, although it declines in 2008 and 2011 as affected by the financial crisis in 2008 and the European debt crisis in 2011. This states that the average number of economies' trading partners in the GRETNs grows and each country builds connections with two additional trading partners per year on average. Similarly, the average trade volume of each country also increases with a growth rate of 5.9% per year on average.

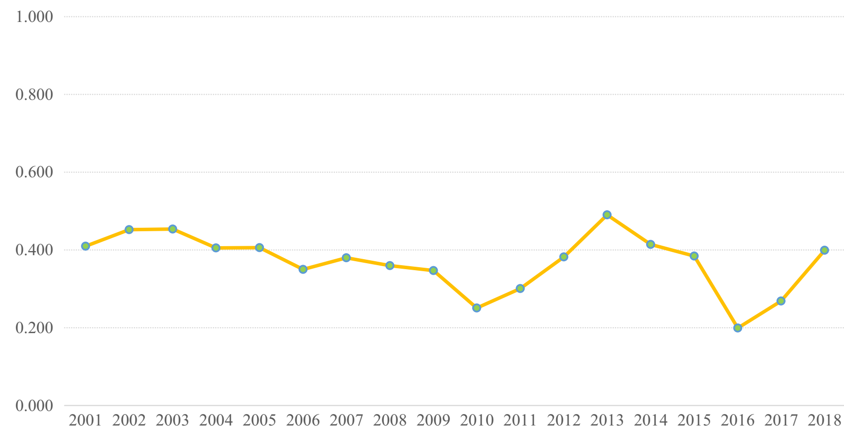
Second, the GRETNs reveal characteristics of a small-world network and reciprocity. Small-world network is between a random network and an ordered network, featured by a higher average clustering coefficient ($\overline{C}$) and a lower average path length (APL) (Watts and Strogatz 1998). Results in Table 2 show that APL is 2 with its value continuously decreasing, and the diameter (D) is 3 or 4. This means the distances between economies are so small in GRETNs that any two economies can trade if there is 1 "bridge" country between them on average, and 3 bridge economies at most through the shortest path. Moreover, the $\overline{C}$ of GRENTs shows a growing trend and increases from 0.563 in 2000 to the peak value of 0.650 in 2017. This means the number of closed triangles in the GRENTs increases gradually with the increase of renewable energy product trade relations, showing the agglomeration effect. According to the above analysis, GRETNs have a higher $\overline{C}$ and shorter APL, which conforms to the characteristics of small-world networks. For the reciprocity (R), results show that the R increases over years, and is about 0.5, meaning that there are many two-way reciprocal renewable energy product trade relationships.

Third, the GRETNs exhibit degree disassortative and export volume heterogeneity. The negative assortativity values state an obvious feature of degree disassortative in the GRETNs. In other words, economies with more renewable energy trade partners are more inclined to trade with economies with fewer trading partners. Meantime, we find that in-strength entropy (E^{in}) is more than out-strength entropy (E^{out}) during the study period, which indicates that GRETNs have great heterogeneity in the export volume, but are more random in the import volume. That is to say, there is such a big difference in the renewable energy product export volume of economies that only a few economies dominate most renewable energy product exports, while the difference is much smaller in imports. This characteristic can be explained by the uneven distribution of renewable energy product production technology, with only a few economies having mastered their production techniques.

Medium-community patterns

The community structure is that a GRETN is divided into several groups based on the strength and tightness of relations of the renewable energy product trade (Newman and Park 2003), which can assist us in better understanding the patterns of GRETNs (Fan et al. 2014). Using the spin-glass community detection algorithm (Reichardt and Bornholdt 2006), we have divided the GRETNs into several communities and found that the intra-community connections are denser than inter-community ones.

Fig. 3 NMI of GRETN change in 2000–2018



As shown in Fig. 2a, the GRETN is divided into four communities in 2000, including community 1 with China (CHN) at its core and 27 members, community 2 with the Australian (AUS) at its core and 15 members, community 3 with the USA at its core and 33 members, and community 4 with Germany (DEU) and the UK (GBR) at its core and 126 members. This community structure exposes that most economies in the same community are geographic neighbors, which suggests that how geographically far the economies are is an essential factor in forming the renewable energy product trade links. With the advancement of economic globalization and the refinement of the labor value chain, more and more economies are involved in the GRETNs, and the community structure has undergone a reshuffle. The community structure of 2018 has evolved into community 1 constituted of 55 economies and centered on China (CHN) and the USA, community 2 consisted of the United Arab Emirates (ARE) at the core and 15 other economies, community 3 comprising 43 members and centered on AUS and Brazil (BRA), and community 4 made up of 90 economies and centered on DEU and the GBR. This new pattern breaks the previous geographic neighbors with the decreasing transportation costs and improvement of other infrastructures.

To examine the stability of GRETN community, we calculate the NMI and record changes in Fig. 3. The result shows that the NMI value is less than 0.5, which means that the GRETN community structure fluctuates greatly every year. There are two reasons. First, such community structure fluctuations are caused by the entry and exit of economies from the GRETNs. Second, the renewable energy product competition and complementation among economies make their community pattern fluctuate greatly. In addition, the values of NMI in 2010 and 2016 are local minimum. The possible reason is that the 2008 financial crisis had a great external impact on the GRETN in 2010. Moreover, the Paris Agreement, signed at the Paris Climate Change Conference in 2015, has led to increased demand for renewable energy, which made the global trade pattern of renewable energy products undergo a reshuffle in 2016.

Micro-node patterns

To better illustrate the topological characteristics of GRETNs at the micro-node level, we calculate economies' four typical centrality index covering out- and in-degree centrality, as well as out- and in-strength centrality from 2000 to 2018. As shown in Fig. 4, we display the top 5 economies.

For Fig. 4a, the top 5 out-degree centrality economies in GRETNs are GBR, USA, DEU, France (FAR), and Italy (ITA) before 2006, all developed economies with exporting partners more than 175 in total. Since 2006, China (CHN) has been in the top 5 economies, and its ranking is relatively stable, becoming one of the largest exporters in the GRETNs. It may lie in the acceleration of China's industrialization; the support of renewable energy industrial policies and the export-oriented development strategy have promoted the expansion of China's exports. As for in-degree centrality shown in Fig. 4b, the USA, DEU, FRA, GBR, and Netherlands (NLD) are the top 5 in most years, and Canada (CAN) and Mexico (MEX) are in the top 5 economies in GRETNs in 2011–2012 and 2016–2017, respectively.

