Empirical Research Article

International Tourism Dynamics in a Globalized World: A Social Network Analysis Approach

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Abstract

A complex network of tourism has emerged in the globalized world, but there is little research on the dynamics of global tourism networks and the underlying forces that affect those dynamics. Using international tourism data for 124 countries between 2000 and 2013, we integrated cluster analyses and social network models to identify the structures of global tourism networks and uncover factors affecting changes in international tourist flows. Results indicate that global tourism networks have become highly consolidated over time and that reduced transaction costs (e.g., language, distance, and visa policies) are more important in attracting international tourists than natural and cultural attractions. Furthermore, cost of living differences between countries decreased in importance over time. Finally, international tourist flows are resilient to political instability and terrorism risks. Our approach and findings highlight the key strategic factors for decision-making to implement proactive tourism policies.

Keywords

international tourism, social network model, cluster analysis, metacoupling, cultural ecosystem service

Introduction

Globally, tourism is booming, generating complex global networks with expanding economic power that consumes increasingly larger resources (Glaesser et al. 2017; Higham and Miller 2018; Song, Li, and Cao 2017). The globalization of tourism is increasing the interdependence between sending systems (supply areas, origins, departures) and receiving systems (demand areas, destinations, arrivals) worldwide, contributing to socioeconomic and environmental ties across regions (Dwyer 2015; Glaesser et al. 2017; van der Zee and Vanneste 2015; von Bergner and Lohmann 2014). The proportion of the world economy occupied by tourism is rapidly increasing, accounting for approximately 10% of global GDP and employment in 2017 (Scott and Gössling 2015; World Travel and Tourism Council 2018). In addition, annual global tourism consumes approximately 16,700 PJ of energy, 138 km^3 of fresh water, 62,000 km^2 of land, and 39.4 Mt of food, and leads to 4.5 Gt of CO_2 emissions (Gössling and Peeters 2015; Lenzen et al. 2018). As tourism encourages extensive interactions between human and natural systems (Jones, Hillier, and Comfort 2016; Liu et al. 2015), the tourism sector contains many opportunities to enhance global sustainability regarding job creation, economic growth, and environmental protection (Jones, Hillier, and Comfort 2016; Scheyvens 2018; World Tourism Organization 2018). These

trends raise important questions about the impacts of the growing connectivity and interdependency of globalized tourism networks, yet research has not kept pace with these changes. A holistic conceptualization and quantification is therefore urgently needed.

In a globalized world, tourist flows fluctuate in response to a variety of socioeconomic and environmental factors across regions, which complicate tourism management by making supply and demand difficult to predict (Albrecht 2013; Liu et al. 2015; Song, Li, and Cao 2017; van der Zee and Vanneste 2015; von Bergner and Lohmann 2014). Historically, international tourism mostly occurred between high-income countries, but in the mid-1990s international tourist arrivals increased rapidly in middle- and low-income

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countries (Scott and Gössling 2015). Some of the tourism to middle- and low-income countries may have been nature-based and cultural tourism, but the effectiveness of conservation efforts (e.g., protected areas and World Heritage sites) in attracting more international tourists is uncertain (Cellini 2011; Cuccia, Guccio, and Rizzo 2016; Patuelli, Mussoni, and Candela 2013; Yang, Lin, and Han 2010; Yang and Lin 2011). There is also ongoing debate as to whether international tourism is resilient to political instability and terrorism risks (Liu and Pratt 2017; Saha and Yap 2013; van der Zee and Vanneste 2015). Thus, tourism studies should explore the increased complexity of global tourism networks and how they respond to natural resources and social and political conditions.

Until now, quantitative research has been lacking to understand how the dynamics of global tourism networks have changed over time and how these networks affect, and are affected by, tourism supply and demand. Social network analysis is a sophisticated way to quantify the network structures of the tourism sector (Albrecht 2013; Casanueva, Gallego, and García-Sánchez 2016). Social network analysis also proves useful for uncovering the drivers of tourist flows in both sending and receiving systems (Albrecht 2013; Merinero-Rodríguez and Pulido-Fernández 2016). However, most tourism studies that use social network analysis concentrate on the structural characteristics of personal and organizational networks (e.g., density, centrality, and clusters) in the destinations (Casanueva, Gallego, and García-Sánchez 2016; van der Zee and Vanneste 2015). In addition, although many network models have been developed to estimate both network dependencies (e.g., reciprocation) and parameters as the drivers of network structures with statistical inference (e.g., standard errors, p-values, or posterior distributions) (Snijders 2011), little tourism research applies network models to investigate the environmental and socioeconomic drivers of tourism.

To fill this research gap, we integrate a social network model with cluster analysis to uncover the network structure of international tourist flows and examine the factors of international tourism. Utilizing longitudinal data, the network model identifies the influence of environmental and socioeconomic factors on international tourism while accounting for statistical dependencies within global tourism networks. We answer two questions: (1) How has the network structure of international tourism changed over time? and (2) Which factors contribute to increased international tourist flows over time? By establishing a theoretical foundation within a social network framework, we quantify the spatial and temporal changes of global tourism networks. On a practical front, measuring network dependencies and the factors involved in global tourism networks on both the supply and demand sides provides valuable insights for researchers, policymakers, and stakeholders implementing tourism development and destination management in a globalized world.

The next section begins with a literature review of social network analysis in tourism and factors that contribute to international tourism. The third section describes the data collection, processing, and network methods. The fourth section presents results from global-level network analyses. The paper concludes with a discussion of the theoretical and practical implications of employing these methods for future research and decision making.

Literature Review

Our approach is based on an application of network science to describe international tourist flows as a network. This section is a narrative review that covers three topics: (1) the theoretical background of social network analysis in tourism, (2) the application of social network analysis to investigations of the dynamics of global tourism networks, and (3) the environmental and socioeconomic factors of international tourism used in this study.

Social Network Analysis

Social network analysis uses network and graph theory to investigate social structures (Baggio, Scott, and Cooper 2010; Otte and Rousseau 2002; Wasserman and Galaskiewicz 1994). Social networks form a relational structure of ties (or edges) between actors (or nodes), such as friendships between individuals or trade between countries (Albrecht 2013; Snijders 2011). Similarly, international tourism forms a relational network by connecting the sending system (supply area, origin, departure) to attractions in the receiving system (demand area, destination, arrival) that is manifest in tourist flows (Albrecht 2013; Sainaghi and Baggio 2017).

The use of social network analysis to analyze tourism has grown rapidly over the last two decades (Baggio, Scott, and Cooper 2010; Casanueva, Gallego, and García-Sánchez 2016; Pulido-Fernández and Merinero-Rodríguez 2018). Importantly, such approaches allow for the examination of both tourism supply perspectives (Pulido-Fernández and Merinero-Rodríguez 2018; Sainaghi and Baggio 2017) and tourism demand perspectives (Money 2000; Tyler and Dinan 2001). However, most tourism literature that uses social network analysis has focused on personal and organizational networks in tourism destinations (tourism supply-side) (Casanueva, Gallego, and García-Sánchez 2016; van der Zee and Vanneste 2015). For example, tourism studies have used social network analysis to investigate effects of collaborations among tourism stakeholders (Baggio 2011; Pulido-Fernández and Merinero-Rodríguez 2018), marketing (Bhat and Milne 2008; Wang and Xiang 2007), sustainable tourism (Albrecht 2013), and geography (Jin, Cheng, and Xu 2017; Lee et al. 2013) in tourism destinations.

