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Evolution of structural properties and its determinants of global waste paper trade network based on temporal exponential random graph models

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ABSTRACT

As an important recyclable and reusable resource, waste paper is traded in millions of dollars around the world every year. Global waste paper trade not only addresses resource scarcity issues, alleviates environmental pressures and brings substantial economic gains, but also contributes to the development of global circular economy. Using complex network methods, bilateral waste paper trade data, and temporal exponential random graph models (TERGM), we construct global waste paper trade networks (GWPTNs) during 2000–2018, and examine their structural evolution and determinants. We report that: (I) GWPTNs display obvious features of small-world network, low reciprocity, heterogeneity and disassortativity; (II) Asia is the leading recipient of global waste paper, while Europe and North America are the main exporters; (III) China and India dominate the waste paper import markets while the United States is the largest exporter, and Germany plays an essential role in both importing and exporting hubs of waste paper; (IV) The evolution of the GWPTNs is significantly influenced by endogenous reciprocity, transitivity and preferential attachment, and economies with more partners or within the same continents are more likely to trade waste paper. Economies with higher urbanization rates, more per capita income, stricter environmental regulation, or lower industrialization rates are more likely to export waste paper; conversely, they are more likely to be the importers. Economy-pairs sharing a language or religion, being a former colony of the same colonizer, historical colonial relationship or a border, or signing regional trade agreements are more likely to trade waste paper.

1. Introduction

Millions of tons of waste paper are produced every year in the world and its growth rate is accelerating with the rapid urbanization, increasing literacy rates and industrial development [1,2]. Recycling and reusing useable resources from waste paper contribute to solving numerous environmental problems, as well as promoting socioeconomic and environmental sustainability [3], which has been important research fields of sustainability. Meanwhile, recycling and recovery of waste paper is a key component of the global circular economy [4,5]. Due to the geographically uneven distribution of paper and the associated product production and consumption, global trade of waste paper has experienced a dramatic increase since the 21st century. During 2000–2018, global waste paper trade increased from 2,136.5 million dollars in 2001 to the peak of 12,204.3 million dollars, a more than five-fold growth (Fig. 1). Global waste paper trade not only effectively addresses the resource scarcity issue [6], alleviates the pressure of waste paper disposal and brings substantial economic gains in some economies [4,7], but also favorably contributes to the sustainable utilization of waste paper resources on a global scale and the development of global circular economy [8]. Therefore, the study of waste paper trade is of paramount significance and a comprehensive understanding of the evolution of global waste paper trade and its determinants is crucial for policymakers to better develop policies for sustainable development of the global economy and environment.

Previous studies on waste paper focused mainly on the waste paper recycling seeking to explain the recovery and utilization rate [9–13], and assessing the associated economic, environmental and social

Abbreviations: GWPTNs, Global Waste Paper Trade Networks; TERGM, Temporal Exponential Random Graph Model.

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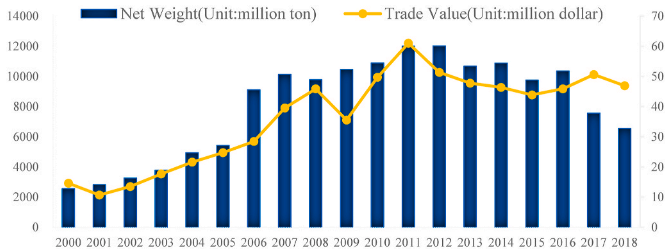

Fig. 1. Annual weight and value of global waste paper trade from 2000 to 2018. *Note:* Data source is UN Comtrade Database.

impacts [1,14–17]. The issue of waste paper trade is not broadly covered, except in some studies (such as Van Beukering & Bouman, 2001; Van Beukering & Van den Bergh, 2006; Li et al., 2018; Luo & Pan, 2019; Kellenberg, 2012; Sun, 2020) [9,18–22]. Some of them focused on the international waste paper trade pattern of developed economies dumping waste paper into developing economies or otherwise the features of waste paper trade in a specific economy (e.g. China). Others integrated waste paper trade into recyclable waste trade to investigate the development of recyclable waste trade. However, these studies pertaining to the waste paper trade pattern lacked comprehensiveness,[1] largely focusing on specific economies or relying on the perspective of the whole recyclable waste. There is a paucity of a study to comprehensively and systematically analyze global waste paper trade despite the large and growing waste paper trade flows as an important components in recyclable waste trade.

Global waste paper trade reflects trade flows among economies, which can be mapped as a network by viewing the economies as the nodes and trade flows between the economies as the edges. Guided by the complex network theory, there are growing studies analyzing international trade from the perspective of complex network with examples by Snyder & Kick (1979) [23], Fagiolo et al. (2010) [24], Fan et al. (2014) [25], Andrade & Rêgo (2018) [26]. Their research efforts provide a scientific and valid method for analyzing trade flows between economies, understanding evolutionary patterns of trade, community structure, and roles of economies in international trade [27]. In recent years, complex networks have also been applied to trade involving waste recycling, such as electrical and electronic equipment [28–33], plastic waste [34–36], second-hand clothes [37,38], scrap metal [39,40], and the recycling of materials [6]. However, there is a lack of research on the evolutionary patterns and structural characteristics of global waste paper trade from the network perspective. More importantly, most of these studies analyzed the overall features and evolutionary patterns of various trades with essentially descriptive statistics of the network indicators (i.e., density, average path length, clustering degree, community detection, and node-centrality), failing to explain the formation of their network pattern [41].

Some studies attempt to explain the international waste trade patterns with various factors. Specifically, they theoretically and empirically explored the impact of income (i.e., GDP, capital/labor ratios and GDP per capita) [42], environmental regulations [21], transport costs [43,44] and particular economic policies (e.g., trade restrictions, taxes, international environmental agreements) [45–50] of each economy on international waste trade based on international trade theory, waste trade hypotheses (e.g., pollution haven hypothesis, waste haven hypothesis) and models (e.g., gravity model, negative binomial regression model, fixed effect model) using waste trade data between economies. Moreover, D'Amato & Zoli (2012) [51] detailed the role that corrupt politicians and organized crime play in a variety of circumstances related to waste trade and management in different economies. These studies have offered prima facie understanding of the drivers of waste trade among economies, but most of them assumed that waste trades between the economies are independent of each other, particularly when using the gravity model to analyze the influencing factors of global waste trade. In fact, the waste trade relationships between economies are not as simple as dyad but instead becoming even more complex and interdependent than ever under the accelerating process of globalization [27]. More importantly, studies that examined the impact of national attributes (e.g., income, environmental regulations, transport costs, and economic policies) on waste trade, largely ignored the endogenous dependence of waste trade (e.g., reciprocity, transitivity, and connectivity) or the external embedding relationships. The emerging temporal exponential random graph model (TERGM) is an effective tool for the analysis of longitudinal international trade network, as it can comprehensively consider factors of various endogenous dependence, exogenous national attributes and embedding relationships [52–54].

To remedy the aforementioned deficiencies, we construct global waste paper trade networks (GWPTNs) during 2000–2018 using bilateral trade data collected from UN Comtrade database based on complex network method. We analyze the evolutionary features of the GWPTNs, and empirically test the factors that affect the formation and evolution of the GWPTNs using the TERGM. Then, we provide scientific basis and policy implication for how to effectively promote a virtuous circle of global waste paper trade towards realizing the sustainable utilization of waste paper resources. The contributions of the present study are threefold. First, this study separates waste paper trade from waste trade and constructs GWPTNs for the first time to our best knowledge, and systematically elucidates the evolutionary characteristics, revealing a more nuanced interpretation on the statuses and roles of the economies in the network from macro-, medium-, and micro-levels. Second, the analytical framework incorporates not only economy attributes but also the endogenous pure structure effects and external relations embedding effects for an integrated assessment of the factors that affect the formation and evolution of the GWPTNs. Third, the TERGM is employed to analyze the influencing factors of the GWPTN formation of with temporal change based on longitudinal networks, which enriches the literature on the applications of the TERGM beyond the cross-section network formation.

The rest of the paper is organized as: Section 2 is devoted to the data source, the process of constructing the global waste paper trade networks, and the methodology of the network analysis. Section 3 presents the findings of the analysis of the global waste paper trade networks and explores the network formation using TERGM. Conclusions and policy implications are drawn in Section 4.

2. Methodology

2.1. Network feature indicators

2.1.1. Macro-level indicators

Macro-level indicators depict overall topological properties and include the numbers of nodes and edges, density, average clustering coefficient, average path length, reciprocity, average degree, average strength degree, assortativity and strength entropy. Among them, the number of nodes (N_v) and edges (N_e) measure the numbers of trading economies and bilateral trade relations, respectively. Density (ρ), defined as $\rho = N_e / N_v(N_v - 1)$, measures the tightness of the connections within GWPTN. The larger the value, the denser the GWPTN.

The average clustering coefficient (*ACC*) is the mean of the clustering coefficients of all economies, and the average path length (*APL*) is the average number of edges along the shortest path for all possible economy-pairs in the GWPTNs. In this case, larger clustering coefficient means that an economy's trade partners are more likely to be partners [55], and a shorter *APL* means higher efficiency. According to Barrat

[1] Global waste paper trade is more complex than the case of developed economies dumping waste paper into developing economies, and there are a large number of cases of trade in the pattern of developed economies importing and developing economies exporting, developed economies importing and exporting and developing economies importing and exporting [7,36].

et al. (2004) [56], these two indicators are calculated as follows:

$$ACC=\frac{1}{N_v}\sum_{i=1}^{N_v}C_i \tag{1}$$

$$APL=\frac{1}{N_v(N_v-1)}\sum_{i\geq j}d_{ij} \tag{2}$$

Where d_{ij} denotes the shortest path from economy i to j. $C_i=\frac{1}{s_i(k_i-1)}\sum_{j,h}\frac{(w_{ij}+w_{ih})}{2}a_{ij}a_{ih}a_{jh}$ represents the clustering coefficient of economy i, where s_i indicates the trade volume of economy i, k_i indicates the partners of economy i. a_{ij} indicates elements in adjacency matrix of a GWPTN, and when there is an edge from economy i to j, $a_{ij}=1$; otherwise 0. w_{ij} indicates the trade volume between economy i and j.

Reciprocity (R) measures the tendency of economy-pairs to form mutual connections with each other. The larger the value, the more reciprocal the trade relationships. Reciprocity is defined as $R=\sum_{i\neq j}a_{ij}a_{ji}/N_e$.

For a given economy, average degree (AD) is the average number of trading partners, and average strength (AS) is the average trade volume. Strength entropy (G) describes the heterogeneity of economies' trading volume and can be divided into out-strength entropy (G^{out}) and in-strength entropy (G^{in}) in the directed GWPTNs. The larger the G, the more different the economies in the trading volume, and the greater the heterogeneity in economies' strength centrality [57]. G^{out} and G^{in} are defined as:

$$G^{out}=-\sum_{i=1}^{N_v}I_i^{out}\ln I_i^{out}, G^{in}=-\sum_{i=1}^{N_v}I_i^{in}\ln I_i^{in} \tag{3}$$

Where $I_i^{out}(I_i^{in})$ represents the proportion of economy i's waste paper exports (imports) in world trade.