In terms of the out-strength centrality (Fig. 4c), the USA, CHN, DEU, and JPN are the usual top 5 economies and South Korea (KOR), FAR, ITA, and Taiwan (TWN) are in the top 5 list in some years, which are the main exporters as well as important participants in the GRETNs. During the first "boom" stage (2000–2011), their exports in renewable energy products grew rapidly on account of the wave of globalization but declined in 2009 following the 2008 global recession. What is special is that their growth rates have changed significantly since the 2009 decline and CHN has turned out to be the fastest-growing exporter of global renewable energy trade with a surprising growth rate of 56%. The second "adjustment" stage (2012–2015) has witnessed several fluctuations. Influenced by the European debt crisis in 2011, exports of the top 5 economies decrease and fluctuate moderately. At the third "new growth" stage (2016–2018), the export volumes start a new round of growth. The probable reason is that the Paris Agreement signed at the Paris Climate Change

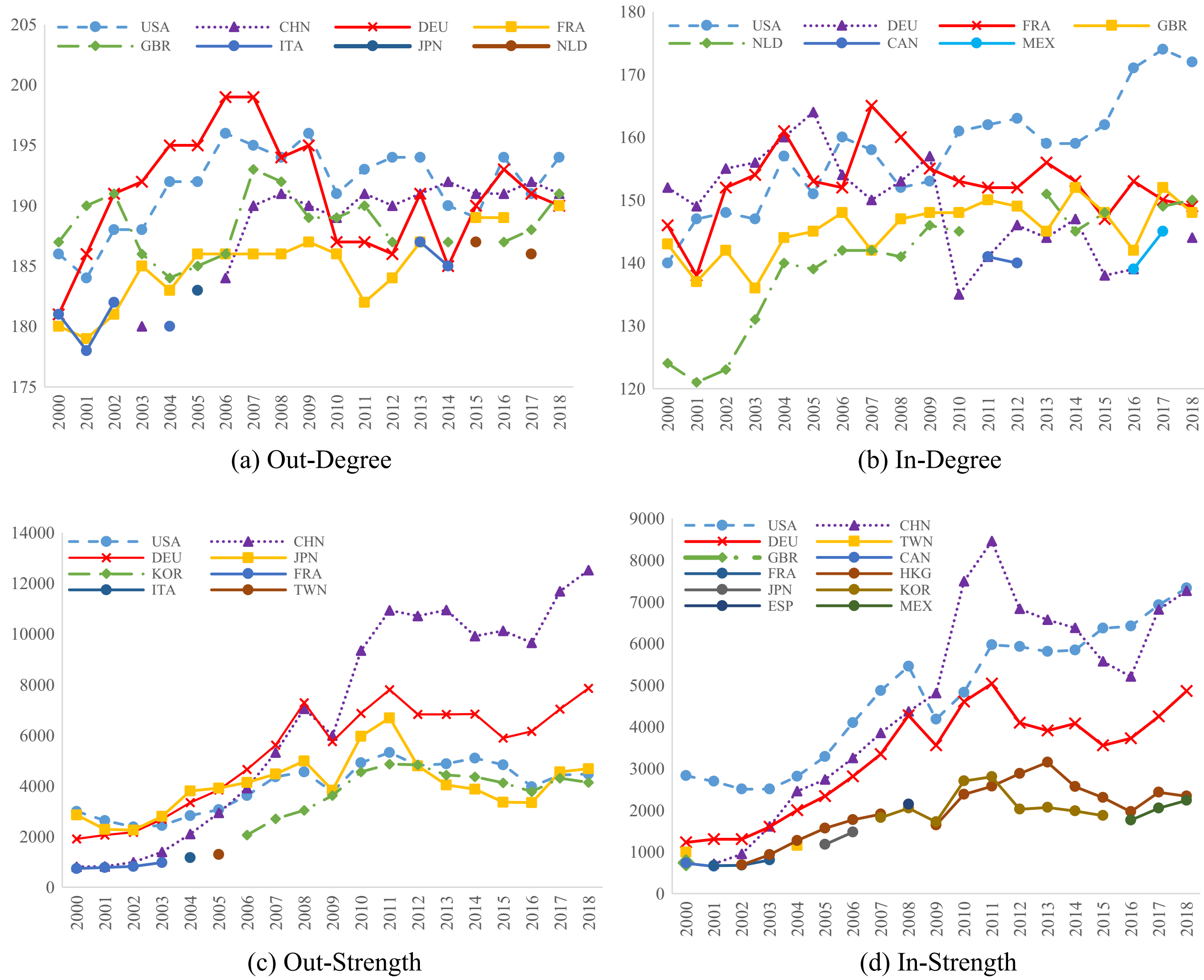


Fig. 4 Top 5 economies ranked by node centrality in 2000–2018

Conference in 2015 has increased global demand for renewable energy to reduce emissions.

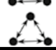
In terms of in-strength centrality (shown in Fig. 4d), the USA, CHN, and DEU always rank the top 5 while GBR, FRA, JPN, Spain (ESP), TWN, CAN, Hong Kong (HKG), KOR, and MEX are in the top 5 for some time. Particularly, CHN is the fastest-growing importer whose growth was impressively evident even when the global trade fell in the wake of the 2008 financial crisis and kept the top 1 during 2009–2014. One explanation is that with the CHN's accession to the WTO in 2001 and deeper participation in economic globalization, CHN has opened its domestic market and allowed more imports of renewable energy products from other economies along with increasing exports to the world market. The other is that CHN's export-oriented trade policies have successfully made CHN the world's factory, leading to a huge demand for renewable energies.

Triadic motif patterns

Triadic motifs can relate the local configuration of the network to its overall patterns and elucidate the evolving structural mechanism of complex networks (Guan et al. 2020). To explore the GRETN patterns among economies from local configuration, we identify the small connected subgraphs (triadic motifs) that repeatedly appear and analyze which triadic motifs play a significant role in the GRETNs. It is important to note that we only report the result of motifs pattern in 2018 due to the similar results of motifs triadic statistics.