Additionally, the most commonly used methods of social network analysis in tourism studies are concentrated on investigating static structural network properties (e.g., size,

density, betweenness, and clusters) (Baggio, Scott, and Cooper 2010; Benckendorff and Zehrer 2013; Lee et al. 2013; Pulido-Fernández and Merinero-Rodríguez 2018; Raisi et al. 2017; Scott, Cooper, and Baggio 2008). Although tourism network properties may change significantly over time (Westveld and Hoff 2011), few tourism studies have included any quantitative analysis of longitudinal data sets using a social network analysis approach (Baggio and Sainaghi 2016; Jin, Cheng, and Xu 2017). Recent exceptions include bibliometric network visualizations showing changes in tourism research output over time (Güzeller and Çeliker 2018; Jiang, Ritchie, and Benckendorff 2017; Li, Ma, and Qu 2017).

Social network analysis accounts for dependencies among ties between sets of actors (e.g., reciprocity and transitivity) (Snijders 2011). For example, international tourism leads to dependence between sending and receiving countries if two countries have reciprocal tourism flows. Various statistical models have been developed to capture network dependencies between actors (Snijders 2011). These statistical network models can estimate parameters to express network structures with statistical inference (e.g., standard errors, p-values, or posterior distributions).

The p_2 network model has been shown to yield a robust estimation procedure that accounts for network dependencies associated with common senders and receivers of network ties as well as potential reciprocal relationships between pairs of actors (Hoff 2005; van Duijn, Snijders, and Zijlstra 2004). The p_2 model parameters are estimated with Bayesian inference based on a Markov-Chain Monte Carlo (MCMC) algorithm (Hoff 2005; van Duijn, Snijders, and Zijlstra 2004). Bayesian inference is a method for statistical inference used to compute the conditional probability of an event after taking into account new evidence or information that the event has occurred (Gamerman and Lopes 2006). The MCMC is a mathematical method for generating the probability distribution of a parameter by randomly sampling from a complex probabilistic space (Andrieu et al. 2003).

Social networks also contain temporal dependencies, wherein changes in network ties depend on the earlier structure of network ties (e.g., the evolution of international tourism networks) (Hoff 2015; Snijders 2011; Ward and Hoff 2007). Longitudinal network data with regular temporal intervals are often referred to as network dynamics (Snijders 2011). For longitudinal network data, statistical modeling approaches such as ordinary least squares and generalized linear models risk overestimating the significance of parameters by ignoring network and temporal dependencies with the assumption of independence (Westveld and Hoff 2011). But Westveld and Hoff (2011) developed a mixed effects model to account for both network and temporal dependencies as a stochastic process. The mixed effects model extended the p_2 model of van Duijn, Snijders, and Zijlstra (2004) and Hoff (2005). This model (1) uses a latent space approach to produce visualizations of the network structure

with the latent space positions, (2) develops a generalized linear modeling framework that allows for continuous data, and (3) outlines a general Bayesian estimation approach for model parameters with the MCMC algorithm (Westveld and Hoff 2011).

Despite recent developments in social network models, there is a significant absence of application of these models in tourism studies. With the social network model for longitudinal data, we provide a unique perspective on the dynamics of global tourism networks by quantifying both network and temporal dependencies. We also integrate social network modeling and cluster analysis to examine which environmental and socioeconomic factors influence changes in international tourist flows across countries. Thus, the application of social network models in tourism studies provides a better orientation to understand the processes of tourism development and destination management worldwide.

Hypothesized Factors Affecting International Tourism

Following previous studies that investigated factors shaping tourism demand (Balmford et al. 2015; Lim 1997, 1999; Marrocu and Paci 2013; Peng, Song, and Crouch 2014; Song and Li 2008; Song et al. 2012a; Witt and Witt 1995), the most widely used factors affecting international tourism were considered for inclusion in the social network model regarding the characteristics of sending countries, receiving countries, and their pairs. These factors represent environmental, political, social, economic, and demographic features in both sending and receiving countries. We note that the factors used in tourism demand models may change extensively, depending on the research questions, time periods, methodologies, and selection of countries (Dogru, Sirakaya-Turk, and Crouch 2017). Based on the above literature review, we examine whether transaction costs (e.g., language, geographic distance, and visa policy) and demographic forces (e.g., population and income growth) are more important in attracting international tourists than natural and cultural attractions (e.g., protected areas and World Heritage sites) and political stability.

First, transaction costs of travel include visa-free status, national price-level difference, shared language, and proximity. International tourists prefer to travel to visa-free countries. Visa restrictions and requirements in destination countries can have a negative impact on the number of tourist arrivals (Balli, Balli, and Cebeci 2013; Cheng 2012; Neumayer 2010). Additionally, international tourists prefer to travel to countries that have advantageous prices relative to their home countries (Cheng 2012; Dogru, Sirakaya-Turk, and Crouch 2017; Saha and Yap 2013). There are two types of measurements for price-level differences in the tourism demand model (1) relative prices of the place of origin to the prices in the destination and (2) substitute prices of the destination to the prices in competing destinations (Dogru,

Sirakaya-Turk, and Crouch 2017; Kronenberg et al. 2016). As a measurement of the price-level differences between countries, relative price standardized by exchange rates has been found to be more significant than the exchange rate alone (De Vita and Kyaw 2013; Dogru, Sirakaya-Turk, and Crouch 2017). International tourists also prefer to travel to countries that use the same language as their home country. Thus, a shared language between sending and receiving countries plays an essential role in promoting tourist flows (Eilat and Einav 2004; Khadaroo and Seetanah 2008). Finally, international tourists prefer to travel to nearby countries. Greater distances between sending and receiving countries have a negative impact on international tourist flows (Lim 1999; Patuelli, Mussoni, and Candela 2014; Yang, Lin, and Han 2010). The number of direct flights between countries also contributes to increases in international tourist flows (Lohmann et al. 2009; Rehman Khan et al. 2017).

Second, demographic forces include population size and GDP per capita. Population and income growth are important determinants for international tourist arrivals and departures. Tourism studies typically use real GDP per capita and population as proxies for relative income and market size (Lim 1997; Peng, Song, and Crouch 2014; Witt and Witt 1995). Higher per capita GDP in both sending and receiving countries positively affect international tourist flows (Lim 1999; Saha and Yap 2013; Song, Kim, and Yang 2010). International tourist flows also increase in sending and receiving countries with higher populations (Khadaroo and Seetanah 2008; Llorca-Vivero 2008; Yang, Lin, and Han 2010).