Assortativity (A) describes the tendency that nodes with similar the number of partners are more likely to connect, measuring assortativity of a network [58]. The GWPTNs are assortative networks if $A\geq 0$; otherwise, it is a disassortative network. Assortativity is defined as:

$$A=\frac{1}{\sigma_q^2}\sum_{ij}ij(e_{ij}-q_iq_j) \tag{4}$$

where e_{ij} is the fraction of edges connecting nodes i and j, $q_i=\sum_j e_{ij}$, and σ_q is the standard deviations of q.

2.1.2. Medium-level indicators

Medium-level indicators provide normalized mutual information (NMI). NMI is used to measure the stability of the community structure in a network by comparing members within the community in different years. The larger the value, the more stable the network community structure. NMI is defined as:

$$NMI_{(t,t+1)}=\frac{\sum_{h=1}^{k^t}\sum_{l=1}^{k^{t+1}}n_{h,l}\log\left(\frac{n.n_{h,l}}{n_h^tn_l^{t+1}}\right)}{\sqrt{\left(\sum_{h=1}^{k^t}n_h^t\log\frac{n_h^t}{n}\right)\left(\sum_{l=1}^{k^{t+1}}n_l^{t+1}\log\frac{n_l^{t+1}}{n}\right)}} \tag{5}$$

where t is the time, n_h^t indicates the number of economies in community h at t, n_l^{t+1} indicates the number of economies in the community l at $t+1$, $n_{h,l}$ is the number of economies that are in community h at t and move to community l at $t+1$, and n is the number of economies in the GWPTN at t.

2.1.3. Micro-level indicators

Micro-level indicators measure the roles individual economies play in a network including degree centrality and strength centrality. Degree centrality (D) depicts the number of an economy's waste trade partners and an economy with a higher D indicates more trade partners. It can be divided into out-degree centrality (D^{out}) and in-degree centrality (D^{in}) in the directed GWPTNs, calculated as $D_i^{out}=\sum_{j=1}^{N_v}a_{ij}, D_i^{in}=\sum_{j=1}^{N_v}a_{ji}$.

Strength centrality (S) measures the ability of resource control of economies, and can be divided into out-strength centrality (S^{out}) and in-strength centrality (S^{in}). S^{out} is the export waste paper volume of economies, and S^{in} is the import waste paper volume of economies. They are calculated by $S_i^{out}=\sum_{j=1}^{N_v}w_{ij}, S_i^{in}=\sum_{j=1}^{N_v}w_{ji}$.

2.2. Temporal exponential random graph model

The temporal exponential random graph model (TERGM) is an extension of the exponential random graph model (ERGM) designed to accommodate inter-temporal dependence in longitudinally observed networks [54]. Thus, it is necessary to describe the ERGM before introducing the TERGM. The ERGM specifies the probability that an observed network y appears in any random network Y given a set of n nodes and condition θ [59]. The process of specifying an ERGM consists of designing network statistics that capture the generative processes underlying the network. Applying the Hammersley–Clifford theorem to the dependence graph GWPTNs [60], the form for an ERGM is a probability distribution of graphs and can be derived as:

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

Where κ is the normalized constant, α, β and γ are the configurations of endogenous structural factors [61], the economies' attributes factors [62,63], and other external networks factors [64] that affect the formation of the GWPTNs [59], respectively. $g_\alpha(y)$ is the network statistic corresponding to endogenous network configuration α, measuring the endogenous structural effects in the formation of the GWPTNs. $g_\beta(y,x)$ is the network statistic corresponding to the configuration β referring to economy's attributes x, capturing the economy's attribute effects in the formation of the GWPTNs. $g_\gamma(y,g)$ is the network statistic corresponding to the configuration γ referring to the other network g, measuring the external relations embedding effects in the formation of the GWPTNs. θ_α^T, θ_β^T and θ_γ^T, which need to be estimated, configure endogenous structural effects, economy's attribute effects and external relations embedding effects for a particular set of data, respectively; the probability of the network depends on how many of those configurations appear, and the parameters inform us of the importance of each configuration [65].

However, the ERGM can only be applied to the analysis of the formation of a cross-section network. To capture the temporal dependence of the observed y, previously observed lagged networks are included into $g(y), g(y,x), g(y,g)$ in Eq. (6) for y at time t (y^t), which is called the TERGM [53,54] based on the idea of panel regression. In a sequence of observations, lagged earlier observations or derived information thereof can be used as predictors for later observations [52,66]:

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

Where $K \in \{0, 1, ..., T-1\}$ represents the lag order, the $\kappa(\theta, y^{t-K}, ..., y^{t-1})$ is the normalized constant, and $g_\alpha(y^t, y^{t-1}, ..., y^{t-K})$, $g_\beta(y^t, y^{t-1}, ..., y^{t-K}|x_t)$ and $g_\gamma(y^t, y^{t-1}, ..., y^{t-K}|g_t)$ are network statistics as a temporal change in endogenous structural effects, economy attribute effects, and external relations embedding effects. However, Eq. (7) only specifies a TERGM for a single network at a single point in time, y^t. To explore the factors affecting the dynamic evolution of the observed network y between times $K+1$ and T, we construct the joint probability model of the observing networks by taking the product of the probabilities of the individual networks conditional on the others:

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

Markov Chain Monte Carlo for maximum likelihood estimation (MCMC-MLE) is employed to estimate the parameters θ of TERGM [61]. The goodness-of-fit (GOF) of the TERGM is evaluated by comparing the statistical mean of endogenous and exogenous variables between the model-based simulated network and the observed network. Thus, we can explore the factors that influence the formation and evolution of the GWPTNs based on the coefficients and significance of variables. The ***btergm*** packages in **R** are used to estimate the TERGM.

2.2.1. Endogenous structural effects

Network relationships have endogenous dependence, and they can organize themselves into patterns, which is called the endogenous structural effects [65]. For the GWPTNs, the results in Section 3.1 indicate that it has the characteristics of reciprocity, small-world and disassortativity. So, the endogenous structural effects included in the TERGM are reciprocity, transitivity, connectivity and preferential attachment.

Reciprocity describes the interaction processes in directed networks, explaining the feedback effect of the GWPTNs formation. That is, economy i is more likely to export waste paper to economy j (which is the import source of economy i) than other economies due to the lower transaction and information cost, and moral hazard [67]. Transitivity is similar to the logic 'a friend's friends are friends in sociology [55,63], and is that a triad with two ties is likely to form the third tie, reflecting the network clustering. The cluster plays an important role in the formation and evolution of the GWPTNs. First, if economy i exports waste paper to economy j and economy j exports waste paper to economy k, this will send a signal to economy i that economy k has demand for waste paper. Consequently, economy i will export waste paper to economy k like economy j, which creates a triad closure. Second, choosing a trade partner's waste paper partners might reduce transaction and search cost when identifying a waste paper importer [68]. Moreover, the results of Section 3.3 show that there are economies, such as Germany, not only importing waste paper from some economies, but also exporting waste paper to others, acting as a middle person. Thus, connectivity may play an important role in the evolution of GWPTNs. The preferential attachment occurs where an economy with more trade partners has greater incentives to trade with others [69], and it also appears in the GWPTNs. This can be explained in two aspects: first, economies with more trade partners are willing to expand the market for waste paper to process more waste paper and ensure the stability of waste paper trade. Meanwhile, it is easier for economies with more trade partners to search and establish waste paper trade based on existing trade relationships [67]. Second, economies with more trade partners are more likely to be selected as a waste paper trade partner by others for the dominant position in the GWPTNs. Thus, the following hypothesis is proposed:

Hypothesis 1. The formation and evolution of the GWPTNs are influenced by reciprocity, transitivity, and connectivity, and economies with more partners are more likely to trade waste paper with others.

2.2.2. Economy attribute effects

Economies that bring their own comparative advantages, resource endowment and implemented policies are also very important for the formation of the GWPTNs [70], which is called economy attribute effects. For the formation and evolution of the GWPTNs, economy attribute effects include not only homophily, but also the sender effect, receiver effect and Matthew effect. Homophily is the tendency of individuals to associate with others who have similar characteristics [71], while the sender effect and receiver effect are that attributes may encourage individuals to be more active (expressed by higher out-degree) and more popular (expressed by higher in-degree), respectively [65]. The Matthew effect is that economies with a stronger attribute tend to trade with others.

Compared to economies from different continents, economies within the same continent have smaller distances between them with more available transportation options. Thus, the cost of waste paper trade is lower, and waste paper is traded more frequently between economies. Studies by Berglund et al. (2002) [10], van Beukering & van den Bergh (2006) [18] and Arminen et al. (2013) [13] show that the urbanization rate can positively influence the recovery rate of waste paper since the collection system is more cost-effective in densely populated urban areas. As the difference in the waste paper recovery rate between economies determines their trade pattern, the urbanization rates is shown to play an important role in waste paper trade. Furthermore, economies with higher urbanization rates have higher waste paper recovery rates and lower utilization rates, while economies with lower urbanization rates are on the contrary, which creates a trade triangle [10,13]. Thus, economy-pairs with asymmetrical urbanization rates are more likely to trade waste paper, and economies with higher urbanization rate are more likely to export, and those with lower urbanization rates to import. In addition, economic development and per capita income are important factors affecting waste paper trade [7,42]. In general, economies with higher economic development are more likely to trade with others due to the higher trade dependence. More, economies with higher per capita income produces and recycles more waste paper because consumers' environmental consciousness increases with the growing per capita income [7], resulting in the more waste paper to dispose and in turn increasing the amount shipped outside their borders. Meanwhile, economies with lower per capita income consume and recycle less waste paper because of the poorer infrastructure and environmental awareness, associated with greater demand for waste paper as inputs in future production [9,42,72]. As a result, a large amount of waste paper flows from economies with higher per capita income to those with lower. In addition, waste paper has become a strategic resource for many economies with high manufacturing development due to the lower price, less pollution and energy consumption [13,17], making industrial structure an important factor affecting waste paper trade. Economies with high manufacturing development need more waste to meet their demand for raw materials, so they import more waste paper. On the contrary, economies with low manufacturing development export waste paper. Economies with larger economic development appear more active in waste paper trade.

More importantly, the strength of environmental regulation across economies is an important determinant of waste trade patterns [21,73]. Previous studies, such as those by Ederington & Miner (2003) [74], Baggs (2009) [42], Kellenberg (2010) [44] and Kellenberg (2012) [21], show that there is a waste haven effect in waste, meaning economies with weaker environmental regulations will become pollution havens of economies with stronger regulations. The reason is that economies with stricter environmental regulations have higher costs of waste disposing and recycling, creating an incentive to export the waste to others for their lower disposal costs. Conversely, economies with weaker regulations have comparative advantages in disposing and recycling waste paper because of the lower pollution taxes and wage. This promotes waste paper flows from economies with stricter environmental regulations to those with weaker regulations. Based on the above review, the following hypotheses are proposed:

Hypothesis 2. Economy-pairs within the same continent, with asymmetrical urbanization rates, per capita income, industrialization rates or environmental regulation strength are more likely to trade waste paper.

Hypothesis 3. Economies with higher urbanization rates, per capita income, environmental regulation strength or lower industrialization rates are more likely to export waste paper, and those with lower urbanization rates, per capita income, environmental regulation strength or higher industrialization rates are more likely to import. Economies with higher economic development are more likely to trade waste paper with others.