As shown in Table 3, triadic motifs 111U, 021D, 210, 300, and 201 appear most frequently in GRETNs, which are more than 70,000. Among them, triadic motifs 111U, 300, and 201 are significant, meaning that the frequency of these

Table 3 Triadic motif statistic analysis of GRETNs in 2018

Name	Structure	F_{real}	$F_{random-mean}$	σ_{random}	R	Z-$score$	P	Sig.
021D		77122	77593	181.6	0.994	-2.595	0.995	
021U		7013	7306	103.7	0.960	-2.826	0.998	
021C		19692	20360	235.9	0.967	-2.834	0.998	
111D		23283	23383	172.9	0.996	-0.580	0.719	
111U		158243	157914	196.8	1.002	1.673	0.047	**
030T		9789	10259	145.9	0.954	-3.222	0.999	
030C		416	458	18.8	0.908	-2.247	0.988	
201		70477	70092	265.4	1.005	1.451	0.073	*
120D		5544	5440	69.7	1.019	1.490	0.068	*
120U		49416	49564	132.7	0.997	-1.112	0.867	
120C		9606	10128	139.0	0.948	-3.758	1.000	
210		73216	73724	211.1	0.993	-2.409	0.992	
300		71903	71251	180.1	1.009	3.622	0.000	***

F_{real} is the frequency of real network, $F_{\text{random-mean}}$ is the mean frequency of a random network, σ_{random} is the standard deviation of the random network, $R = F_{\text{real}}/F_{\text{random-mean}}$, $Z = (F_{\text{real}} - F_{\text{random-mean}})/\sigma_{\text{random}}$

*Significant at 5%

**Significant at 1%

***Significant at 0.1%

triadic motifs in GRETNs is much higher than that in random networks. Triadic motifs 111U, 300, and 201 show that there are characteristics of reciprocity and structural embeddedness in the GRETNs, which indicates that reciprocity and structural embeddedness have an important influence on the formation of the GRETNs and their structural characteristics. However, although triadic motifs 021D and 210 appear more frequently than others, their impacts on the overall structure of GRETNs are not significant. In contrast, although triadic motif 120D is significant, its frequency is relatively small, indicating that triadic motif 120D represents clustering and may only play a certain role in some local structures of the GRETNs. This phenomenon may be attributed to a limited number of intermediary economies in the GRETNs.

Determinants of the GRETNs

Variable selection of ERGM and TERGM

ERGM views the process of network formation as the accumulation of local substructures (Lusher et al. 2012). Thus, its explanatory variables are network configurations. Explanatory variables in ERGM models can be divided into the following three categories of network effects.

Endogenous structural effects

One kind of spontaneous internal structure of the network, which is completely constructed by the internal system and does not involve economic attributes or other exogenous factors, is called the endogenous structural effects. Analogous to statistical inference models, the Edges intercept term reflects the network density (Robins et al. 2007). Reciprocity describes the preference for two-way trade relationships between economies in a network. Structural embeddedness reveals network location opportunities to ensure redundant paths for resources (Nahapiet and Ghoshal 1998). Outdegree popularity captures the tendency of country i to connect with country j which has the more outgoing ties in GRETNs (Cranmer et al. 2017). To verify the above effects on the formation of GRETNs, we have added the *Edges*, *Mutual*, *Nodecov(Degree)*, and *Odegreeppopularity* counterparts to ERGM and TERGM (Table 4). Once the coefficients of these terms pass the significance test, it means that they have statistically significant impacts on the development of GRETNs. And positive coefficients suggest that, under other conditions, these effects affect the network structure much more than expected, contributing to the formation and evolution of the observed GRETNs.

Table 4 ERGM and TERGM variables and their implications

Classification	Variable Name	Meaning	Configuration	Statistic
Endogenous Structural Variables	Edges	Network density		$\sum_{i,j} y_{ij}$
	Mutual	Feedback effect		$\sum_{i,j} y_{ij} y_{ji}$
	Nodecov(Degree)	Structural embeddedness effect	Degree +	$\sum_{i,j} Degree_i y_{ij} + \sum_{i,j} Degree_j y_{ij}$
	Odegreepopularity	Out-degree popularity effect		$\sum_{i,j} Out-degree_j y_{ij}$
Country Attributes Variables	Homophily(Continent)	Continent homophily	Continent	$\sum_{i,j} y_{ij} Continent_i Continent_j$
	Homophily(APEC)	APEC homophily	APEC	$\sum_{i,j} y_{ij} APEC_i APEC_j$
	Homophily(WTO)	WTO homophily	WTO	$\sum_{i,j} y_{ij} WTO_i WTO_j$
	Homophily(GDP)	Economic homophily	GDP	$\sum_{i,j} y_{ij} GDP_i GDP_j$
	Homophily(PerGDP)	Per capita GDP homophily	PerGDP	$\sum_{i,j} y_{ij} PerGDP_i PerGDP_j$
	Homophily(Area)	Area homophily	Area	$\sum_{i,j} y_{ij} Area_i Area_j$
	Nodecov(GDP)	Economic Matthew effect	GDP +	$\sum_{i,j} GDP_i y_{ij} + \sum_{i,j} GDP_j y_{ij}$
	Nodecov(perGDP)	Per capita GDP Matthew effect	perGDP +	$\sum_{i,j} perGDP_i y_{ij} + \sum_{i,j} perGDP_j y_{ij}$
	Nodecov(Area)	Area Matthew effect	Area +	$\sum_{i,j} Area_i y_{ij} + \sum_{i,j} Area_j y_{ij}$
	Nodecov(TD)	Trade dependence Matthew effect	TD +	$\sum_{i,j} TD_i y_{ij} + \sum_{i,j} TD_j y_{ij}$
	Nodecov(Industry)	Industrialization Matthew effect	Industry +	$\sum_{i,j} Industry_i y_{ij} + \sum_{i,j} Industry_j y_{ij}$
	Nodecov(Urban)	Urbanization Matthew effect	Urban +	$\sum_{i,j} Urban_i y_{ij} + \sum_{i,j} Urban_j y_{ij}$
	Nodecov(EPI)	Environmental regulation Matthew effect	EPI +	$\sum_{i,j} EPI_i y_{ij} + \sum_{i,j} EPI_j y_{ij}$
External Network Variables	Edgecov(COL)	Common language embedding effect	COL	$\sum_{i,j} y_{ij} COL_{ij}$
	Edgecov(CRN)	Common religion embedding effect	CRN	$\sum_{i,j} y_{ij} CRN_{ij}$
	Edgecov(CCL)	Colonial embedding effect	CCL	$\sum_{i,j} y_{ij} CCL_{ij}$
	Edgecov(RTA)	RTA embedding effect	RTA	$\sum_{i,j} y_{ij} RTA_{ij}$
	Edgecov(CUR)	Common currency embedding effect	CUR	$\sum_{i,j} y_{ij} CUR_{ij}$
	Edgecov(CGN)	Common geographic boundary embedding effect	CGN	$\sum_{i,j} y_{ij} CGN_{ij}$