Third, many tourism studies have investigated the role of conservation efforts (e.g., protected areas and World Heritage sites) for tourism demand (Song et al. 2012a). Larger protected areas have been found to attract more tourists (Balmford et al. 2015; Chung, Dietz, and Liu 2018b). Protected areas are good at attracting nature-based tourists while conserving biodiversity (Balmford et al. 2015; Chung, Kang, and Choi 2015). Furthermore, nature-based tourism often contributes to the management and conservation of protected areas by providing financial resources (Buckley et al. 2015; Buckley, Zhong, and Ma 2017). However, there is an ongoing debate regarding the effectiveness of World Heritage sites in promoting tourist arrivals (Cellini 2011; Cuccia, Guccio, and Rizzo 2016; Patuelli, Mussoni, and Candela 2013; Yang, Lin, and Han 2010; Yang and Lin 2011). While some studies show that the presence of World Heritage sites attracts more visitors as a result of proper management and accessibility (Richards 2011; Su and Lin 2014; Yang, Lin, and Han 2010), others show that World Heritage sites do not affect the number of tourist arrivals (Cellini 2011; Cuccia, Guccio, and Rizzo 2016, 2017).

Fourth, empirical research lacks agreement regarding the effects of political instability and terrorism risks on both international tourist arrivals and departures (Liu and Pratt 2017; Saha and Yap 2013; van der Zee and Vanneste 2015). Some studies have found that political instability and terrorism risks (e.g., public violence, riots, civil wars, and military coups) negatively influence international tourist arrivals (Eilat and Einav 2004; Llorca-Vivero 2008; Saha and Yap 2013; Sönmez 1998). But others have claimed that international tourists are resilient to political instability and terrorism risks (Liu and Pratt 2017; van der Zee and Vanneste 2015).

Materials and Methods

Data Collection

Data on international tourist arrivals were obtained from the UN World Tourism Organization (UNWTO). This raw data set covers more than 200 countries from 1995 to 2013. UNWTO defines visitors to include both tourists (overnight visitors) and excursionists (same-day visitors) (World Tourism Organization 2016a). Following UNWTO methods for estimating the number of international tourists, we excluded excursionists prior to selecting 124 countries over the period from 2000 to 2013 for analysis. The selected countries cover approximately 90% of international tourist arrivals in the specified time period.

Although the UNWTO data are the best available international tourist arrival data set, the UNWTO data set has some weaknesses inherent in how different jurisdictions collect visitor arrival data (World Tourism Organization 2016a). When countries did not report international tourist arrivals at national borders (referred to as TF), we supplemented by using other data sets following UNWTO methods: international visitor arrivals at national borders (VF), international tourist arrivals at hotels and similar establishments (THS), or international tourist arrivals at collective tourism establishments (TCE) (World Tourism Organization 2016b).

To test our hypotheses, we collected data regarding possible factors influencing international tourism: transaction costs of travel and environmental, political, and demographic factors. Transaction costs of travel included visa requirements for tourism, price-level ratio to the market exchange rate, shared language, and geographic distances between sending and receiving countries. At the level of the pair of countries, the visa-free score is 1 if a receiving country waives visa requirements for a sending country, including both visa-free and visa-on-arrival entry (https://www.passportindex.org). The price-level ratio measures the amount of a country's currency that is required to purchase a dollar's worth of goods relative to the United States (= 1) (The World Bank 2017). The price-level differences between countries were calculated by subtracting the price-level ratio of each receiving country from each sending country. Countries having a shared language was also included, where if two countries share an official language (e.g., Canada and the United Kingdom), their language factor was 1. Geographic distances between the centroids of pairs of countries were calculated using GeoDa (Anselin, Syabri, and Kho 2006) and remained constant over the study period. The number of direct flights

between countries was obtained from Openflights (https://openflights.org).

Environmental factors included the size of protected areas in receiving countries (IUCN and UNEP-WCMC 2017), restricted to protected areas that are legally and officially designated at the national or subnational level. Marine protected areas were excluded as well as the International Union for Conservation of Nature (IUCN) Category I protected areas, where tourism is prevented for strict conservation. Additionally, World Cultural Heritage sites were included as an environmental factor (UNESCO 2017). World Natural Heritage sites were excluded to avoid double counting a site. Protected areas and World Cultural Heritage sites were used to represent a country's cultural ecosystem services (Balmford et al. 2015; Chung et al. 2018a; Yang, Lin, and Han 2010).

Political factors included the index of political stability and the absence of violence and terrorism (The World Bank 2017). The index of political stability and the absence of violence and terrorism measures the likelihood of political instability and politically motivated violence, ranging from −2.5 to 2.5 (The World Bank 2017). In both sending and receiving countries, population size was a demographic factor (The World Bank 2017). Additional economic factor included per capita GDP (The World Bank 2017).

Cluster Analyses

We used Kliquefinder software to identify clusters of countries within global tourism networks (Frank 1995, 1996). The raw data for this analysis consist of the total tourist flows between each pair of countries over a given interval. The algorithm maximizes the odds ratio of flows within clusters relative to between clusters by switching actors among clusters repeatedly. Because countries in the same cluster have a higher probability of sending tourists to each other than countries in different clusters, the Kliquefinder algorithm can identify clusters of countries that can then be investigated to see if they are focused around income level or other factors such as population or geographic location. To test the statistical significance of the clustering, Kliquefinder is applied to a random redistribution of flows. This is repeated 1,000 times, and the measure of fit is noted to generate a Monte Carlo sampling distribution under the null hypothesis of no clustering in the data (data are generated at random). The observed measure of fit is then compared to the Monte Carlo–generated sampling distribution to obtain a p value.

To perform the cluster analysis, we examined the number of international tourists in two different ways: by analyzing the average of the data from the first three years (2000–2002) and the last three years (2011–2013) in the UNWTO data sets, and by analyzing each year (from 2000 to 2013) separately. Although some significant political, social, and natural events occurred during the study period (e.g., the events of 9/11, the Indian Ocean tsunami, global financial crisis, the Arab Spring, and Olympics events), we consider our analyses to be valid because there are rarely multiyear periods in which a significant political, social, or natural event does not occur somewhere in the world. Furthermore, we believe that the use of both three-year averages and single-year data accounts for such occurrences. We performed cluster analyses with Kliquefinder for each of the temporal periods, and tested for evidence of clusters in each period.

For the results from the analyses of both the 3-year periods and each individual year, we used the *igraph* package in R to visualize the cluster results. In the graphs, we used the number of international tourists to identify the core and peripheral countries in global tourism networks based on the k-core decomposition approach, an iterative approach that determines the most central nodes by consecutively cutting out the least connected nodes in a given network (Barberá et al. 2015). We also presented the cluster results by country on a global map using ArcGIS (ESRI 2015).

Mixed Effects Model

In addition to the cluster analyses, we used a mixed effects (including random and fixed effects) model for longitudinal tourism network data with the dependent variable as the number of international tourist arrivals from a sending country to a receiving country. The mixed effects model was developed by Westveld and Hoff (2011) to account for both network and temporal dependencies. Westveld and Hoff (2011) provided R code script that we deployed using the *MCMCpack* package in R. The results provide means and regression estimates of the factors affecting global tourism networks, as well as evidence of statistical dependencies. By using a generalized linear model framework, this model can adopt the gravity approach described in the next paragraph, which models the set of bilateral tourist flows (Khadaroo and Seetanah 2008; Morley, Rosselló, and Santana-Gallego 2014; Westveld and Hoff 2011; Yang, Lin, and Han 2010).