2.2.3. Relations embedding effects

The formation and evolution of the GWPTNs is also affected by external binary relations, such as language, religion, regional trade agreements, and geographic boundaries. Since these external binary relations show the associated characteristics of the GWPTNs, it is called the relations embedding effects [75].

Culture plays an important role in international trade [76]. Cultural differences, such as differences in language, customs, and religious beliefs [77–79], can be a critical barrier (adding information or transaction cost) to trade between economies [77]. Thus, economies with similar cultures promote trade among themselves, while language and religion can directly affect the trade between economies [80]. Meanwhile, culture differences between economies, being former colony of the same colonizer or with historical colonial relationship, tend to be smaller because of the influence of the common colonial culture. Thus, being a former colony of the same colonizer and having a historical colonial relationship can be proxy for cultural similarity.

Furthermore, signing regional trade agreements (RTAs) is a nontrivial issue, whose lower tariffs and nontariff barriers for goods, services, investments, intellectual properties, and government procurement between signatories help facilitate mutual trade and shape the pattern of global trade [81]. Chen & Joshi (2010) [82] and Lake & Yildiz (2016) [83] show that economy-pairs' signing RTAs promotes trade between RTA members due to the trade creation effect but reduces the trade between members and non-members due to the trade diversion effect, which shapes the pattern of global trade. Thus, economy-pairs' signing of an RTA promote waste paper trade.

Finally, geographical distance importantly affects trade between economies. From the theoretical and empirical analysis, Eaton and Kortum (2002) [84] and Anderson & Wincoop (2003) [85] show that trade volume is inversely proportional to geographical distance. Whether economies are geographical neighbors can be used as a proxy variable for geographical distance [57]. Thus, economies with a common geographic boundary are more likely to trade waste paper. Based on the above, we propose the following hypothesis for the formation and evolution of GWPTNs:

Hypothesis 4. Economy-pairs sharing a common language, religion or geographic boundary, as well as being a former colony of the same colonizer or having historical colonial relationships, and signing an RTA are more likely to trade waste paper.

2.3. Network construction and data

2.3.1. Global waste paper trade network and data

The data of waste paper trade used in this study come from the United Nations Commodity Trade Statistics Database (UN Comtrade Database).[2] The Harmonized System (HS) codes of waste paper used are HS470710, HS470720, HS470730and HS470790 [21,22]. Due to the data discrepancy between export and import sources attributed to the different statistical types used, the time lag between exports and imports, the omission of statistics of illegal trade [86], and deliberately underreported trade to avoid being criticized by their people [36,87], we employ only the export trade value provided by each economy.

Based on this bilateral waste paper trade data, we construct the global waste paper trade networks (GWPTNs) for 2000–2018, covering 185 economies (see Appendix Table A1). Following the complex network theory, the GWPTNs are constructed by making the exporting economies the starting node represented by the vector $\mathbf{V}_i = (v_1, v_2, \ldots, v_n)$, making the importing economy the destination node represented by vector $\mathbf{V}_j = (v_1, v_2, \ldots, v_n)$, and using the weight matrix $\mathbf{W} = [w_{ij}](i \in \mathbf{V}_i, j \in \mathbf{V}_j, i \neq j)$ to represent the weighted edge for trade volume between $\mathbf{V}_i$ and $\mathbf{V}_j$, $\mathbf{V}_i$, $\mathbf{V}_j$ and $\mathbf{W}$ constitute the directed-weighted GWPTNs. The GWPTN for 2018 is shown in Fig. 2.

2.3.2. TERGM variables and data

Table 1 shows the TERGM variables used in this study. Among them, Mutual, Gwesp, Gwdsp and Nodecov are used to test Hypothesis 1, referring to the feedback, transitivity, connectivity, and the preferential attachment effect. Homophily, Sender, Receiver, Nodecov and Edgecov are selected to test the homophily effect, Sender effect, Receiver effect, Matthew effect, and external network embedding effect with respect to Hypothesis 2 to Hypothesis 4.

Except for endogenous structure, economies' urbanization rate, per capita income, industrialization rate, environmental regulation strength, economic development, cultures, free trade agreements and geographical distance play important roles in the formation and evolution of the GWPTNs. We measure the urbanization rate as the percentage share of the total population living in urban areas (Urban), the per capita income as per capita GDP (PerGDP), the industrialization rate using the second industry as a share of GDP (Industry), and economic development as GDP. These data come from the World Bank database. The Environmental Performance Index (EPI) measures the environmental regulation strength, which provides quantitative metrics for evaluating an economy's environmental performance in different policy categories relative to clearly defined targets. The range of EPI is 0–100, and the larger the EPI value, the stricter the environmental regulation. The data is gathered from Socioeconomic Data and Applications Center (SEDAC). In addition, we use the common official language network (COL), common spoken language network (CSL), common religion network (CRN), same colonizer network (SCN), and historical colonial relationship network (HCL) to describe the cultural similarities between economies. If there is a common language, religion and colonial relationship between economies, the value is 1, and otherwise 0. The regional free trade agreement network (RTA) and national common geographic boundary network (CGN) are used to describe the trade liberalization and geographical proximity between economies, respectively. The value is 1 if an economy-pair signs a free trade agreement or shares a common geographic boundary, and 0 otherwise. Their data come from WTO database and CEPII database, respectively (see Appendix Table A2).

3. Results

3.1. Evolution of structural properties of GWPTNs

3.1.1. Macro-level analysis

The values of indicators for describing the evolution features of the GWPTNs at the macro level are shown in Table 2. First, edges and density show an upward trend, reflecting that waste paper has been flowing around the world, and the scale of global waste paper trade has been increasing under globalization since the 21st century. The number of edges and density increased from 1,295 and 0.049 in 2001 to the peaks of 2,085 and 0.075 in 2017, respectively. The average degree increased from 15.9 in 2001 to 25 in 2017, and the average strength also increased from 1,691.2 up to the peak of 6,009.6 in 2011. The scale of

[2] https://comtrade.un.org.

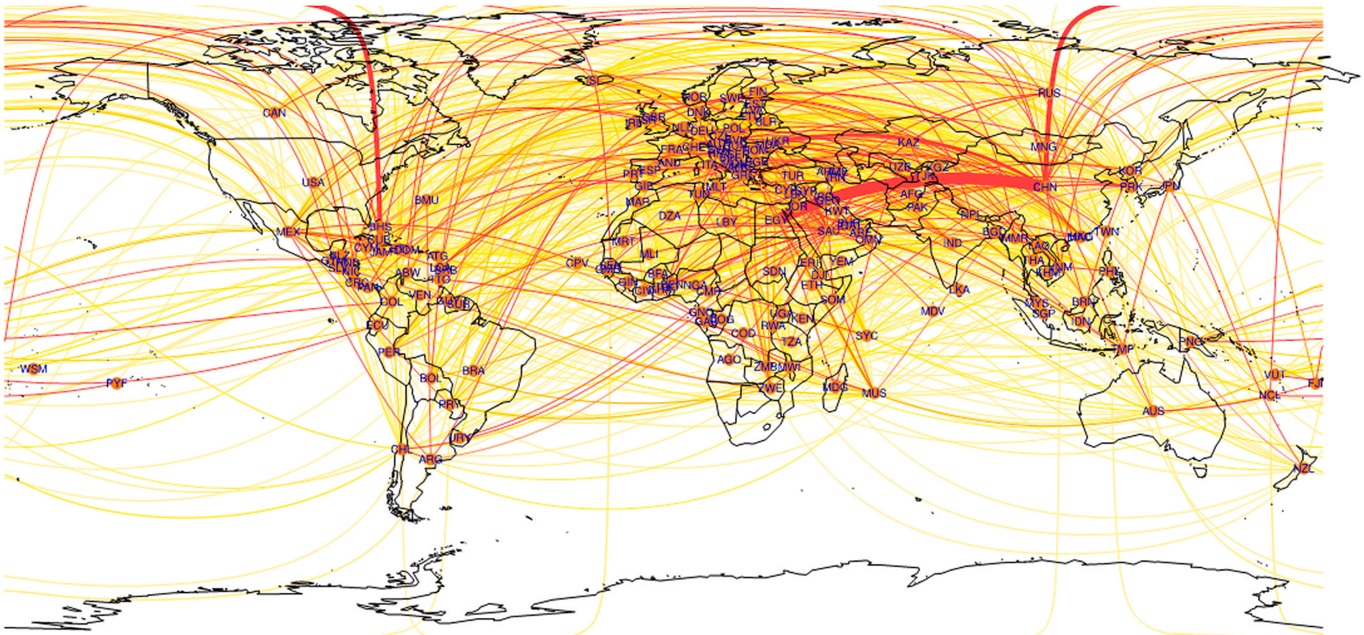

Fig. 2. Global waste paper trade network in 2018. *Note:* Each line represents a relationship of waste paper trade between two economies. The thicker (redder) the line, the greater the trade volume; the thinner (lighter) the line, the smaller the trade volume. The map with trade lines is plotted using R software.

Table 1
TERGM variables and hypotheses.

Classification	Variable Name	Meaning	Configuration	Statistic	Hypotheses
Constant term	Edges	Network density		$\sum_{i,j} y_{ij}$	Constant
Endogenous Structural Statistics	Mutual	Feedback effect		$\sum_{i,j} y_{ij} y_{ji}$	Hypothesis 1
	Gwesp	Transitivity effect		$\sum_{i,j,k} y_{ij} y_{jk} y_{ik}$	
	Gwdsp	Connectivity effect		$\sum_{i,j,k} y_{ij} y_{jk}$	
	Nodecov (Degree)	Preferential attachment effect	Degree	$\sum_{i,j} Degree_i y_{ij} + \sum_{i,j} Degree_j y_{ij}$	
Economy Attributes Statistics	Homophily (Continent)	Continent homophily	Continent	$\sum_{i,j} y_{ij} Continent_i Continent_j$	Hypothesis 2
	Homophily (Urban)	Urbanization homophily	Urban	$\sum_{i,j} y_{ij} Urban_i Urban_j$	
	Homophily (PerGDP)	Economic homophily	PerGDP	$\sum_{i,j} y_{ij} PerGDP_i PerGDP_j$	
	Homophily (EPI)	Environmental regulation homophily	EPI	$\sum_{i,j} y_{ij} EPI_i EPI_j$	
	Homophily (Industry)	Industrialization homophily	Industry	$\sum_{i,j} y_{ij} Industry_i Industry_j$	
	Receiver (Urban)	Urbanization receiver effect	Urban	$\sum_{i,j} Urban_j y_{ij}$	Hypothesis 3
	Receiver (PerGDP)	Per capita GDP receiver effect	PerGDP	$\sum_{i,j} PerGDP_j y_{ij}$	
	Receiver (EPI)	Environmental regulation receiver effect	EPI	$\sum_{i,j} EPI_j y_{ij}$	
	Receiver (Industry)	Industrialization receiver effect	Industry	$\sum_{i,j} Industry_j y_{ij}$	
	Sender (Urban)	Urbanization sender effect	Urban	$\sum_{i,j} Urban_i y_{ij}$	
	Sender (PerGDP)	Per capita GDP sender effect	PerGDP	$\sum_{i,j} PerGDP_i y_{ij}$	
	Sender (EPI)	Environmental regulation sender effect	EPI	$\sum_{i,j} EPI_i y_{ij}$	
	Send(Industry)	Industrialization sender effect	Industry	$\sum_{i,j} Industry_i y_{ij}$	
	Nodecov (GDP)	Economic Matthew effect	GDP	$\sum_{i,j} GDP_i y_{ij} + \sum_{i,j} GDP_j y_{ij}$	
Relations Embedding Statistics	Edgecov (COL)	Common language embedding effect	COL	$\sum_{i,j} y_{ij} COL_{ij}$	Hypothesis 4
	Edgecov (CSL)		CSL	$\sum_{i,j} y_{ij} CSL_{ij}$	
	Edgecov (CRN)	Common religion embedding effect	CRN	$\sum_{i,j} y_{ij} CRN_{ij}$	
	Edgecov (HCL)	Colonial embedding effect	HCL	$\sum_{i,j} y_{ij} HCL_{ij}$	
	Edgecov (SCN)		SCN	$\sum_{i,j} y_{ij} SCN_{ij}$	
	Edgecov (RTA)	RTA embedding effect	RTA	$\sum_{i,j} y_{ij} RTA_{ij}$	
	Edgecov (CGN)	Common geographic boundary embedding effect	CGN	$\sum_{i,j} y_{ij} CGN_{ij}$	

Table 2
Macro-level structural evolution characteristics of GWPTNs during 2000–2018.