Economies' attribute effects and variables

Economies' comparative advantages, resource endowments, economic characteristics, geographical conditions, and institutional environments are classical influential factors in trade networks (Emirbayer and Goodwin 1994; Kilduff and Krackhardt 2008; Parkhe et al. 2006), which are usually called economies' attribute effects in ERGMs. Homophily is the principle that economies with similar attributes are more likely to trade (McPherson et al. 2001; Golub and Jackson 2012). Matthew effects refer to the phenomenon that the rich get richer and the poor get poorer (Howley 1995), which in GRETNs means that the stronger an economy's certain economic endowment, the greater its desire to trade in renewable energy products.

Compared with economies that are on different continents, economies on the same continent have smaller geographical distances, more means of transportation, and lower transportation costs. Also, economies have full access to many trade promotion and incentive policies if economies are the members of Asia–Pacific Economic Cooperation (APEC) and the World Trade Organization (WTO), such as lower tariffs, financial supports, and preferential tax policies (Jing et al. 2020). Based on the theory of preference similarity, economies with a similar level of economic development, income, and area are also more inclined to trade for similar preferences and demand (Kemp and Linder 1965). Since economies with higher economic development have higher productivity and lower prices for renewable energy products, they are more motivated to actively participate in trade to earn more profits. Besides, economies with higher dependence on foreign trade usually pay more attention to trade facilitation construction, including increasing infrastructure construction, reducing tax revenue, and providing policy support, which is conducive to reducing trade barriers and promoting the development of renewable energy product trade. Moreover, studies by Sadorsky (2013), Shahbaz et al. (2017), Mrabet et al. (2019), and Yu et al. (2020) show that urbanization speeds up the agglomeration of labor, capital, and technology, which not only promotes the urban economy but also increases the energy demand. Similarly, economies with higher industrialization rates are more active in GRETNs because of their higher production capacity and energy demand (Jiang and Lin 2012). Finally, environmental regulation is another crucial determinant of international energy trade patterns (Cole and Elliott 2003), which helps stimulate economies' innovations to build comparative advantages (Costantini and Mazzanti 2012; Groba 2014; Kuik et al. 2019). Thus, economies with stricter environmental regulations have been more active.

Relational embeddedness effects and variables

In addition to the endogenous structural effects and economic attribute effects, the relational embeddedness effects are also an important component that cannot be ignored in the GRETNs, such as cultural relations, economic agreements, geographical distance, and other exogenous binary relations (Granovetter 1985; Lusher et al. 2012).

As an essential part of the informal institution, culture has increasingly become an important factor influencing international trade (Tadesse et al. 2017), considering that greater cultural distances lead to more uncertainty and higher transaction costs due to asymmetric information and complicated communications (Guiso et al. 2009; Cyrus 2015; Tadesse et al. 2017). Based on the overlapping demand theory, Dubois et al. (2014) find that culture distances could influence other economies' consumer demand through preference diffusion while cultural similarity could reduce penetration costs (Turco and Maggioni 2016). For example, under the long-term influence of colonists, colonies often evolve similar cultural backgrounds (Rose 2000). Thus, we employ linguistic similarity, religious similarity, and the relation of colonist-colony as proxy variables of cultural similarity (Dunlevy 2006; Hanousek and Kocenda 2014). Furthermore, RTAs (regional free trade agreements) can shape the patterns of international trade as signing RTAs is an effective means to eliminate tariff barriers and promote economic integration (Magee 2008). Kemp and Wan (1976), Ghosh and Yamarik (2004), Goyal and Joshi (2006), Baier and Bergstrand (2007), and Eicher et al. (2012) show that there are the trade creation effect and trade diversion effect when two economies sign a formal RTA, which are conducive to promoting the growth of members' international trades (Baier and Bergstrand 2007). Moreover, sovereign monies are among the major non-tariff barriers to international trade (Rose and Wincoop 2001). According to the research of Glick and Rose (2002), the use of common currency has a continuous and stable promotion effect on the trade development of economies, since compared with the economies using different currencies, the trade volume of economies using common currency has increased by two times. Geographical distance is also a significant factor affecting renewable energy trade. Leibenstein and Tinbergen (1966), Pöyhönen (1963), and Anderson (1979) first analyzed theoretically and empirically based on the gravity model that the trade volume between two economies is inversely proportional to the geographical distance due to the high transportation cost. In this paper, based on the study of Fadly and Fontes (2019), we also use whether economies have a common geographic border as a proxy variable for geographic distance.

In summary, Table 4 lists relevant ERGM and TERGM variables used in this paper, and Table 9 gives an introduction to data sources for the structural statistics and how they are constructed.

ERGM and TERGM empirical results

Baseline model and ERGM results

To enhance the fitting of combinations of variables in TERGM, we first analyze and evaluate the simplicity and effectiveness of the baseline model by comparing the values of AIC and BIC, assessing goodness of fit, and examining motif in the cross-sectional GRETN in 2016 referring to He et al. (2019) and Tang and Cui (2020). Table 5 shows the addition of endogenous structural effects, economies' attribute effects, and relational embeddedness effects to the ERGM step-by-step in model 1–model 3. The consistency and significance between the actual coefficient and theoretical reasoning, as well as the smaller values of AIC and BIC, together determine model 3 as the most appropriate ERGM baseline model.