Since tourism is a type of trade in services, tourist flows can also be analyzed using the gravity approach for bilateral trade (Cheng 2012; Eilat and Einav 2004; Kimura and Lee 2006; Morley, Rosselló, and Santana-Gallego 2014). The gravity model has been widely applied on both the tourism supply and demand sides over the last decade (Marrocu and Paci 2013; Morley, Rosselló, and Santana-Gallego 2014). The gravity model of international trade can be derived from the Heckscher-Ohlin theory based on international differences in factor endowments (Deardorff 2007). Furthermore, Morley, Rosselló, and Santana-Gallego (2014) derived a theoretical framework to support the gravity model for bilateral tourist flows by using consumer utility theory.

The gravity model assumes that international tourist flows between sending and receiving countries increase with a country's size (e.g., population and income) and decrease with transportation costs between countries (e.g., distance) (Eilat and Einav 2004; Khadaroo and Seetanah 2008; Witt

and Witt 1995). Some studies also include some dummy variables (e.g., visa requirements or shared language) in addition to the gravity model (Eilat and Einav 2004; Neumayer 2010), an approach we followed in our study. The basic gravity model for bilateral trade is shown as

$$T_{ij} = B \frac{m_i^{\beta_1} m_j^{\beta_2}}{d_{ij}^{\beta_3}} E_{ij}, \qquad (1)$$

where T_{ij} is the amount of trade flows between two regions i and j; m_i and m_j are the characteristics of each region's size (e.g., national income or population); d_{ij} is the geographical distance between region i and region j; E_{ij} is a normal distributed error term; and B, β_1, β_2, and β_3 are coefficients to be estimated. By taking the natural log transformation in equation (1), the basic gravity equation for estimation purposes can be expressed as follows:

$$\ln T_{ij} = \beta + \beta_1 \ln m_i + \beta_2 \ln m_j + \beta_3 \ln d_{ij} + \varepsilon_{ij} \qquad (2)$$

where ε_{ij} is a residual error term.

We applied this gravity model to annual international tourist arrivals between 124 countries for each year from 2000 to 2013. The model for longitudinal tourist flows is:

$$\begin{aligned}
&\ln \# \, of \, International \, Tourists_{i,j,t} = \beta_{0,t} + \beta_{1,t} \ln PA_{j,t} + \\
&\beta_{2,t} \ln World \, Heritage_{j,t} + \beta_{3,t} Political \, Stability_{i,t} + \\
&\beta_{4,t} Political \, Stability_{j,t} + \beta_{5,t} Visa \, Free_{i,j} + \\
&\beta_{6,t} Language_{i,j} + \beta_{7,t} \ln D_{i,j,t} + \beta_{8,t} \ln Price \, Level_{i,j,t} + \\
&\beta_{9,t} \ln GDP_{i,t} + \beta_{10,t} \ln GDP_{j,t} + \\
&\beta_{11,t} \ln Pop_{i,t} + \beta_{12,t} \ln Pop_{j,t} + s_{i,t} + r_{j,t} + g_{i,j,t}
\end{aligned} \qquad (3)$$

where International Tourists$_{i,j,t}$ is the number of international tourist arrivals from sending country i to receiving country j at time t; PA$_{j,t}$ is the size of protected areas in the receiving country at time t; World Heritage$_{j,t}$ is the size of World Cultural Heritage sites in the receiving country at time t; Political Stability$_{i,t}$ and Political Stability$_{j,t}$ are the political stability and absence of violence and terrorism indices for the sending and receiving countries at time t, respectively; Visa Free$_{i,j}$ is the visa-free score between the sending and receiving country; Language$_{i,j}$ is shared language factor between the sending and receiving countries; D$_{i,j,t}$ is the geographic distance from the centroid of country i to the centroid of country j; Price Level$_{i,j,t}$ is the national price-level difference between sending and receiving countries; GDP$_{i,t}$ and GDP$_{j,t}$ are the per capital GDP in the sending and receiving countries at time t, respectively; Pop$_{i,t}$ and Pop$_{j,t}$ denote the population size in the sending and receiving countries at time t, respectively; $s_{i,t}$ is a sender effect; $r_{j,t}$ is a receiver effect; and $g_{i,j,t}$ is a residual error term. The sender ($s_{i,t}$) and receiver ($r_{j,t}$) random effects measure the average deviations of the levels of tourist arrivals and

departures in each country. With these effects, we can identify which countries are the most or least active in global tourism networks. In international tourism, International Tourists$_{i,j,t}$ is the directed flow from sending country i to receiving country j at time t; International Tourists$_{i,j,t}$ is not equal to International Tourists$_{j,i,t}$.

For the sake of clarity, we also used an alternative model, which compared the proportion of protected areas and World Cultural Heritage sites to the total land area of a country instead of compared to the absolute size of protected areas and World Cultural Heritage sites. This alternative model also included the number of direct flights between countries instead of the geographic distance.

To estimate both models, an MCMC algorithm iterated 11,000 times, and we dropped the first 1,000 iterations to allow convergence to the stationary distribution. Our model parameters were automatically saved every 10th scan. Then, we calculated means and 95% confidence regions of the parameters using the joint posterior distribution. For 95% confidence regions, we used Highest Posterior Density (HPD) interval.

Results

This section presents the results of our global-level network analyses in two parts: cluster analyses and the social network model. The first part of the analyses began by examining the network structure of international tourism in the two temporal periods (2000–2002 and 2011–2013) and in each year (from 2000 to 2013) individually. To test the sensitivity of our cluster results to the choice of the temporal periods, we examined the network structure of international tourism in each year from 2000 to 2013. The second part of the analyses determined which factors contributed to changes in international tourist flows over time and quantified network and temporal dependencies in global tourism networks.

Consolidated Global Tourism Networks

While global tourism networks from 2000 to 2002 were divided into eight clusters (Figure 1A), the network structure from 2011 to 2013 had only two clusters (Figure 1B). Figure 1 also identified the core and peripheral countries in global tourism networks. The core countries (e.g., USA and western European countries) located in the center played active roles in both tourist arrivals and departures.