Year	N_v	N_e	ρ	*ACC*	*APL*	*R*	*AD*	*AS*	*A*	G^{out}	G^{in}
2000	163	1343	0.051	0.386	2.742	0.241	16.5	2204.7	−0.205	0.453	0.651
2001	163	1295	0.049	0.368	2.646	0.246	15.9	1691.2	−0.209	0.466	0.641
2002	163	1413	0.054	0.391	2.635	0.241	17.3	1905.4	−0.201	0.480	0.634
2003	170	1564	0.054	0.382	2.646	0.231	18.4	2223.0	−0.238	0.482	0.600
2004	169	1596	0.056	0.402	2.635	0.240	18.9	2625.9	−0.219	0.492	0.581
2005	165	1618	0.060	0.409	2.607	0.251	19.6	2972.1	−0.193	0.500	0.537
2006	166	1650	0.060	0.413	2.559	0.229	19.9	3141.9	−0.201	0.509	0.522
2007	166	1817	0.066	0.437	2.433	0.280	21.9	3987.9	−0.210	0.530	0.516
2008	166	1894	0.069	0.439	2.525	0.269	22.8	4524.3	−0.228	0.540	0.504
2009	166	1803	0.066	0.439	2.554	0.249	21.7	3579.7	−0.201	0.527	0.471
2010	170	1944	0.068	0.434	2.548	0.257	22.9	5006.6	−0.212	0.536	0.496
2011	166	1990	0.073	0.435	2.515	0.255	24.0	6009.6	−0.245	0.555	0.488
2012	165	1915	0.071	0.431	2.469	0.265	23.2	5283.3	−0.263	0.545	0.456
2013	168	1945	0.069	0.420	2.532	0.261	23.2	4888.1	−0.245	0.549	0.465
2014	164	1900	0.071	0.426	2.556	0.254	23.2	4874.3	−0.227	0.553	0.484
2015	167	1872	0.068	0.428	2.648	0.282	22.4	4673.1	−0.206	0.546	0.463
2016	168	1899	0.068	0.431	2.487	0.281	22.6	4791.8	−0.246	0.554	0.472
2017	167	2085	0.075	0.442	2.513	0.274	25.0	4922.4	−0.245	0.582	0.509
2018	163	1991	0.075	0.443	2.535	0.273	24.4	4762.0	−0.232	0.568	0.528

Note: N_v and N_e are the number of economies and edge of GWPTNs. ρ is density, *ACC* is average clustering coefficient, *APL* is average path length. *R* is reciprocity, *AD* is average degree, *AS* is average strength degree, *A is assortativity, and* G^{out} and G^{in} are out-strength and in-strength entropy, respectively. What calls for special attention is that G^{out} and G^{in} are normalized for the comparability of results, and the range of them is [0, 1].

the GWPTNs decreased in 2009, 2012 and 2018 accompanied by global economic fluctuations or improvement of environmental regulations in some economies, such as China.

Second, the GWPTNs display an outstanding feature of the small-world network. Generally, the small-world network has a small average path length (*APL*) and a high average clustering coefficient (*ACC*) [88]. For the GWPTNs, the *APL* is 3 and gradually becomes smaller, meaning that the GWPTNs have high connectivity and low

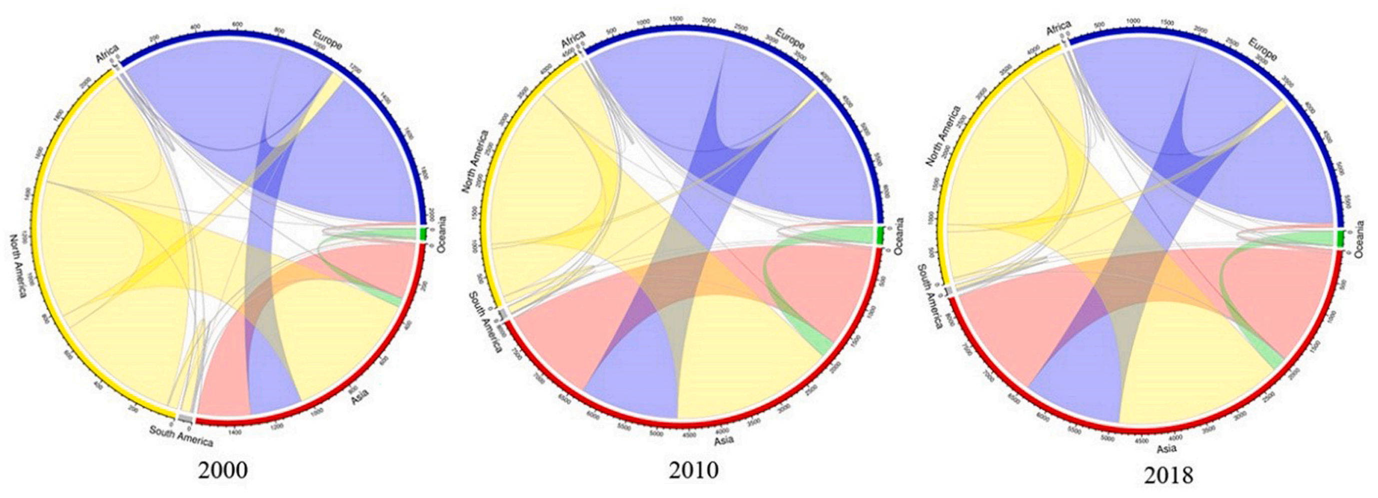

Fig. 3. Trade volume evolution of inter- and intra-continental GWPTNs in 2000–2018 (Unit: million dollars).

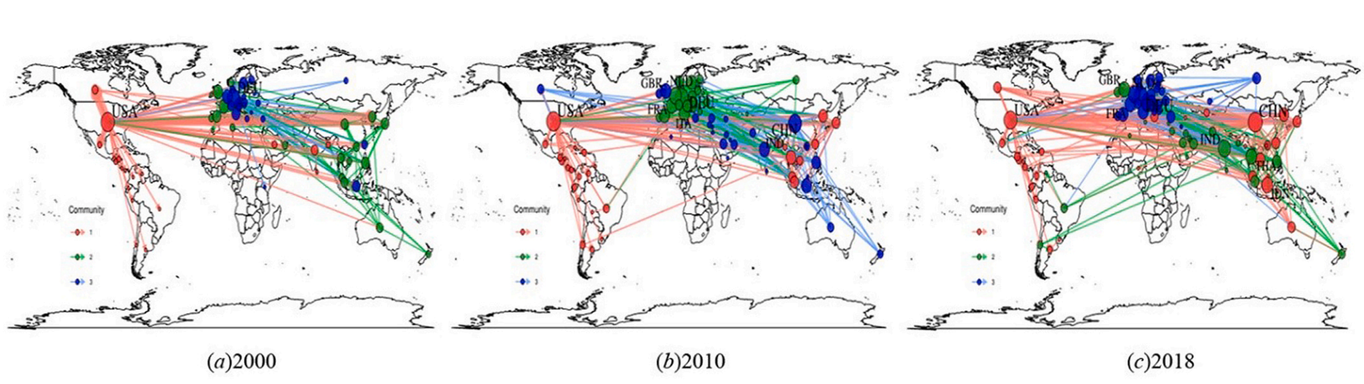

Fig. 4. Community structure evolution of GWPTNs in 2000–2018. *Note*: The same color of the node represents that it belongs to the same community, and the size of the node corresponds to its degree centrality. Only the trade relationships with a trade volume of more than 2 million dollars are shown, and these Figures are plotted using R software.

Fig. 5. NMI of GWPTNs in 2000–2018.

distance. That is, waste paper trade relations can be established between economies, which requires only two "bridge" economies on average. The *ACC* is 0.419, which is high, and displays an upward trend. Thus, the GWPTNs have low *APL* and high *ACC*, which is consistent with what the small-world network is featured. This feature is attributed to the development of globalization.

Third, the GWPTNs exhibit low reciprocity, heterogeneity and disassortativity. The result shows that the reciprocity (R) is between 0.241 and 0.282, which indicates that there is two-way reciprocal waste paper trade, albeit not common. The out-strength entropy (G^{out}) and in-strength entropy (G^{in}) are between 0.453 and 0.651 during 2000–2018, indicating that the GWPTNs are highly heterogeneous networks. A few economies dominate the global waste paper trade volume and more economies control the less. Comparing G^{out} and G^{in}, we find that G^{out} shows an upward trend, but G^{in} shows a downward trend. After 2006, G^{out} is greater than G^{in}. In addition, the assortativity (A) of the GWPTNs is negative, suggesting the feature of disassortativity. In other words, economies hacing more partners tend to trade with those economies having the fewer partners. Then, economies with more partners would be connected by many economies and become the core of the GPWTNs, while economies with fewer partners would be sparsely connected and be the peripheral economies, which will lead to the exhibited core-periphery structure of the GWPTNs.

3.1.2. Medium-level analysis

At the medium level, we calculate the inter- and intra-continental aggregate waste paper trade volume, and explore the relations in intra-community and inter-community. The waste paper trade patterns between continents in 2000, 2010, and 2018 are mapped in Fig. 3. It is important to note that Antarctica is not included in this analysis as there is no economy.