Table 5 Baseline model estimated results for GWPTN in 2017

	Model 1	Model 2	Model 3
Endogenous structural statistics			
Edges	−2.389 (0.060)***	−2.377 (0.062)***	−9.091 (0.024)***
Mutual			0.518 (0.010)***
Nodecov(Degree)			0.017 (0.000)***
Odegreepopularity			0.190 (0.001)***
Economies' attribute statistics			
Homophily(Continent)	0.761 (0.026)***	0.756 (0.026)***	1.587 (0.010)***
Homophily(APEC)	0.100 (0.032)**	0.093 (0.032)**	−0.009 (0.010)
Homophily(WTO)	0.031 (0.022)	0.025 (0.022)	0.071 (0.007)***
Homophily(GDP)	0.007 (0.004)	0.007 (0.004)	−0.004 (0.001)***
Homophily(perGDP)	−28.078 (9.308)**	−25.924 (9.490)**	0.479 (0.014)***
Homophily(Area)	0.007 (0.024)	−0.003 (0.024)	−0.020 (0.008)*
Nodecov(GDP)	0.005 (0.004)	0.005 (0.004)	0.006 (0.001)***
Nodecov(perGDP)	48.526(8.272)***	45.528(8.452)***	−18.619(0.022)***
Nodecov(Area)	0.000 (0.000)***	0.000 (0.000)***	−0.000 (0.000)***
Nodecov(TD)	0.002 (0.000)***	0.002 (0.000)***	−0.000 (0.000)***
Nodecov(Industry)	−0.011 (0.001)***	−0.010 (0.001)***	0.003 (0.000)***
Nodecov(Urban)	0.008 (0.000)***	0.008 (0.000)***	0.002(0.000)***
Nodecov(EPI)	0.005 (0.000)***	0.005 (0.000)***	0.000 (0.000)***
Relational embeddedness statistics			
Edgecov(COL)		0.101 (0.035)**	0.006 (0.011)
Edgecov(CRN)		−0.060 (0.024)*	0.144 (0.008)***
Edgecov(CCL)		0.004 (0.040)	0.152 (0.011)***
Edgecov(RTA)		0.124 (0.036)***	0.079 (0.011)***
Edgecov(CUR)		−0.134 (0.087)	0.088 (0.023)***
Edgecov(CGN)		0.150 (0.098)	0.114 (0.022)***
AIC	48,194	48,175	23,847
BIC	48,315	48,348	24,045

The values are stable standard errors in parentheses

*Significant at 5%

**Significant at 1%

**Significant at 0.1%

Results of TERGM

Based on the baseline model (model 3), we use TERGM to analyze the mechanism of dynamic changes in the GRETNs during 2000–2018, and the model 4 of Table 6 lists the corresponding model estimates. First, regarding statistics on endogenous structure, the coefficients of *Mutual*, *Edge*, *Nodecov(Degree)*, and *Odegreepopularity* all pass the rigorous significance test. In more detail, the significantly negative coefficient of *Edge* echoes previous theoretical analysis that when two economies establish a trade relationship for renewable energy products, it will affect the establishment of another trade relationship in the GRETNs, with a probability of 0.009%.[1] Moreover, the coefficient of *Mutual* is positive and quite significant, indicating that reciprocity is obviously involved in the formation and evolution of GRETNs, mainly due to lower transaction costs, lower information costs, and fewer moral hazards when economies choose their renewable energy export/import partners that have imported/exported renewable energy (Chaney 2014). And the probability of country i choosing its importing-source country j as its export destination is 93.3% (exp (0.659) − 1), higher than randomly selected economies. In addition, the coefficients of *Nodecov(Degree)* and *Odegreepopularity* also show positive significance, which means that structural embeddedness and out-degree popularity are also indispensable components. The probability of economies with more trade partners trading renewable energy products with others is 1.7% (exp (0.017) − 1), and the probability of being selected as a trading partner by other economies

[1] It is calculated as exp(−9.359) / (1 + exp(−9.359)).

Table 6 TERGM estimated results for GRETNs

	Model 4 2000–2018	Model 5 2000–2010	Model 6 2007–2018	Model 7 2000–2018 (step = 2)
Endogenous structural statistics				
Edges	−9.395 (0.051)***	−9.183 (0.042)***	−10.077 (0.042)***	−9.312 (0.042)***
Mutual	0.659 (0.028)***	0.760 (0.021)***	0.424 (0.026)***	0.633 (0.020)***
Nodecov(Degree)	0.017 (0.000)***	0.017 (0.000)***	0.018 (0.000)***	0.017 (0.000)***
Odegreepopularity	0.190 (0.002)***	0.194 (0.001)***	0.180 (0.002)***	0.187 (0.002)***
Economies' attribute statistics				
Homophily(Continent)	1.086 (0.018)***	1.024 (0.031)***	1.175 (0.021)***	1.083 (0.021)***
Homophily(APEC)	0.232 (0.021)***	0.215 (0.021)***	0.195 (0.025)***	0.218 (0.020)***
Homophily(WTO)	0.332 (0.017)***	0.358 (0.014)***	0.220 (0.017)***	0.293 (0.016)***
Homophily(GDP)	−0.059 (0.013)***	−0.079 (0.015)***	−0.018 (0.013)	−0.056 (0.012)***
Homophily(perGDP)	−56,664 (0.024)***	−66.583 (6.016)***	−73.227 (0.084)***	−74.905 (0.026)***
Homophily(Area)	0.180 (0.022)***	0.144 (0.020)***	0.164 (0.018)***	0.155 (0.012)***
Nodecov(GDP)	0.058 (0.013)***	0.076 (0.015)***	0.017 (0.013)	0.055 (0.012)***
Nodecov(perGDP)	−14.977 (0.006)***	−3.495 (14.140)	2.572 (0.070)***	−11.008 (0.021)***
Nodecov(Area)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Nodecov(TD)	−0.001 (0.000)***	−0.001 (0.000)***	−0.001 (0.000)***	−0.001 (0.000)***
Nodecov(Industry)	0.008 (0.000)***	0.007 (0.000)***	0.005 (0.000)***	0.008 (0.000)***
Nodecov(Urban)	0.003 (0.000)***	0.003 (0.000)***	0.002 (0.000)***	0.002 (0.000)***
Nodecov(EPI)	−0.002 (0.000)***	−0.001 (0.000)***	0.006 (0.000)***	−0.001 (0.000)*
Relational embeddedness statistics				
Edgecov(COL)	0.544 (0.028)***	0.575 (0.021)***	0.619 (0.024)***	0.623 (0.024)***
Edgecov(CRN)	0.123 (0.019)***	0.142 (0.018)***	0.063 (0.015)***	0.082 (0.015)***
Edgecov(CCL)	0.490 (0.025)***	0.466 (0.020)***	0.536 (0.030)***	0.428 (0.020)***
Edgecov(RTA)	0.763 (0.039)***	0.949 (0.057)***	0.602 (0.031)***	0.692 (0.026)***
Edgecov(CUR)	0.708 (0.006)***	0.693 (0.054)***	0.570 (0.013)***	0.542 (0.015)***
Edgecov(CGN)	1.651 (0.009)***	1.566 (0.050)***	1.797 (0.006)***	1.722 (0.013)***
Obs	857,964	496,716	541,872	451,560