At the first time point (2000–2002), the largest cluster included 54 countries highlighted by yellow circles in Figure 1A. All high-income countries were located in this group. The remaining seven clusters included middle- and low-income countries, grouped by geographic locations (the Caribbean Sea, central and southern America, southern Africa, eastern and western Africa, central Asia, southern Asia, and eastern Europe) (Figure A1, panel A). The dominant cluster sent a large number of tourists to countries within
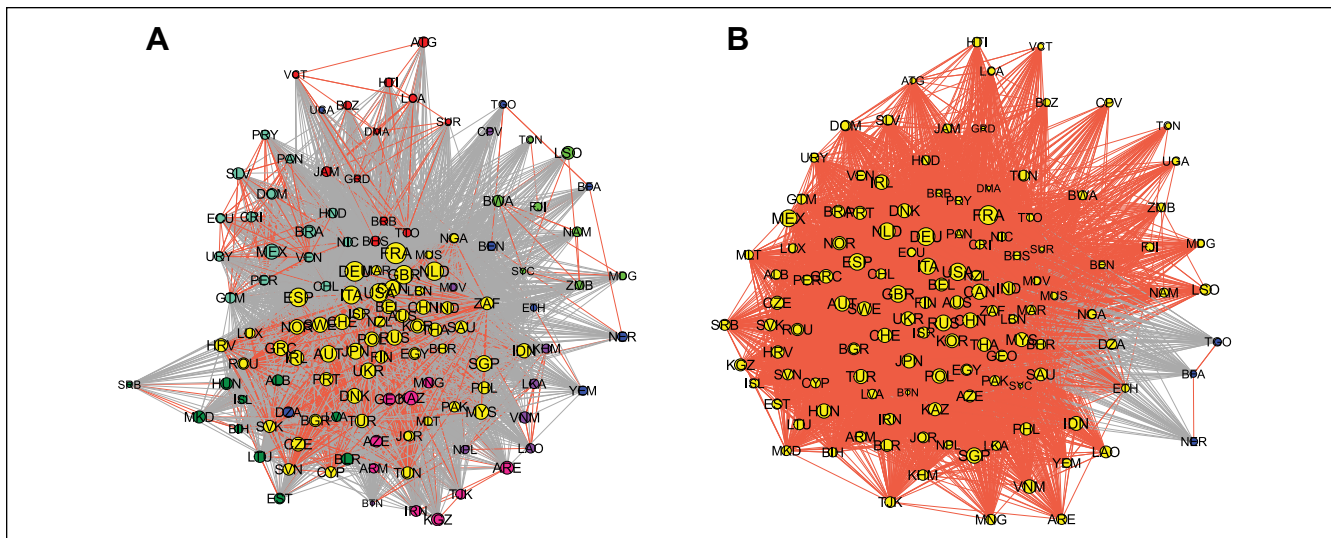
Figure 1. Clusters of global tourism networks in (A) 2000–2002 and (B) 2011–2013. The size of each node indicates the sum of international tourist arrivals and departures. Red ties indicate tourist flows within the same cluster, and gray ties indicate tourist flows between different clusters. The countries' locations in the cluster map represented the strength of the interactions between countries based on the number of international tourists. The core countries were located in the center of the cluster maps.

Table 1. Odds Ratios for Cluster Analysis and P-Value Based on Simulations Followed by Mean, Median, and 95% Quantile Interval of Simulations.

	n	Odds Ratio	P-Value	Mean	Median	2.5%	97.5%
2000–2002	8	0.792	<0.001	0.596	0.604	0.365	0.636
2011–2013	2	0.828	<0.001	0.561	0.563	0.532	0.591

the same cluster (red lines in Figure 1) and to the other seven clusters (gray lines in Figure 1). Interestingly, over the period of 2011–2013, the dominant cluster expanded to include 121 countries. The consolidated cluster contained all countries in our data set, excepting only Burkina Faso, Niger, and Togo in western Africa (Figure A1, panel B).

The cluster results for each individual year from 2000 to 2013 also indicated the same pattern—that global tourism networks have become consolidated over time (Figure A1). Specifically, the number of clusters in 2009 was highest (12 clusters) over the 14-year period, followed by 2004 (11 clusters). These clusters were mainly based on geographic location (Figure A1). After 2009, the number of clusters decreased, from nine in 2010 to two in 2012 (Table A1). Informed by the Monte Carlo sampling distribution, we confirmed the existence of clusters in global tourism networks in each time period (Table 1 and Table A1, P < 0.001).

Factors Related to International Tourism

By using a mixed effects model, we were able to estimate the effect of each independent variable on international tourist arrivals, as well as of network and temporal dependencies within global tourism networks. Figure 2 shows the mean for each coefficient and its 95% HPD confidence intervals from 2000 to 2013. Regarding receiving countries, the size of protected areas and World Cultural Heritage sites did not have a significant relationship with international tourist flows. From 2000 to 2013, the coefficients for protected areas and World Cultural Heritage sites changed little and their confidence intervals contained zero (Figure 2A and B). In the alternative model, the proportions of protected areas and World Cultural Heritage sites to the total land area were also not statistically significant (their confidence intervals contained 0) between 2000 and 2013 (Figure A2).

Regarding sending countries, the coefficients for political stability and absence of violence and terrorism did not shift, and their intervals consistently contained zero (Figure 2C). However, with respect to receiving countries, the coefficients of political stability and absence of violence and terrorism declined from 2000 to 2011 and then shifted upward from 2011 to 2013 (Figure 2D).

Third, the coefficients for visa-free score and shared language were positive over the entire study period (Figures 2E and F). There was an increase in the coefficients for visa-free score from 2000 to 2013.