The results show that Asia, Europe, and North America are major players in global waste paper trade. Asia is the leading recipient of global waste paper, while Europe and North America are the main exporters. This finding can be supported by the following pieces of evidence. First, waste paper trade of Asia, Europe, and North America accounts for a 97% share of world waste paper trade during the study period, and shows a slight upward trend. Meanwhile, waste paper trade

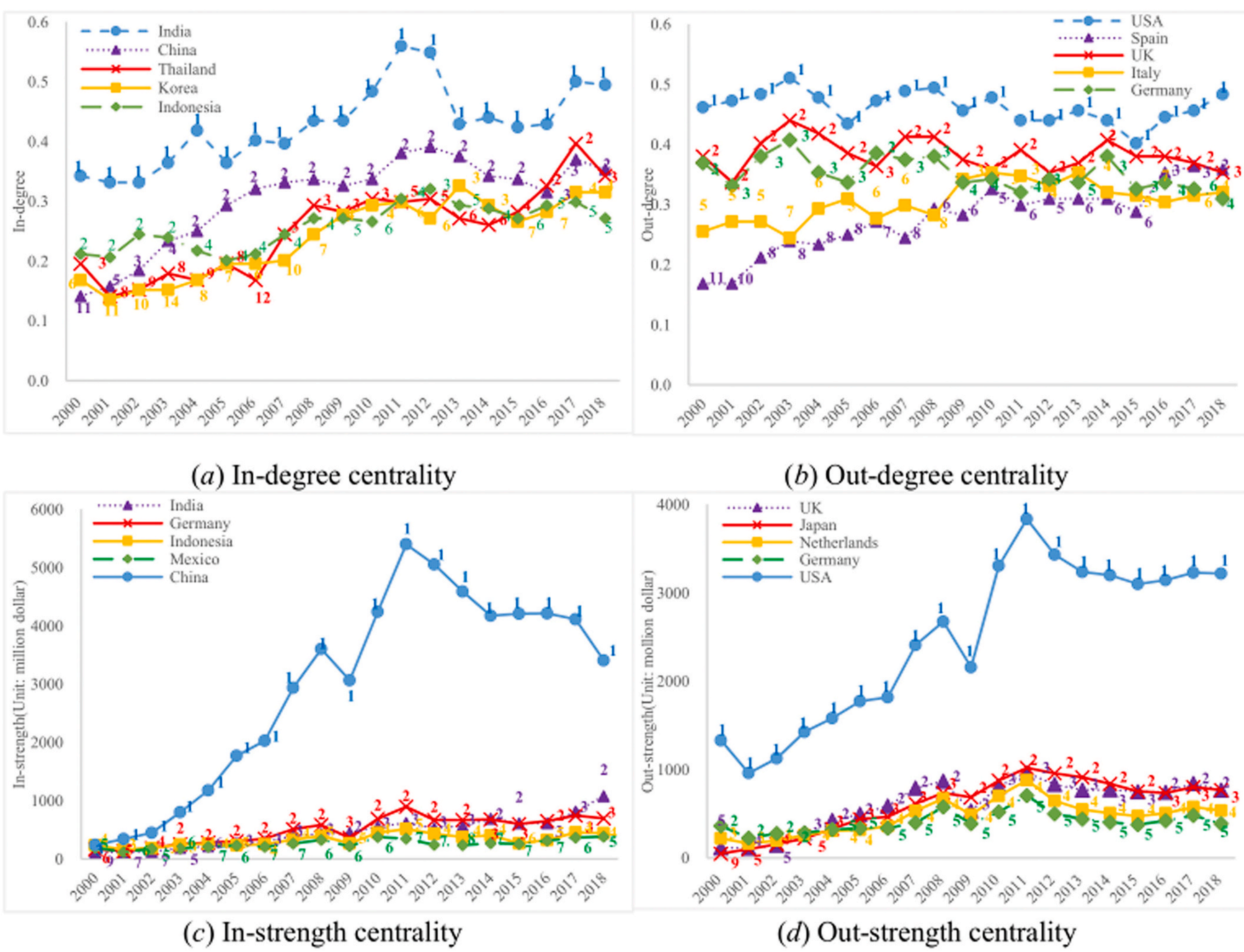

Fig. 6. Top 5 Economies ranked by degree and strength centrality in 2018. *Note*: the number beside point is the rank of economy in GWPTNs.

Table 3
Estimated results of TERGM for GWPTNs in 2000–2018.

	Model 1	Model 2	Model 3
Endogenous Structural Statistics			
Edges	−3.400 (0.008)***	−8.922 (0.066)***	−6.112 (0.032)***
Nodecov (degree)			0.040 (0.000)***
Gwesp			0.636 (0.011)***
Gwdsp			−0.070 (0.001)***
Mutual			0.262 (0.029)***
Economy Attributes Statistics			
Homophily (Continents)		1.205 (0.017)***	0.908 (0.017)***
Homophily (Urban)		0.003 (0.001)***	0.001 (0.000)**
Homophily (PerGDP)		−0.000009 (0.000)***	−0.000003 (0.000)
Homophily (EPI)		−0.009 (0.001)***	−0.012 (0.000)***
Homophily (Industry)		0.002 (0.001)*	−0.004 (0.001)***
Reveiver (Urban)		−0.001 (0.000)**	−0.003 (0.000)***
Reveiver (PerGDP)		−0.00001 (0.000)***	−0.000004 (0.000)*
Reveiver (EPI)		0.004 (0.001)***	−0.012 (0.000)***
Reveiver (Industry)		0.010 (0.001)***	0.006 (0.000)***
Sender (Urban)		0.011 (0.000)***	0.006 (0.000)***
Sender (PerGDP)		0.000007 (0.000)***	0.000005 (0.000)**
Sender (EPI)		0.022 (0.000)***	0.003 (0.000)***
Sender (Industry)		−0.006 (0.001)***	−0.004 (0.001)***
Nodecov (GDP)		−0.0000001 (0.000)***	−0.00000007 (0.000)***
Relations Embedding Statistics			
Edgecov (COL)	−0.704 (0.026)***	0.238 (0.035)***	0.333 (0.016)***
Edgecov (CSL)	0.932 (0.023)***	0.884 (0.033)***	0.716 (0.014)***
Edgecov (CRN)	0.277 (0.014)***	0.119 (0.018)***	0.239 (0.018)***
Edgecov (HCL)	1.652 (0.029)***	0.333 (0.035)***	0.702 (0.009)***
Edgecov (SCN)	−0.464 (0.023)***	0.490 (0.029)***	0.207 (0.025)***
Edgecov (RTA)	1.469 (0.013)***	0.402 (0.019)***	0.396 (0.024)***
Edgecov (CGN)	1.659 (0.024)***	2.259 (0.032)***	2.487 (0.019)***

Notes: *significant at 5%; **significant at 1%; ***significant at 0.1%. The values are stable standard errors in parentheses.

in Oceania, Africa, and South America accounts for a relatively low share of global waste paper trade, with 2.47%, 2.36% and 2.12% of global waste paper trade in 2000, 2010 and 2018, respectively, a continuing decline through time. Second, in terms of intra-continents and inter-continents, the proportions of intra-continental waste paper trade of Europe and North America gradually decrease during 2000–2018, from 40.86% to 30.33% in 2000 to 34.81% and 16.93% in 2018, respectively. Intra-continental waste paper trade in Asia, in contrast, increases from 17.19% to 22.24%. Previous studies [18–22] focused on that developed economies, such as those in Europe and the US, export recyclable waste to developing economies such as those in Asia, but they neglected the export of recyclable waste among developing economies in Asia. Meanwhile, inter-continental waste paper trade between Asia and Europe and North America rapidly increases. Third, for the direction of trade, exports of waste paper from North America and Europe account for more than 68% of the total imports of waste paper in Asia during 2000–2018. Moreover, the annual total export volume of Europe to Asia increases, from 269.14 million dollars in 2000 to 1,572.21 million dollars in 2018, which account for 23.94% and 43.26% of the total size in Europe. Similarly, the proportion of waste paper exported from North America to Asia rapidly increases, from 47.69% in 2000 to 74.52% in 2018. Asia becomes the giant recipient of global waste paper, possibly because Asia has relatively inexpensive labor forces, lax environmental regulations, low costs and huge demand for waste paper as raw materials [21,87].

In the GWPTNs, different communities are formed for the strength and tightness of waste paper trade relations. Exploring the relations in intra-community and inter-community can more intuitively reflect the faction [25], facilitating the understanding of the organizational structure of networks [89,90]. In this paper, the Spinglass community detection algorithm is used to divide the communities of the GWPTNs. The results for 1993, 2005, and 2018 are mapped in Fig. 4, and the evolution and stability of the GWPTNs communities using NMI are shown in Fig. 5.

The economies can be divided into three communities in 2000–2018. Specifically, as shown in Fig. 4 (*a*), the GWPTN in 2000 formed the American community (the US is the core), the European community (Germany is the core), and the Asian-Oceania community (made up by the economies in European, Oceania and Asian, which do not form a prominent core). With the development of globalization, more economies have been involved in global waste paper trade by 2010 (Fig. 4 (*b*)). Some Asian ecomomies, such as Korea, Japan, China Taiwan, became members of the American community because of close trade relationships with the US. Meanwhile, waste paper trade among European economies further strengthened, and the European community expanded. China and India imported more waste paper from others and were the hub of the Asian-Oceania community. In addition, the ties between the Europe and American communities and the Asia-Oceania community increased dramatically. As shown in Fig. 4 (*c*), the pattern of the GWPTNs communities was adjusted in 2018, with China and Indonesia having joined the American community, forming the American-China-Indonesia community. India and Thailand became the core of the Asian-Oceania community.

As shown in Fig. 5, the pattern of the GWPTNs communities and their members change over time. To further analyze the stability of the GWPTNs community structure, we calculate the NMI. According to Fig. 5, NMI fluctuates between 2000 and 2014 and increases gradually after 2014. This means that during 2000–2014, the pattern of the GWPTNs communities is unstable, going through separations, mergers, and reorganizations. Plausible reasons include the impact of global economic fluctuations, adjustment of environmental policy, and industrial policy of each economy. However, its community structure gradually stabilizes after 2014, as revealed by the monitonically increasing trend of NMI, indicating that economies in global waste paper trade tend to establish stable trade relationships.