The values are stable standard errors in parentheses.

*Significant at 5%

**Significant at 1%

***Significant at 0.1%

increases by 20.9% for every 1 unit increase in the number of export trading partners, respectively. According to Bastomski et al. (2017), the mechanism is that economies with more renewable energy trade partners have more competitive advantages to expand trade markets and enable their benefits to be realized (Coleman 1988; Weng 2018).

Second, economic attributes affect the emergence of GRETNs. For the homophily, *Homophily(Continent)*, *Homophily(APEC)*, *Homophily(WTO)*, and *Homophily(Area)* are significantly positive. The positive *Homophily(Continent)* confirms the concept that the trade is more likely to occur in economies on the same continent due to the more available transportation ways and lower transportation costs compared with economies in different continents. Moreover, compared with APEC (or WTO) members and non-members, the trade probability among APEC (or WTO) members would increase by 26.1% (39.4% for WTO). The positive *Homophily(Area)* states the homophily in areas, where the renewable energy product trade is more possible to happen between economies with symmetrical areas. Unexpectedly, the coefficients of *Homophily(GDP)* and *Homophily(perGDP)* pass the significance test at the 0.1% level with a negative effect, which demonstrates heterophily in economic development as well as per capita income. The convincible reason is that the greater difference in economic development or per capita income between economies has resulted in stronger complementarity of their renewable energy productdevelopment, and eventually led to trade links. The parameters of Matthew effects are significantly negatively correlated, including *Nodecov(perGDP)*, *Nodecov(Area)*, *Nodecov(TD)*, and *Nodecov(EPI)*, stating that there are not obvious Matthew effects in per capita income, area, trade dependence, and environmental regulation for the evolution of GRETNs. In other words, it is economies with lower per capita income and trade dependence, smaller areas, and weaker environmental regulations that are more active to trade in the GRETNs. The significantly positive coefficients of *Nodecov(GDP)*, *Nodecov(Industry)*, and *Nodecov(Urban)* show that economies exhibit obvious economic development, urbanization, and industrialization rates of Matthew effects in choosing renewable energy product trade partners. These are consistent with the facts. Economies with higher economic development, urbanization, and industrialization rates have higher product production capacity or energy demand, so they are active to trade with others.

Third, for the external relationship embeddedness statistics, the coefficients of *Edgecov(COL)*, *Edgecov(CRN)*, and *Edgecov(CCL)* are all positive and statistically significant. These results are consistent with our prediction that economies with similar cultural backgrounds tend to trade renewable energy products for lower uncertainty, transaction costs, and similar energy consumption demands. More specifically, the possibility of country-pairs trading renewable energy products increases by 72.3%, 13.4%, and 63.2%, respectively, when they use a common language, practice the same religion, or once belonged to the same colonists. Among them, the coefficient of *Edgecov(COL)* is the biggest, suggesting that common language relationships have the strongest embeddedness effects on the dynamic evolution of the GRETNs. Furthermore, the significant and positive *Edgecov(RTA)* and *Edgecov(CUR)* indicate that significant external binary relationship embedding effects are established through the signing of regional trade agreements or the use of a common currency, in which lower tariff barriers, lower exchange rate fluctuation risks, and trade diversion effects play an important role. The coefficient of *Edgecov(CGN)* is also significantly positive at 0.1% level and is the largest in external network statistics. It states that geographical distance is invariably a classical and vital factor of GRETNs, and economies are more likely to trade with their neighbors for lower transportation costs.

Moreover, to examine the robustness of the TERGM results of GRETNs, the results of model 5–model 7 (Table 6) are reported. To be specific, we estimate TERGM results for the subsample periods 2000–2010 (model 5) and 2007–2018 (model 6). Then, we adjust the time step of longitudinal GRETNs in 2000–2018 from 1 to 2 (model 7). The above further test results are consistent with the results of model 4, which indicates that the results of model 4 are robust, that is, the endogenous structure effects, economies' attribute effects, and relational embeddedness effects do have significant performance in the formation and evolution of GRETNs.

Conclusions and discussion

The renewable energy product trade is important to global economic prospects, and its rapid development has made it a key issue in the field of international economics. In this paper, we construct GRETNs during 2000–2018 based on the method of complex network and bilateral trade data collected from the UNcomtrade Database. The evolutionary patterns of GRETNs and their determinants are empirically tested using the ERGM and TERGM. Some meaningful conclusions are drawn, and several policy implications are proposed as follows.