Fourth, international tourists prefer to travel to nearby countries. Geographic distance between sending and receiving countries was negatively associated with the number of international tourists from 2000 to 2013 (Figure 2G). In the
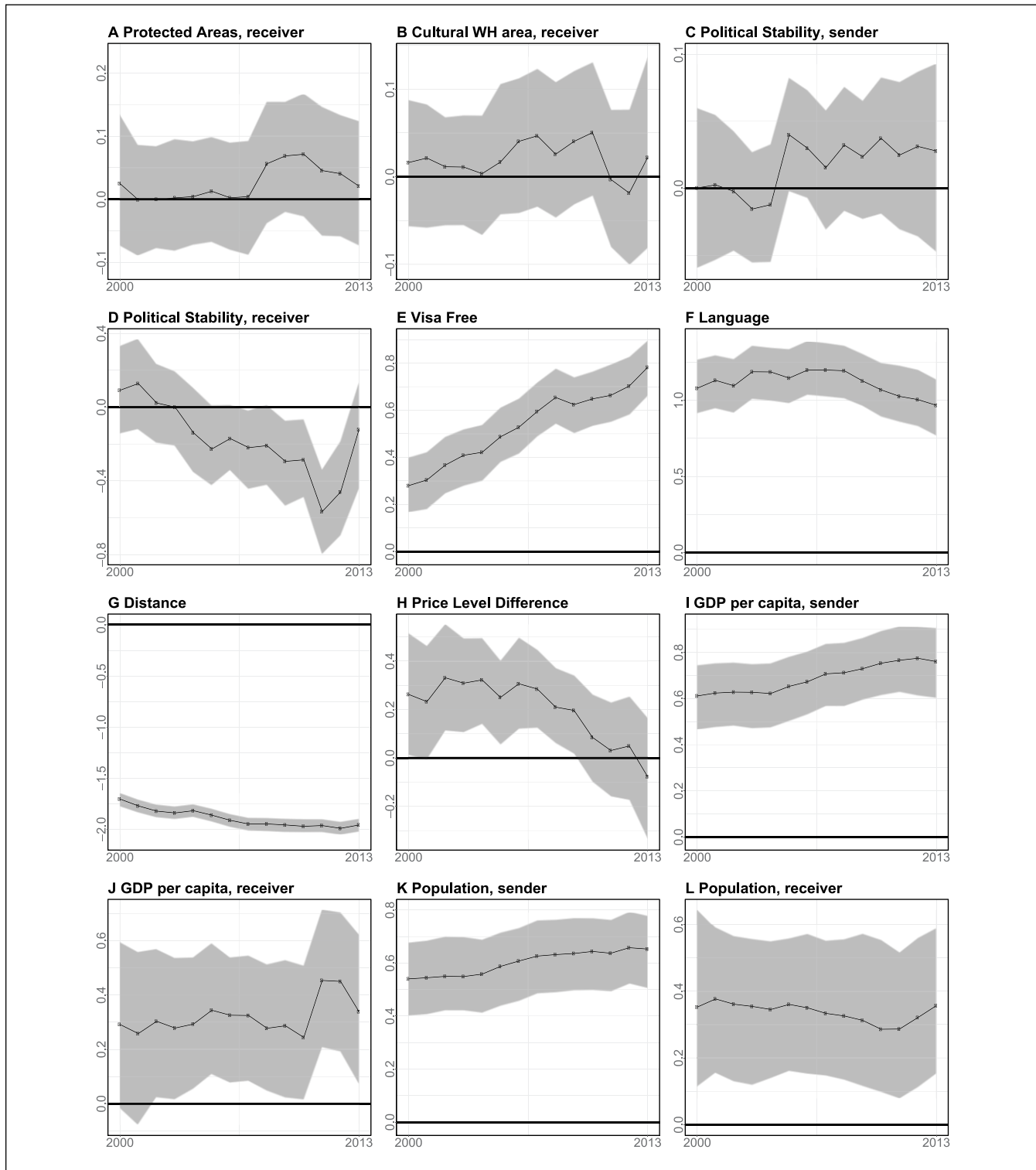
Figure 2. Mean and 95% highest posterior density (HPD) confidence intervals of the coefficients from 2000 to 2013: (A) the size of protected areas in receiving countries (km^2), (B) the size of World Cultural Heritage sites in receiving countries (km^2), (C) political stability in sending countries (index), (D) political stability in receiving countries (index), (E) visa-free status between sending and receiving countries (visa-free=1), (F) shared language between sending and receiving countries (shared language=1), (G) distances between countries (km), (H) national price-level difference between sending and receiving countries (price-level ratio), (I) per capita GDP in sending countries (constant 2010 US dollars), (J) per capita GDP in receiving countries (constant 2010 US dollars), (K) population size of sending countries (person), and (L) population size of receiving countries (person).

alternative model, the number of direct flights between sending and receiving countries also was positively associated with the number of international tourists over time (Figure A2).

Fifth, the coefficients for price-level difference between sending and receiving countries declined over the study period (Figure 2H). The confidence intervals were positive from 2000 to 2009 but contained zero from 2010 to 2013.

Sixth, in sending and receiving countries, higher income levels increase the number of both international tourist arrivals and departures. The coefficients for per capita GDP in sending countries increased over time (Figure 2I). In receiving countries, the confidence intervals for per capita GDP shifted upward (Figure 2J).

Finally, in both sending and receiving countries, population size was positively associated with the number of international tourists. Over the study period, all population coefficients were positive, and their intervals were consistently above zero (Figures 2K and 2L). This trend suggests that international tourism between countries with high per capita GDP and rapid population growth was above the global average. In receiving countries, the inferences we would make regarding per capita GDP and population size were more uncertain than for those in sending countries because of the larger confidence intervals over time.

Phi parameter estimates identified the autoregressive effect of the previous year on tourist arrivals, departures, and reciprocity of the current year (Table 2). The medians of the posterior distribution of Φ_s and Φ_{sr} were 0.998 and 0.003. This means that the number of international tourist departures in the current year highly depended on the level of international tourist departures from the previous year. Yet international tourist arrivals in the previous year did not have an impact on the current international tourist departures. In addition, the medians of Φ_r and Φ_{rs} are 0.967 and 0.004, respectively. When countries had a high number of international tourist arrivals in the previous year, they also tended to have large international tourist arrivals in the current year. However, the number of international tourist arrivals in the current year did not depend on the number of international tourist departures in the previous year. Finally, the median of Φ_{gg} was 0.014. This indicates that the level of reciprocity in the previous year may not explain the level of reciprocity in the current year.

In 2000–2002 and 2011–2013, sender and receiver random effects were investigated at the country level (Figure 3). The random effects estimated the deviations of the number of international tourist arrivals from the predicted values by the mixed effects model. The positions of the countries changed slightly from 2000–2002 to 2011–2013. USA, Canada, and Australia played crucial roles as both senders and receivers in global tourism networks, even after accounting for controls in the regression model. From 2000 to 2013, China, Spain, and Russia became active tourists-senders while South Africa, India, Malaysia, and Maldives became

Table 2. Phi Parameter Estimates with Median and 95% Quantile Intervals.

Parameter	Median	2.5%	97.5%
Φ_s	0.998	0.996	0.999
Φ_{sr}	0.003	0.000	0.005
Φ_{rs}	0.004	−0.009	0.018
Φ_r	0.967	0.958	0.975
Φ_{gg}	0.014	0.013	0.016

active tourists-receivers. Over the period of 2011–2013, China and Russia emerged as both important senders and receivers in global tourism networks.

Discussion

Reasons behind Consolidated Global Tourism Networks

Using cluster analysis and a mixed effects model for longitudinal network data, we investigated the flows and factors relating to international tourism. Social network analysis helped examine how international tourism connects regions and identify temporal changes in the network structure. Results of our cluster analysis show that international tourist flows form a consolidated network over time (Figure 1). Sender and receiver random effects from the mixed effects model then revealed which countries played increasingly active roles in the consolidated networks (Figure 3).

Another finding of the mixed effects model may indicate a causal relationship between the changes in global tourism networks in Figure 1 and Figure A1 and the factors in Figure 2. From 2000 to 2009, the price-level difference between sending and receiving countries was a major factor of international tourist flows based on the law of demand. This result is consistent with previous studies (De Vita and Kyaw 2013; Dogru, Sirakaya-Turk, and Crouch 2017). However, after 2010, the price-level difference became a less important factor for international tourism. This result shows that middle- and low-income countries with rapid income and population growth, such as China, increasingly play an important role as sending countries (see also Buckley et al. 2015; Scott and Gössling 2015). Despite the price-level differences, developing countries send more tourists to both developed and developing countries.