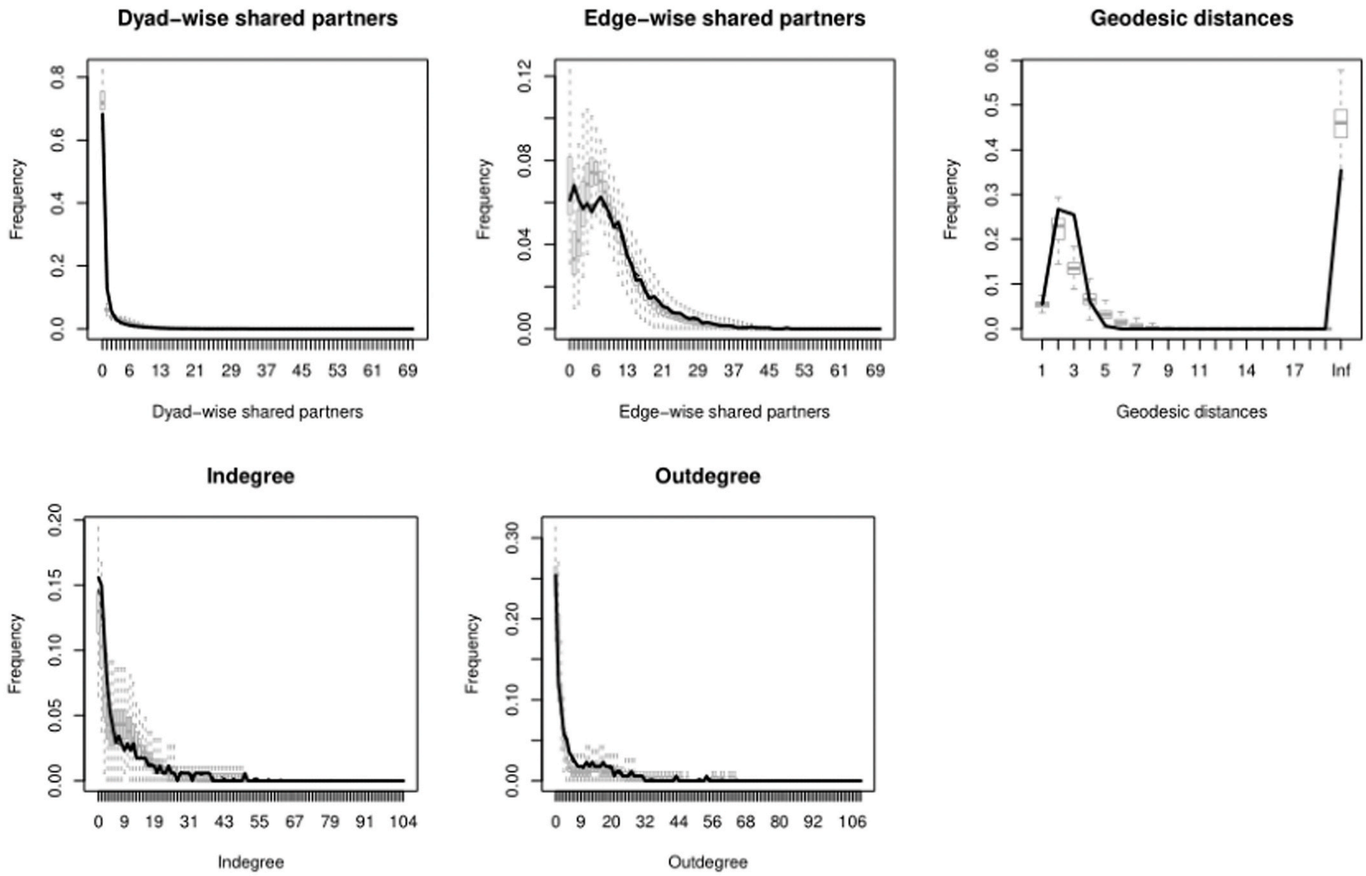

Fig. 7. The goodness-of-fit assessment of TERGM for GWPTNs (model 3). *Note:* The solid black line in the figure represents the statistical characteristics of the observed GWPTNs, and the box plot represents the network structure characteristics of model-based simulations.

3.1.3. Micro-level analysis

To better understand the pattern of the GWPTNs from the micro-level and review the role each individual economies play, we calculate economies' out-degree centrality (D^{out}), in-degree centrality (D^{in}), out-strength centrality (S^{out}), and in-strength centrality (S^{in}) in 2000–2018. As shown in Fig. 6, we display the line charts for the top five economies (ranked in 2018) according to D^{out}, D^{in}, S^{out} and S^{in} [36].

According to Fig. 6, as the in-degree centrality of the GWPTNs is concerned, the top 5 listed waste paper importers are all in Asia, and most of them are developing economies. Among them, India always ranked the first, and the number of import partners shows an overall growing trend during 2000–2018, meaning that India has the most waste paper import partners in the GWPTNs. China has experienced an extraordinary growth not only in its ranks, but also in the number of its import partners since 2000. A possible reason is that China's accession to the WTO in 2001 reduces the resistance to trade with others. The tariff reduction not only provides a broader market for China to obtain waste paper as raw materials for production, but also facilitates the export of waste paper from many economies to China. In addition, Thailand, Korea, and Indonesia also play an important role in the GWPTNs. In terms of out-degree centrality, the US, Spain, the UK, Italy, and Germany are the cores in the global waste paper export, ranking the top 5 in the GWPTNs and developing the most waste paper export partners. The top 5 waste paper exporters are in North America and Europe, and all of them are developed economies. Specifically, the US is always ranked the first, and exports waste paper to most of the economies in the world.

For in-strength centrality, China was ranked in the first in the GWPTNs during 2000–2018, and its waste paper import volume experienced a dramatic growth from 114 million dollars in 2000 to 5,398 million dollars in 2011. This means that China has become the largest waste paper importer in the world with the development of globalization, which is potentially driven by the rapidly growing resource demand, lax environmental policies with low processing labor costs, and substantial profits [22,34]. However, China's waste paper imports keep going down in the sub-period of 2011–2018 due to the global economic fluctuations and the more rigid waste import policies (such as Green Fence campaign in 2013) China has increasingly implemented. Meanwhile, India is an important importer in the GWPTNs, with its import volumes growing rapidly over years and ranking the second or the third in recent years. As mentioned above, India has the most waste paper importing partners, but it is not the largest waste paper importer. Compared with China, which has fewer partners yet the largest import volume, the waste paper imports of India are more dispersed, and its competitive advantage is smaller than China in the global largest scrap markets, such as the US and EU. A possible reason is that the scale of Chinese manufacturing sector is larger, and its growth is faster than India [91]. In addition, Germany, Indonesia, and Mexico are also hubs in the GWPTNs.

For out-strength centrality, the US, the UK, Japan, Germany, and the Netherlands (all of them are developed economies) are the top 5 economies, holding the important position as waste paper exporters. Among them, the US is most notable, since it ranks the top 1 every year and its waste paper exports are far greater than the other four economies, making it the world's leading exporter of waste paper. Meanwhile the export volume of these top 5 economies experienced two stages: the "boom period" (2000–2011) and the "downturn period" (2012–2018). In the first stage (2000–2011), the waste paper exports of this top 5 economies grew rapidly, and there were only small dips in 2001 and 2008 accompanied by the "9/11" event and financial crisis, respectively. With the acceleration of economic globalization in the early 21st

Table 4
Robustness test results of TERGM.

Variables	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Endogenous Structural Statistics						
Edges	−6.303 (0.007)***	−6.501 (0.003)***	−6.066 (0.003)***	−6.245 [-6.527; −6.072]*	−6.030 (0.003)***	−6.775 (0.003)***
Nodecov (Degree)	0.038 (0.000)***	0.040 (0.000)***	0.040 (0.000)***	0.045 [0.045; 0.046]*	0.039 (0.000)***	0.040 (0.000)***
Gwesp	0.676 (0.011)***	0.565 (0.012)***	0.578 (0.010)***	0.555 [0.500; 0.593]*	0.638 (0.011)***	0.500 (0.009)***
Gwdsp	−0.061 (0.001)***	−0.081 (0.001)***	−0.082 (0.001)***	−0.093 [-0.098; −0.089]*	−0.080 (0.001)***	−0.083 (0.001)***
Mutual	0.310 (0.007)***	0.338 (0.006)***	0.343 (0.003)***	0.416 [0.340; 0.477]*	0.168 (0.005)***	0.322 (0.025)***
Economy Attributes Statistics						
Homophily (exportC)	–	–	–	–	−0.061 (0.011)***	−0.168 (0.012)***
Homophily (Continent)	0.907 (0.014)***	0.822 (0.017)***	0.830 (0.014)***	0.825 [0.779; 0.868]*	0.889 (0.015)***	0.850 (0.013)***
Homophily (Urban)	0.001 (0.000)***	0.002 (0.000)***	0.004 (0.000)***	0.003 [0.002; 0.004]*	0.005 (0.000)***	−0.002 (0.000)***
Homophily (PerGDP)	−0.000001 (0.000)	−0.000005 (0.000)*	−0.000006 (0.000)***	−0.000005 [-0.000; −0.000]*	−0.000002 (0.000)	−0.000004 (0.000)*
Homophily (EPI)	−0.012 (0.000)***	−0.009 (0.000)***	−0.014 (0.000)***	−0.010 [-0.011; −0.007]*	−0.008 (0.000)***	−0.007 (0.000)***
Homophily (Industry)	−0.006 (0.001)***	−0.001 (0.001)*	−0.002 (0.001)***	−0.002 [-0.004; −0.001]*	−0.007 (0.001)***	0.002 (0.000)***
Receiver (Urban)	−0.002 (0.000)***	−0.005 (0.000)***	−0.004 (0.000)***	−0.002 [-0.003; −0.001]*	−0.003 (0.000)***	−0.008 (0.000)***
Receiver (PerGDP)	−0.000009 (0.000)***	−0.000004 (0.000)*	−0.000003 (0.000)	−0.000 [-0.000; −0.000]*	−0.000003 (0.000)	−0.0000008 (0.000)
Receiver (EPI)	−0.009 (0.000)***	−0.008 (0.000)***	−0.013 (0.000)***	−0.010 [-0.012; −0.006]*	−0.010 (0.000)***	−0.007 (0.000)***
Receiver (Industry)	0.006 (0.000)***	0.007 (0.001)***	0.011 (0.000)***	0.007 [0.006; 0.009]*	0.006 (0.000)***	0.010 (0.000)***
Sender (Urban)	0.008 (0.000)***	0.008 (0.000)***	0.008 (0.000)***	0.007 [0.005; 0.007]*	0.002 (0.000)***	0.011 (0.000)***
Sender (PerGDP)	0.000005 (0.000)***	0.000004 (0.000)*	0.000006 (0.000)***	0.000005 [0.000; 0.000]*	0.000006 (0.000)	−0.000001 (0.000)
Sender (EPI)	0.001 (0.000)***	0.004 (0.000)***	0.002 (0.000)***	0.001 [-0.001; 0.005]	0.002 (0.000)***	0.013 (0.000)***
Sender (Industry)	−0.004 (0.001)***	−0.004 (0.001)***	−0.007 (0.000)***	−0.003 [-0.005; −0.001]*	−0.0003 (0.001)	−0.010 (0.000)***
Nodecov (GDP)	−0.00000005 (0.000)***	−0.00000006 (0.000)***	−0.00000007 (0.000)***	−0.00000006 [-0.000; −0.000]*	−0.00000006 (0.000)***	−0.00000003 (0.000)***
Relations Embedding Statistics						
Edgecov (COL)	0.475 (0.013)***	0.448 (0.011)***	0.247 (0.005)***	0.323 [0.281; 0.362]*	0.334 (0.011)***	0.487 (0.007)***
Edgecov (CSL)	0.537 (0.005)***	0.562 (0.007)***	0.753 (0.015)***	0.617 [0.576; 0.666]*	0.678 (0.007)***	0.619 (0.014)***
Edgecov (CRN)	0.203 (0.018)***	0.254 (0.017)***	0.256 (0.016)***	0.230 [0.207; 0.252]*	0.233 (0.016)***	0.102 (0.015)***
Edgecov (HCL)	0.928 (0.004)***	0.971 (0.001)***	0.481 (0.003)***	0.794 [0.704; 0.885]*	0.782 (0.002)***	0.654 (0.003)***
Edgecov (SCN)	0.146 (0.011)***	0.361 (0.009)***	0.143 (0.005)***	0.201 [0.169; 0.245]*	0.223 (0.006)***	0.376 (0.018)***
Edgecov (RTA)	0.295 (0.021)***	0.203 (0.019)***	0.234 (0.016)***	0.264 [0.192; 0.353]*	0.289 (0.006)***	0.133 (0.015)***
Edgecov (CGN)	2.110 (0.015)***	2.487 (0.003)***	2.422 (0.005)***	2.123 [2.075; 2.177]*	2.283 (0.002)***	2.401 (0.004)***

Notes: *significant at 5%; **significant at 1%; ***significant at 0.1%. The values are stable standard errors in parentheses and the values is 95% confidence interval in square brackets.

century, the development of global waste paper export markets was also expedited. In the second stage (2012–2018), the waste paper exports of them showed a downward trend. There can be two reasons for this situation besides the impact of the 2011 European debt crisis: first, several important waste paper importers increased environmental consciousness and adopted stricter waste control regulations, which blocked some waste paper exports of these economies. Second, since 2011, the top 5 economies have implemented a plan to revitalize the development of manufacturing industry, such as the development strategy for advanced manufacturing economies issued by the US in 2012 and the German industry 4.0 plan, which has increased their demand for waste paper as raw material, so their export showed a downward trend. Notably, Germany is not only the hub importer of waste paper, but also an important exporter. The reason is that Germany exports low-grade waste paper to China, India, and Thailand, but competes with China, India, and Thailand for higher-grade waste paper to meet the domestic requirements of its industries [92]. Moreover, to simplify the GWPTNs and better describe the pattern of global waste paper trade and the positions of economies, we only keep each economy's strongest waste paper trade export and import relations (see Fig. A1 in Appendix).