For the macro-overall patterns, the scale of global renewable energy trade expands over years except in 2008 under the Great Recession. The GRETNs show obvious features of a small-world, reciprocity, degree disassortative, and export volume heterogeneity, which means GRETNs exhibit the characteristic of a higher average clustering coefficient and a lower average path length, the enhanced tendency of two-way reciprocal trade relationships, the increased trade willingness between economies with many partners and those with few partners, and a big difference in the renewable energy product export volume. Meanwhile, it is worth noting that due to the uneven distribution of renewable energy product production technologies, there is still a common Pareto principle in GRETNs. In terms of medium-community patterns, affected by the entry and exit of economies as well as the competition and complementarity of renewable energy products among economies, the GRETNs gradually form four communities, including community 1 constituted of 55 economies and centered on CHN, community 2 consisted of 16 economies with ARE at the core, community 3 constituted of 43 members and centered on AUS and BRA, and community 4 made up of 90 economies and centered on DEU and GBR. The NMI shows that the GRETN community structure fluctuates greatly. For micro-node patterns, economies in North America, Europe, and Asia play important roles in the global renewable energy trade. To be specific, the USA and DEU are cores of the GRETNs for having the most export and import partners and volumes, and CHN plays an important role in the export of renewable energy products and is the fastest-growing importer. The acceleration of industrialization, the support of renewable energy industrial policies, and export-oriented development strategy have promoted the expansion of China's renewable energy product export trading partners. However, there are no developing or emerging economies in the top 5 economies in in-degree centrality. As for the out-strength centrality, the USA, CHN, DEU, and JPN are the top 5 economies in GRETNs and South Korea (KOR), FAR, ITA, and Taiwan (TWN) are in the top 5 in some years, which are the largest exporters of renewable energy products in the world and play the important roles in the GRETNs. In terms of in-strength centrality, the USA, CHN, and DEU are the economies that are always ranked the top 5 in most years and GBR, FRA, JPN, Spain (ESP), TWN, CAN, Hong Kong (HKG), KOR, and MEX are in the top 5 in some years, meaning that they are the largest importers of renewable energy products and play the major roles in GRETNs. As for the renewable energy product trade patterns among economies from local configuration, triadic motifs 111U, 021D, 210, 300, and 201 appear most frequently in GRETNs.

The results of ERGM and TERGM show that the endogenous structure of reciprocity, structural embeddedness, and out-degree popularity have important influences on the formation and evolution of GRETNs. Economies that export renewable energy products are also more likely to be export destinations for their exporters, economies that already have more partners are more active in establishing more trade links, and economies tend to connect to those economies which have the more outgoing ties in the evolution of GRETNs. There is heterophily in economic development as well as per capita income for the formation of GRETNs meaning that the trade is more likely to occur between economies with asymmetrical economic development and per capita income. Meanwhile, economies with lower per capita income and trade dependence, smaller areas, and weaker environmental regulations or higher economic development, urbanization, and industrialization rates tend to trade renewable energy products. In addition, country-pairs sharing a common language, practicing the same religion, or once belonged to the same colonists, signing RTAs, or having a common geographic boundary are more likely to trade renewable energy products.

Based on the above analysis, we propose the following suggestions to promote the stability and sustainable development of the global renewable energy system. First, leading economies need to maintain their efforts in the development of renewable energy product trade, and the small peripheral economies need to work more actively with strong partners to achieve greater participation in the global division of renewable energy products. Representative countries in the GRETNs should actively exert their advantages in new energy manufacturing, project design, and construction, and help emerging economies such as countries along the "Belt-and-Road" to develop renewable energy, because promoting the development of renewable energy in these countries will not only help reduce the adverse impact of climate change, and protect the environment and people's health, but also accelerate the transformation of the global energy structure. Second, economies should strengthen trade facilitations and regional trade liberalizations, represented by the common currency and RTAs. At the same time, a fair and effective coordination mechanism for renewable energy product trade should be established based on the existing global economic governance system to reduce trade disputes. At present, many countries have more policies than legislations in the field of renewable energy, with the problem that the coordination, stability, and enforcement of policies are not as good as legal rules, so it is necessary to establish a set of renewable energy policies that are clearly different from legal rules, so that they can be coordinated, market-driven, and with long-term performance. Third, international efforts need to be focused on strengthening infrastructure constructions and cultural exchanges to reduce transaction costs and cultural barriers in global renewable energy trade. Especially for emerging developing countries, they should take full use of their structural advantages, strengthen interactions and cooperations with global as well as regional standards organizations, break through the "green regulation lock" of developed countries through multilateral coordination, and focus on discussing new infrastructure standards for renewable energy and cybersecurity standards for renewable energy technologies to jointly standardize the governance rules of smart energy cybersecurity and new infrastructure.

Appendix 1

Table 7 The HS codes of renewable energy products covered this paper

Category	HS codes
Solar energy (17)	700,991, 700,992, 711,590, 730,890, 732,290, 721,090, 830,630, 841,280, 841,919, 841,990, 850,239, 850,440, 854,140, 900,190, 900,290, 900,580, 901,380
Wind energy (19)	730,820, 841,290, 848,210, 848,220, 848,230, 848,240, 848,250, 848,280, 848,340, 850,231, 850,300, 853,710, 853,720, 890,790, 902,830, 903,020, 903,031,903,039, 903,289
Hydro energy (17)	382,450, 681,091, 841,011, 841,012, 841,013, 841,090, 850,161, 850,162, 850,163, 850,164, 850,421, 852,422, 850,423, 850,431, 850,432, 850,433, 850,434
Bio-energy (18)	220,710, 220,720, 380,210, 382,490, 730,900, 741,999, 761,100, 840,682, 840,682, 841,182, 841,620, 841,931, 841,940, 841,989, 842,129, 824,139, 847,920,847,989
Geo-thermal energy (8)	730,431, 730,441, 730,451, 741,121, 741,122, 741,129, 841,861, 841,950
Marine energy (2)	854,449, 854,460