In sending countries, per capita GDP and population size were the most significant factors for international tourism (Song and Li 2008; Song, Kim, and Yang 2010; Yang, Lin, and Han 2010). Per capita GDP and population size represent the effects of income level and market size differences between sending and receiving countries. In the consolidated networks, the roles of these factors in sending countries intensify over time (Lim 1997; Peng, Song, and Crouch 2014; Witt and Witt 1995). In receiving countries, although per capita
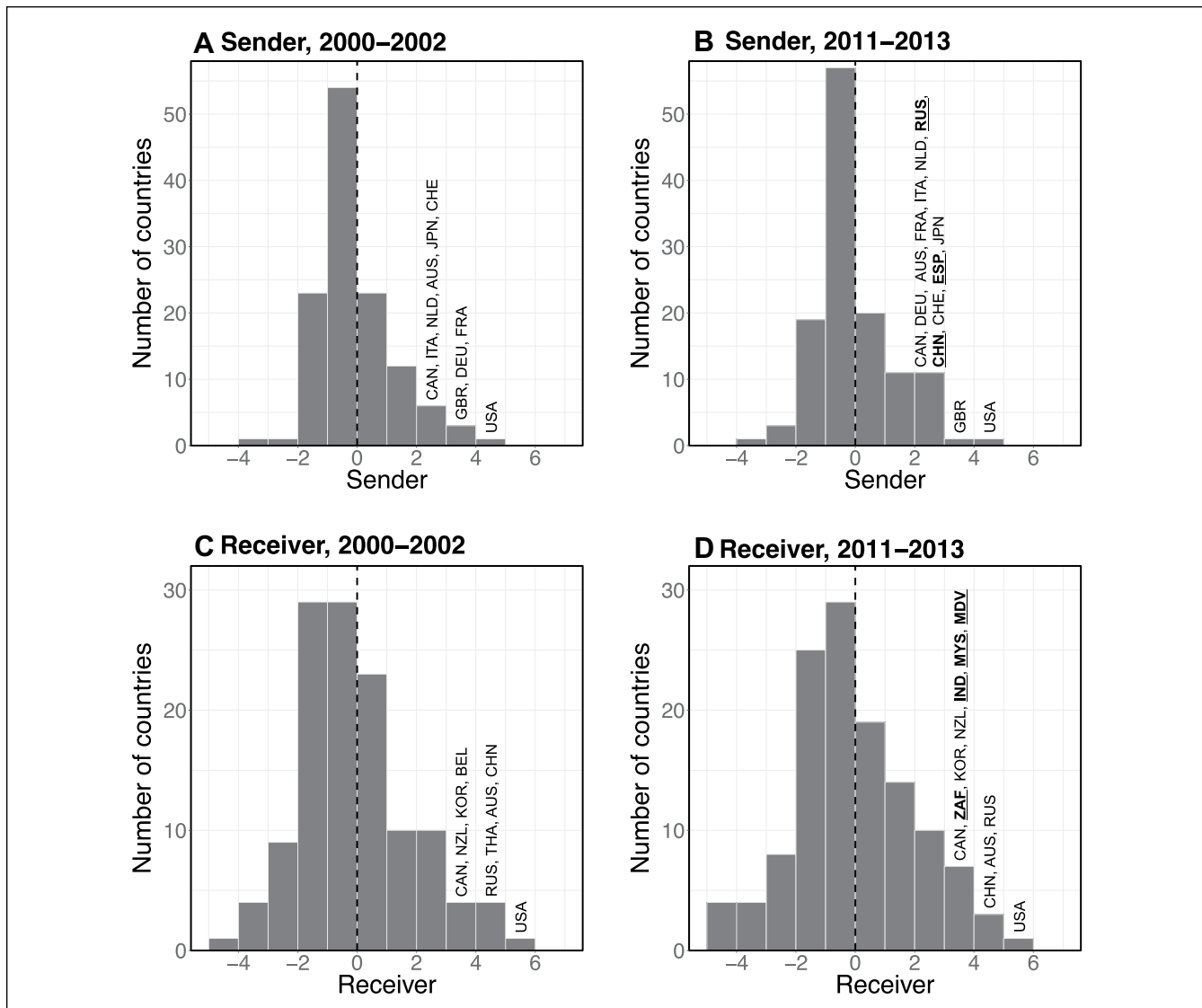
Figure 3. Distributions of (A) the sender effects in 2000–2002, (B) the sender effects in 2011–2013, (C) the receiver effects in 2000–2002, (D) the receiver effects in 2011–2013. Country abbreviations: Australia (AUS), Belgium (BEL), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), Spain (ESP), France (FRA), United Kingdom (GBR), India (IND), Italy (ITA), Japan (JPN), Republic of Korea (KOR), Maldives (MDV), Malaysia (MYS), Netherlands (NLD), New Zealand (NZL), Russian Federation (RUS), Thailand (THA), United States (USA), and South Africa (ZAF).

GDP and population size are significant (Khadaroo and Seetanah 2008; Saha and Yap 2013), the uncertainty of the effects of these factors is high (i.e., large confidential intervals). While more than half of international tourists visit high-income countries, increasing arrivals in new destinations such as Malaysia, a middle- to low-income country with a large population, led to the uncertainty of coefficients.

International tourist flows are complex and dynamic systems affected by many other factors that were not measured in our study. For example, global crisis events such as economic and financial downturns, political instability, terrorist attacks, and natural disasters can affect the size and frequency of international tourist flows (Hall 2010). Our results

may indicate that global crisis events have dispersed the consolidated global tourism networks, based on geographic locations (Figure A1). The global financial crisis from 2007 to 2010 may have caused the rapid increase in the number of clusters by weakening the interdependence between distant countries (see also Campos-Soria, Inchausti-Sintes, and Eugenio-Martin 2015; Hall 2010). In 2004, global tourism networks were separated into 11 clusters, in part because of outbreaks of severe acute respiratory syndrome (SARS) and the Indian Ocean tsunami (see also Hall 2010; Kuo et al. 2008). These types of global events may also contribute to the uncertainty of some coefficients (e.g., political stability variable) in the mixed effects model.

The Role of Conservation in International Tourism

Although nature-based and cultural tourism are the fastest-growing sectors in the tourism industry (Newsome, Moore, and Dowling 2012; World Tourism Organization 2015), the presented results show that efforts to conserve natural and cultural sites were not significant factors contributing to the number of international arrivals in receiving countries. The results from the mixed effects model for the proportions of protected areas and World Cultural Heritage sites show that neither were significant factors between 2000 and 2013.

Within a given country, protected areas have varying success in attracting international tourists from different regions and over time (Diefendorf et al. 2012; Su and Lin 2014). Some protected areas have higher levels of domestic tourist arrivals than international tourist arrivals (Chung et al. 2018a), whereas other protected areas attract more international tourists than domestic tourists (Baral et al. 2017). These varying patterns of international tourist arrivals may have led to an insignificant result in the mixed effects model. In addition, many protected areas are located at high altitudes, far from the major urban areas from which most international tourism emanates (Chung, Dietz, and Liu 2018b; Joppa and Pfaff 2009). The remoteness of protected areas may prevent visits from international tourists (Chung, Dietz, and Liu 2018b). Because of different achievements of international tourist arrivals, decision makers may need to establish different management plans to increase tourism while protecting the environment effectively. For example, protected areas that successfully attract domestic tourists may lack the transportation infrastructure for international tourists. If decision-makers aim to increase international tourism, such protected areas will need additional infrastructure investment to increase accessibility from airports or train stations. However, further infrastructure development could have a negative environmental impact, and therefore should be considered as a part of management and conservation strategies.