3.2. Determinants of the GWPTNs evolution

Table 3 shows the estimated results of the TERGM. Model 1 only includes the relations embedding statistics. All the coefficients are significant at the 0.1% level, but the coefficients of Edgecov (COL) and Edgecov (SCN) are negative. Next, we add the economy attributes statistics to Model 2 based on Model 1. Some coefficients of relations embedding statistics change the direction. Based on Model 2, we further add endogenous structural statistics in Model 3, and most of coefficients are consistent with the theory and significant at the 0.1% level. This states that it is necessary to consider the endogenous structural effect.

The results in Model 3 show that, first, in terms of the endogenous structural effects, the coefficients of Edge, Nodecov (Degree), Gwesp, Gwdsp, and Mutual are significant at the 0.1% level. Specifically, the coefficient of Edge, which represents the baseline probability of forming a tie (similar to the intercept in classic regression models) is significantly negative, meaning that when a new edge is added to a GWPTN, the probability of another economy-pair trade waste paper is 0.368[3]. Moreover, the coefficient of Gwdsp is negative, and its magnitude is less than 0.1, which means that the local connectivity is weaker than we expect. On the contrary, the coefficients of Nodecov (Degree), Gwesp and Mutual are significantly positive at the 0.1% level, indicating that preferential attachment effect, transitivity effect and feedback effect play important roles in the formation and evolution of the GWPTNs, which supports Hypothesis 1.

Second, there are economy attribute effects in the formation and evolution of the GWPTNs. The Homophily (Continent) is significantly positive at the 0.1% level in 2000–2018, indicating most of the economy-pairs trading waste paper are within the same continent due to the lower transportation cost. Moreover, Model 3 shows that the term of Homophily (Urban) is significantly positive at the 1% level in 2000–2018, which is inconsistent with the theoretical statement in Hypothesis 2. The significantly negative coefficient of Receiver (Urban) and the significantly positive coefficient of Sender (Urban) mean that economies with higher urbanization rates tend to export waste paper, and those with the lower are more likely to import. The Homophily (PerGDP) is negative but is not significant in 2000–2018, suggesting that heterophily in per capita income is not obvious. Meanwhile, the coefficient of Receiver (PerGDP) is significantly negative, and Sender (PerGDP) positive. The results mean that economies with lower per capita income are more likely to be importers of waste paper, and those with the higher tend to export, which support Hypothesis 2 and Hypothesis 3. In addition, Nodecov (GDP) is significantly negative at the 0.1% level, but the magnitude is small, stating that there is no economic Matthew effect in the evolution of the GWPTNs. A possible reason for this is that the waste paper imports or exports of economies with high economic development are concentrated in a few economies, e.g., the US exports most of its waste paper to China. This result does not support Hypothesis 3.

The Homophily (EPI) and Homophily (Industry) are significantly negative factors for the evolution of the GWPTNs. The results are similar to Ederington & Miner (2003) [72], Baggs (2009) [42], Kellenberg (2012) [21], where most of waste paper trade is between economies with stringent environmental regulations and those with weak environmental regulations. The significant negative Homophily (Industry) means that economies show obvious heterophily of industrialization rate in choosing waste paper trade partners. Further, the Receiver (EPI) and Sender (Industry) are significantly negative, and the Sender (EPI) and Receiver (Industry) are significantly positive at the 0.1% level in 2000–2018. This supports the notion that economies with more stringent environmental regulations or lower industrialization rates export waste paper, while economies with weaker environmental regulations or higher industrialization rate import.

Third, as for the relations embedding statistics, the coefficients of Edgecov (COL), Edgecov (CSL), Edgecov (CRN), Edgecov (HCL) and Edgecov (SCN) are all significant at the 0.1% level. This indicates that the formation and evolution of the GWPTNs are embedded in external networks, and there is a higher possibility tradeoff trading waste paper between two economies when they share a common language, common religion, or colonial relationship. Among these, the embedding effect of historical colonial relationship on the evolution is the strongest. This might be because the long-term colonial relationship between economies led the colonizers to have a strong preference of developing their colonies as their export partners. The Edgecov (RTA) is significantly positive at the 0.1% level, supporting Hypothesis 4. The free trade agreements signed between economies not only promote commodities trade, but also accelerate the cross-border flow of waste paper. The significantly positive Edgecov (CGN) indicates that distance is an important factor affecting the waste paper trade between economies, and economies tend to trade waste paper with their neighbors due to the lower transportation cost, which also supports Hypothesis 4.

To further test the ability of Model 3 to explain the formation of the GWPTNs, we assess its goodness-of-fit (GOF) by comparing the network structure statistics of model-based simulations with those of the observed GWPTNs. As shown in Fig. 7, we plot several statistics, including Edge-wise Shared Partners, Dyad-wise Shared Partners, Geodesic distance, Odegree and Indegree of model-based simulations against the observed GWPTNs based on Model 3. The results show that the distribution of the five structure statistics is very close between the model-based simulations and the observed GWPTNs. This states that the combinations of variables in TERGM have a good fitting and hence can accurately capture the underlying data and the key mechanism of the GWPTN formation [54].

To test the robustness of Model 3, the other results of the TERGM are reported (shown in Table 4). Here, the TERGM results in the periods of 2000–2011(Model 4) and 2004–2018 (Model 5) are reported. Furthermore, we adjust the time step of longitudinal GWPTNs in 2000–2018 from 1 to 2, and its result is estimated (Model 6). In Model 7, we change the estimation method, and the bootstrapped pseudolikelihood is employed. These results are basically consistent with Model 3, which indicates that Model 3 is robust.

For the environmental governance consideration, China (the world's largest waste paper importer) has implemented a series of policies to restrict the import of solid waste since 2013, which not only resulted in decline of China's recyclable waste import including paper waste, but also threw the global recyclable waste trade into turmoil [34,36]. To explore the impact of China's import restriction policies since 2013 on

[3] The calculation formula of the probability of network edge generation in TERGM is $\frac{\exp(coefficient)}{\exp(1+coefficient)}$.

the pattern of the GWPTNs, we adopted the following strategy. First, we divide the data into two sub-periods of 2000–2013 and 2014–2018 referring to Tang & Cui (2020) [93]. Second, we add the Homophily (exportC) into the TERGM based on the divided data. The Homophily (exportC) is Homophily of waste paper trade between economies that exported waste paper to China last year, which can capture the waste trade changes of these economies that exports waste to China last year, such as do these economies trade their waste paper with each other, or do they export their waste paper to other economies that do not export to China? Third, we can judge pattern changes of the GWPTNs for impact of China's import restriction policies since 2013 by comparing the coefficients of Homophily (exportC) in 2000–2013 and 2014–2018.

Their results of the TERGM in 2000–2013 and 2014–2017 are reported in Model 8 and Model 9, respectively. The results show that the coefficients of Homophily (exportC) in Model 8 and Model 9 are significantly negative, meaning that there is heterophily of waste paper trade between economies that exported waste paper to China last year. Comparing Model 8 with Model 9, we find the coefficients of Homophily (exportC) in Model 8 is far smaller than that in Model 9. These results indicate that impacted by China's import restriction policies since 2013, economies exporting waste paper to China last year are more likely to trade waste paper with other economies that do not export to China, and the pattern of the GWPTNs have been influenced by China's import restriction policies since 2013. In addition, the coefficients of Homophily (Urban) and Sender (PerGDP) in Model 9 become negative different from Model 8. This states that the pattern of the GWPTNs shows the heterophily of urbanization rate and a decrease in the export effect of high-income economies after 2013.

4. Conclusions and policy implications

This study constructs the GWPTNs during 2000–2018 based on the complex network theory using bilateral waste paper trade data collected from UN Comtrade Database. We comprehensively explore the evolutionary features of the GWPTNs and empirically test the factors affecting its formation and evolution using the TERGM. Main results are summarized and major conclusions are drawn as follows.

At the macro-level, the scale of global waste paper trade has been increasing with globalization, while the scale of the GWPTNs decreased in 2009, 2012, and 2018 under the global economic fluctuations or improvement of environmental regulations in several economies. The GWPTNs display prominent features of small-world network, low reciprocity, heterogeneity and disassortativity. In terms of medium-continent and community, Asia, Europe, and North America are major players in global waste paper trade. Asia is a superior recipient of global waste paper, while Europe and North America are main waste paper exporters. The GWPTNs gradually formed the American-China-Indonesia community centered on the US, China and Indonesia; Germany, France, the Netherlands and Italy formed the core of the European community, and India and Thailand formed the Asian-Oceania core. The community structure of the GWPTNs fluctuates greatly in the early stage and gradually stabilizes. At the micro-level, China is the largest global waste paper importer, and India develops the most waste paper import partners. However, China's waste paper imports have kept dropping since 2011. The US, the UK, Japan, Germany, and the Netherlands are major exporters of waste paper, playing an important role, with the US being the largest exporter of waste paper. Meanwhile, waste paper exports of these economies have shown a downward trend in recent years. Germany is not only the hub importer of waste paper, but also an important exporter.

There are significant endogenous structural effects, economy attribute effects, and relations embedding effects on the formation and evolution of the GWPTNs. Specifically, the formation and evolution of the GWPTNs are influenced by reciprocity, transitivity, and preferential attachment effects. In particular, an economy is more likely to choose its import source as waste paper export destination, a waste paper partner's partners are more likely to be partners, and economies with more partners tend to trade waste paper with others in the GWPTNs. Economy-pairs within the same continent are more likely to trade waste paper. The formation and evolution of GWPTNs exhibit asymmetrical per capita income, industrialization rates, or environmental regulation strength, and symmetrical urbanization rates. Economies with higher urbanization rates, more per capita income, stricter environmental regulations, or lower industrialization rates are more likely to export waste paper. Conversely, they are more likely to import. In addition, the GWPTNs are embedded in external binary relations, such as culture, regional trade agreements and geographic boundary. Economy-pairs sharing a common language or religion, as well as being a former colony of the same colonizer, historical colonial relationship or geographic boundary, and signing RTAs are more likely to trade waste paper. Moreover, the pattern of the GWPTNs have been impacted by China's import restriction policies since 2013.