Table 8 List of countries covered in this paper

Name	Code	Name	Code	Name	Code	Name	Code
Afghanistan	AFG	Dominican Republic	DOM	Madagascar	MDG	St. Pierre and Miquelon	SPM
Albania	ALB	Ecuador	ECU	Malawi	MWI	Saint Vincent and the Grenadines	VCT
Algeria	DZA	El Salvador	SLV	Malaysia	MYS	The Republic of San Marino	SMR
Andorra	AND	Equatorial Guinea	GNQ	Maldives	MDV	Sao Tome and Principe	STP
Angola	AGO	Ethiopia	ETH	Mali	MLI	Saudi Arabia	SAU
Antigua and Barbuda	ATG	Eritrea	ERI	Malta	MLT	Senegal	SEN
Azerbaijan	AZE	Estonia	EST	Mauritania	MRT	Serbia	SER
Argentina	ARG	Falkland Islands (Malvinas)	FLK	Mauritius	MUS	Seychelles	SYC
Australia	AUS	Fiji	FJI	Mexico	MEX	Sierra Leone	SLE
Austria	AUT	Finland	FIN	Chinese Taipei	TWN	India	IND
Bahamas	BHS	France	FRA	Mongolia	MNG	Singapore	SGP
Bahrain	BHR	French Polynesia	PYF	Republic of Moldova	MDA	Slovakia	SVK
Bangladesh	BGD	Djibouti	DJI	Montenegro	MON	Viet Nam	VNM
Armenia	ARM	Gabon	GAB	Montserrat	MSR	Slovenia	SVN
Barbados	BRB	Georgia	GEO	Morocco	MAR	Somalia	SOM
Belgium	BEL	Gambia	GMB	Mozambique	MOZ	South Africa	ZAF
Bermuda	BMU	Germany	DEU	Oman	OMN	Zimbabwe	ZWE
Bhutan	BTN	Ghana	GHA	Nauru	NRU	Spain	ESP
Bolivia	BOL	Gibraltar	GIB	Nepal	NPL	South Sudan	SSD
Bosnia and Herzegovina	BIH	Kiribati	KIR	Netherlands	NLD	Sudan	SDN
Brazil	BRA	Greece	GRC	Netherland Antilles	ANT	Suriname	SUR
Belize	BLZ	Greenland	GRL	Aruba	ABW	Sweden	SWE
Solomon Islands	SLB	Grenada	GRD	New Caledonia	NCL	Switzerland	CHE
British Virgin Islands	VGB	Guatemala	GTM	Vanuatu	VUT	Syrian Arab Republic	SYR
Brunei Darussalam	BRN	Guinea	GIN	New Zealand	NZL	Tajikistan	TJK
Bulgaria	BGR	Guyana	GUY	Nicaragua	NIC	Thailand	THA
Myanmar (Burma)	MMR	Haiti	HTI	Niger	NER	Togo	TGO
Burundi	BDI	Honduras	HND	Nigeria	NGA	Tokelau	TKL
Belarus	BLR	Hong Kong (SARC)	HKG	Niue	NIU	Tonga	TON
Cambodia	KHM	Hungary	HUN	Norfolk Island	NFK	Trinidad and Tobago	TTO
Cameroon	CMR	Iceland	ISL	Norway	NOR	United Arab Emirates	ARE
Canada	CAN	Indonesia	IDN	Northern Mariana Islands	MNP	Tunisia	TUN
Cape Verde	CPV	Iran	IRN	Micronesia	FSM	Turkey	TUR
Cayman Islands	CYM	Iraq	IRQ	Marshall Islands	MHL	Turkmenistan	TKM
Central African Republic	CAF	Ireland	IRL	Palau	PLW	Turks and Caicos Islands	TCA
Sri Lanka	LKA	Israel	ISR	Pakistan	PAK	Tuvalu	TUV
Chad	TCD	Italy	ITA	Panama	PAN	Uganda	UGA
Chile	CHL	Cote d'Ivoire	CIV	Papua New Guinea	PNG	Ukraine	UKR
China	CHN	Jamaica	JAM	Paraguay	PRY	The former Yugoslav Republic of Macedonia	MKD
Christmas Islands	CXR	Japan	JPN	Peru	PER	Egypt	EGY
Cocos (Keeling) Islands	CCK	Kazakhstan	KAZ	Philippines	PHL	United Kingdom	GBR
Colombia	COL	Jordan	JOR	Pitcairn	PCN	United Republic of Tanzania	TZA
Comoros	COM	Kenya	KEN	Poland	POL	United States of America	USA
Congo	COG	Democratic People's Republic of Korea	PRK	Portugal	PRT	Burkina Faso	BFA

Table 8 (continued)

Name	Code	Name	Code	Name	Code	Name	Code
Democratic Republic of the Congo	COD	Republic of Korea	KOR	Guinea-Bissau	GNB	Uruguay	URY
Cook Islands	COK	Kuwait	KWT	Timor-Leste (East Timor)	TMP	Uzbekistan	UZB
Costa Rica	CRC	Kyrgyzstan	KGZ	Qatar	QAT	Venezuela	VEN
Croatia	HRV	Lao People's Democratic Republic	LAO	Romania	ROM	Wallis and Futuna Islands	WLF
Cuba	CUB	Lebanon	LBN	Russian Federation	RUS	Samoa	WSM
Cyprus	CYP	Latvia	LVA	Rwanda	RWA	Yemen	YEM
Czech Republic	CZE	Liberia	LBR	Saint Helena	SHN	Zambia	ZMB
Benin	BEN	Libyan Arab Jamahiriya	LBY	Saint Kitts and Nevis	KNA		
Denmark	DNK	Lithuania	LTU	Anguilla	AIA		
Dominica	DMA	Macao (SAR)	MAC	Saint Lucia	LCA		

Table 9 Variable description of ERGM and TERGM

Symbol	Meaning	Data source
GRETNs	The global renewable energy trade networks	UN Comtrade Datadase
GDP	Economic development, gross domestic product	World Bank
Urban	The percentage share of the total population living in urban areas	World Bank
Industry	The second industry as a share of GDP	World Bank
APEC/WTO	1 if a country is a member of APEC/WTO, otherwise 0	World Bank
Area	Area of each economy	World Bank
TD	The imports and exports as a share of GDP	World Bank
EPI	Environmental performance index used to measure environmental regulation strength of each economy	SEDAC[a]
Continent	The continent each economy belongs to	
COL	The common official language network, the two economies use a common official language with a value of 1, otherwise 0	CEPII
CRN	The common religion network, the two economies have a common religious with a value of 1, otherwise 0	CEPII
CCL	The historical colonial relationship network, the two economies have a historical colonial relationship with the value of 1, otherwise 0	CEPII
RTA	The regional trade agreement network, two economies sign a free trade agreement or CU with the value of 1, otherwise 0	WTO
CUR	The common currency network, the two economies use a common currency with a value of 1, otherwise 0	CEPII
CGN	The economy's common geographic boundary network, the two economies have a common boundary with a value of 1, otherwise 0	CEPII

[a]https://sedac.ciesin.columbia.edu/data/collection/epi/sets/browse

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