Based on the major conclusions, we propose the following suggestions to promote a virtuous circle of waste paper trade to realize the sustainable utilization of waste paper resources on a global scale. First, based on the existing Basel Convention and international trade agreements, a unified and orderly coordination mechanism for international waste paper trade should be established to achieve the harmonization between economic development and environmental protection. Second, waste paper importing economies should raise waste paper import standards and establish a regulatory mechanism when actively participating in international trade of waste paper to reduce non-recyclable waste paper entering. Meanwhile, waste paper disposal technology should be further improved to maximize the utilization rate of waste paper and reduce waste residue pollution to the environment; the industrial structure adjustment should be given more attention. At the same time, waste paper exporting economies should further strengthen the efficiency and upgrade the level of waste paper classification and improve waste paper management. Last, given that geographical and cultural distances are important factors hindering waste paper trade, economies should follow the principle of proximity when participating in international waste paper trade to reduce the cost of waste paper trade.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
List of economies covered in this paper.

Code	Name	Code	Name	Code	Name	Code	Name
AFG	Afghanistan	LBR	Liberia	ECU	Ecuador	STP	Sao Tome and Principe
ALB	Albania	LBY	Libyan Arab Jamahiriya	SLV	El Salvador	SAU	Saudi Arabia
DZA	Algeria	LTU	Lithuania	GNQ	Equatorial Guinea	SEN	Senegal
AND	Andorra	LUX	Luxembourg	ETH	Ethiopia	SER	Serbia
AGO	Angola	MAC	Macao, China(SAR)	ERI	Eritrea	SYC	Seychelles
ATG	Antigua and Barbuda	MDG	Madagascar	EST	Estonia	SLE	Sierra Leone
AZE	Azerbaijan	MWI	Malawi	FRO	Faroe Islands	IND	India
ARG	Argentina	MYS	Malaysia	FJI	Fiji	SGP	Singapore
AUS	Australia	MDV	Maldives	FIN	Finland	SVK	Slovakia
AUT	Austria	MLI	Mali	FRA	France	VNM	Viet Nam
BHS	Bahamas	MLT	Malta	PYF	French Polynesia	SVN	Slovenia
BHR	Bahrain	MRT	Mauritania	DJI	Djibouti	SOM	Somalia
BGD	Bangladesh	MUS	Mauritius	GAB	Gabon	ZAF	South Africa
ARM	Armenia	MEX	Mexico	GEO	Georgia	ZWE	Zimbabwe
BRB	Barbados	TWN	Taiwan, China	GMB	Gambia	ESP	Spain
BEL	Belgium	MNG	Mongolia	DEU	Germany	SDN	Sudan
BMU	Bermuda	MDA	Republic of Moldova	GHA	Ghana	SUR	Suriname
BOL	Bolivia	MON	Montenegro	GIB	Gibraltar	SWZ	Swaziland
BIH	Bosnia and Herzegovina	MAR	Morocco	GRC	Greece	SWE	Sweden
BWA	Botswana	MOZ	Mozambique	GTM	Guatemala	CHE	Switzerland
BRA	Brazil	OMN	Oman	GIN	Guinea	SYR	Syrian Arab Republic
BLZ	Belize	NAM	Namibia	GUY	Guyana	TJK	Tajikistan
SLB	Solomon Islands	NPL	Nepal	HTI	Haiti	THA	Thailand
BRN	Brunei Darussalam	NLD	Netherlands	HND	Honduras	TGO	Togo
BGR	Bulgaria	ANT	Netherland Antilles	HKG	Hong Kong, China	TON	Tonga
MMR	Myanmar□Burma□	ABW	Aruba	HUN	Hungary	TTO	Trinidad and Tobago
BLR	Belarus	NCL	New Caledonia	ISL	Iceland	ARE	United Arab Emirates
KHM	Cambodia	VUT	Vanuatu	IDN	Indonesia	TUN	Tunisia
CMR	Cameroon	NZL	New Zealand	IRN	Iran	TUR	Turkey
CAN	Canada	NIC	Nicaragua	IRQ	Iraq	TKM	Turkmenistan
CPV	Cape Verde	NER	Niger	IRL	Ireland	UGA	Uganda
CYM	Cayman Islands	NGA	Nigeria	ISR	Israel	UKR	Ukraine
LKA	Sri Lanka	NOR	Norway	ITA	Italy	MKD	The former Yugoslav Republic of Macedonia
TCD	Chad	PAK	Pakistan	CIV	Cote d'Ivoire	EGY	Egypt
CHL	Chile	PAN	Panama	JAM	Jamaica	GBR	United Kingdom
CHN	China	PNG	Papua New Guinea	JPN	Japan	TZA	United Republic of Tanzania
COL	Colombia	PRY	Paraguay	KAZ	Kazakhstan	USA	United States of America
COG	Congo	PER	Peru	JOR	Jordan	BFA	Burkina Faso
COD	Democratic Republic of the Congo	PHL	Philippines	PRK	Democratic People's Republic of Korea	URY	Uruguay
CRC	Costa Rica	POL	Poland	KEN	Kenya	UZB	Uzbekistan
HRV	Croatia	PRT	Portugal	KOR	Republic of Korea	VEN	Venezuela
CUB	Cuba	TMP	Timor-Leste	KWT	Kuwait	WSM	Samoa
CYP	Cyprus	QAT	Qatar	KGZ	Kyrgyzstan	YEM	Yemen
CZE	Czech Republic	ROM	Romania	LAO	Lao People's Democratic Republic	SCG	Serbia and Montenegro
BEN	Benin	RUS	Russian Federation	LBN	Lebanon	ZMB	Zambia
DNK	Denmark	RWA	Rwanda	LVA	Latvia		
DOM	Dominican Republic	LCA	Saint Lucia				

Table A2
Variable description of TERGM.

Symbol	Meaning	Data source
GWPTNs	The Global waste paper trade networks	UN Comtrade Datadase
GDP	Gross Domestic Product of each economy	World Bank
Urban	Urbanization rate of each economy	World Bank
EPI	Environmental performance index used to measure environmental regulation strength of each economy, the larger the value, the higher strength the economy's environmental regulation.	SEDAC[1]
Continents	Continents each economy belongs to	CEPII
COL	The common official language network, the two economies use a common official language with a value of 1, otherwise 0.	CEPII
CSL	The common spoken language network, the two economies use a common spoken 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
HCL	The historical colonial relationship network, the two economies have a historical colonial relationship with the value of 1, otherwise 0.	CEPII
SCN	The same colonizer network, two economies being a former colony of the same colonizer with a 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
CGN	The economy's common geographic boundary network, the two economies have a common boundary with a value of 1, otherwise 0.	CEPII

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

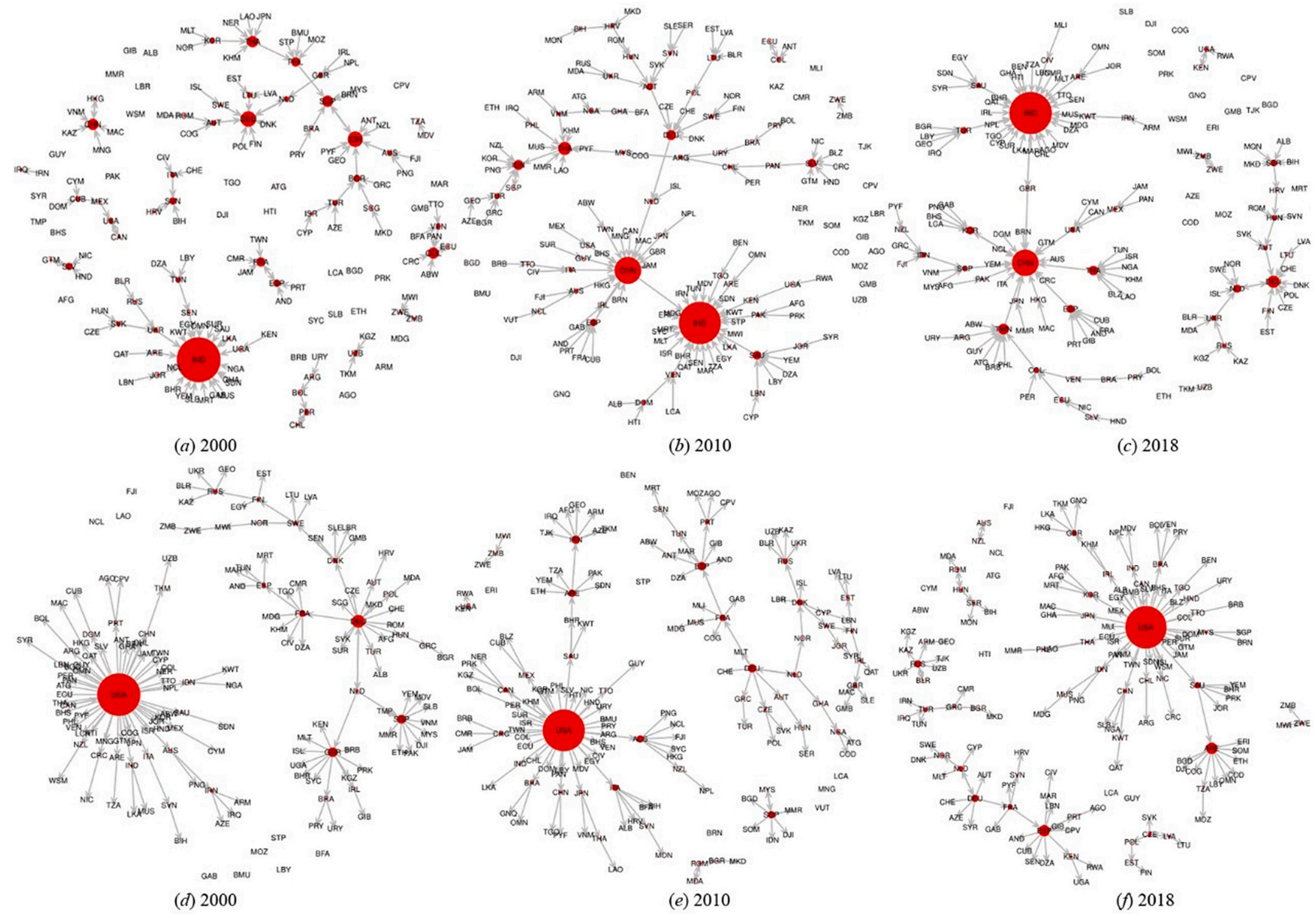

Fig. A1. Global waste paper trade export Top1 and import Top1 network in 2000–2018. *Note*: (*a*), (*b*) and (*c*) are export Top1 network in 2000, 2010, and 2018 respectively, which only keep each economy's strongest waste paper trade export; (*d*), (*e*) and (*f*) are import Top1 network in 2000, 2010 and 2018, which only keep each economy's strongest waste paper trade import. The node size is proportional to the number of partners. These figures are plotted using R software.

Credit author statement

Helian Xu: Data curation, Methodology, Investigation, Writing- Reviewing and Editing. Lianyue Feng: Data curation, Methodology, Software, Writing – original draft preparation. Gang Wu: Conceptualization, Visualization, Investigation, Writing- Reviewing and Editing. Qi Zhang: Writing- Reviewing and Editing.

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