Furthermore, World Cultural Heritage sites were not effective in attracting international tourists in accordance with the findings of Cellini (2011), Cuccia, Guccio, and Rizzo (2016, 2017). This is consistent with the main purpose of World Cultural Heritage sites, which is not to encourage tourism flows but to "raise awareness" and "mobilize sustainable resources for long-term conservation" (Cellini 2011; Cuccia, Guccio, and Rizzo 2016; Su and Lin 2014). In addition, the increase in international tourist arrivals in middle- and low-income countries that have few World Cultural Heritage sites may reduce the attraction of World Cultural Heritage sites for international tourists because more than half of World Cultural Heritage sites are based in high-income European countries (Su and Lin 2014). Although World Cultural Heritage sites are ineffective for international tourism, there are ongoing efforts to encourage cultural tourism to World Cultural Heritage sites. In the rapidly globalizing tourism network,

one of the major challenges at World Cultural Heritage sites is how to encourage cooperation between the tourism and culture sectors. In 2015, UNWTO and UNESCO organized the first World Conference on Tourism and Culture to initiate the sustainable development of cultural tourism (World Tourism Organization 2016c).

The Impact of Policies on International Tourism

Visa-free policies can stimulate flows of international tourists. Between 1980 and 2015, visa openness in middle- and low-income countries increased, with fewer travel requirements than those of high-income countries (World Tourism Organization 2016d). The increase in visa openness in middle- and low-income countries may attract more international tourists. Visa-free policies can also support sustainable economic growth because improving visa openness can contribute to an increase of tourism expenditures and create jobs without additional tourism development (Song, Gartner, and Tasci 2012b; World Tourism Organization 2016d). Particularly, to maximize the effects of visa openness, receiving countries need to prioritize relaxing their visa policies for citizens of sending countries with shared languages and short travel distances.

Further, international tourists are resilient to political instability and terrorism risks in both sending and receiving countries. This result is consistent with Liu and Pratt (2017) and van der Zee and Vanneste (2015). After 2007, international tourist arrivals in receiving countries show a complicated relationship with political instability and terrorism risks. From 2007 to 2011, international tourist arrivals were negatively associated with political stability and the absence of violence and terrorism index. Over the study period, European countries led this trend, as these European countries decreased in political stability and increased in violence and terrorism risks driven by the global financial crisis following the economic recession (Campos-Soria, Inchausti-Sintes, and Eugenio-Martin 2015; The World Bank 2017). The effect was a slight decrease in international tourist arrivals in European countries.

International tourist arrivals in high-income countries may be more resilient to political instability and terrorism risks than those of middle- and low-income countries (Liu and Pratt 2017; Llorca-Vivero 2008). In middle- and low-income countries, political instability and terrorism risks can lead to significant decreases in international tourism because of riots and wars (Sönmez 1998). For example, in 2011, political changes in Middle Eastern and North African countries such as Egypt and Yemen led to decreases in international tourist arrivals (Avraham 2015). As a result, the Arab Spring contributed to the uncertainty of coefficients of political stability and absence of violence and terrorism index. The occurrences of the Islamic State in Iraq and Syria (ISIS) and Syrian refugee crisis generated terrorism risks and political tensions in both the Middle East and the rest of the world

(Khan and Ruiz Estrada 2016). Countries that experience such events can have difficulties in tourism management and planning with unpredictable tourism demand (Issa and Altinay 2006; Saha and Yap 2013). Therefore, tourism policy makers should recognize the impacts of political instability and terrorism risks while planning crisis management strategies for the tourism industry (e.g., restoration of a positive image for international tourists) (Khan and Ruiz Estrada 2016; Saha and Yap 2013).

Conclusions and Implications

Our study is the first international tourism study to adopt a social network analysis approach that quantifies the complex structure of global tourism networks and examines underlying factors over time. The results of our global-level network analyses have several theoretical and practical implications, including identifying emerging countries that need tourism policies and providing key strategic factors for tourism development and destination management in each phase of global tourism networks. From a theoretical point of view, our global-level network analyses made a significant contribution to advancing the application of social network analysis approach in the tourism field since to date, a limited number of tourism studies have utilized a social network approach to perform a longitudinal quantitative study at a global level.

In drawing conclusions, we should also note the limitations of our study. The most compelling limitation regards the lack of data availability at the global level. For instance, due to the lack of time-series data for the visa-free score and the number of direct flights between countries, we assumed the same visa policy and the number of direct flights over the period from 2000 to 2013. Additionally, although our cluster results may indicate that global tourism networks were dispersed following global crisis events (e.g., global financial crisis), we could not detect a causal relationship between global crisis events and changes of network structure in international tourism. Second, it is noted that when using longitudinal network data, it is difficult to discern the most important factors because the pattern of each factor is based on variation among years within a country and/or variation among countries. Third, we identified a few countries that were not predicted from the mixed effects model, which weakened our model. For example, although Australia has large geographic separation from other countries, Australia is the center of global tourism networks. This is because international tourism supply and demand have been influenced by many other factors across local, regional, and global levels. At the local and regional levels, different key factors for international tourism may require strategies different from our global implications, and therefore destination management should be flexible across regions. Future tourism network research will need to extend our methods to include hierarchical network models and examine hierarchical network structures from global to local levels. Furthermore, future tourism research should evaluate socioeconomic and environmental effects of international tourism as well as the agents that are involved in international tourism, in addition to the tourist flows and factors affecting tourism (causes) reported in this study. The new integrated framework of metacoupling (socioeconomic–environmental interactions within and between adjacent and distant systems such as countries) provides a good foundation for such future efforts as it integrates tourist flows, causes, agents, and effects across different systems (Liu 2017).

Despite these limitations, on the practical front, quantifying the network structure of international tourism helps explore how international tourist flows are changing in the face of external social, economic, political, and environmental issues. Our cluster results confirm the consolidation of global tourism networks and identify which countries increasingly contribute to this trend over the past 14 years. Our results support that some global crisis events (e.g., global financial crisis and the Indian Ocean tsunami) may weaken the structure of international tourist flows from consolidated networks to separated networks based on geographic location. This result indicates that social, economic, political, and environmental changes in emerging countries may have more significant impacts on other countries in the same cluster than those in other clusters. Policy makers can use the results of our cluster analysis to understand the cross-border impacts of tourism development and destination management to attract more international tourists across countries.

Our mixed effects model provides essential strategic factors for proper tourism development and destination management. In consolidated global tourism networks, results indicate that transaction costs (e.g., shared language, geographic distance, and visa policy) are more important in attracting international tourists than natural and cultural attractions (e.g., protected areas and World Cultural Heritage sites). We suggest that middle- and low-income countries that increasingly depend on the tourism industry should maintain their political stability and enhance visa-free policies to encourage more international tourist arrivals. In this situation, these countries have put more effort into tourism development such as transportation and accommodation. However, a high degree of tourism development traditionally conflicts with environmental protection. One of the best ways to balance between tourism development and environmental protection is to integrate tourism development plans into conservation policies. Our results show that conservation efforts (e.g., protected areas) may contribute to balancing the benefits and risks of tourism development for international tourism, and thus avoid over-development in the long run. In conclusion, the presented approach and findings provide a better foundation for evidence-based decision making to implement proactive tourism policies.
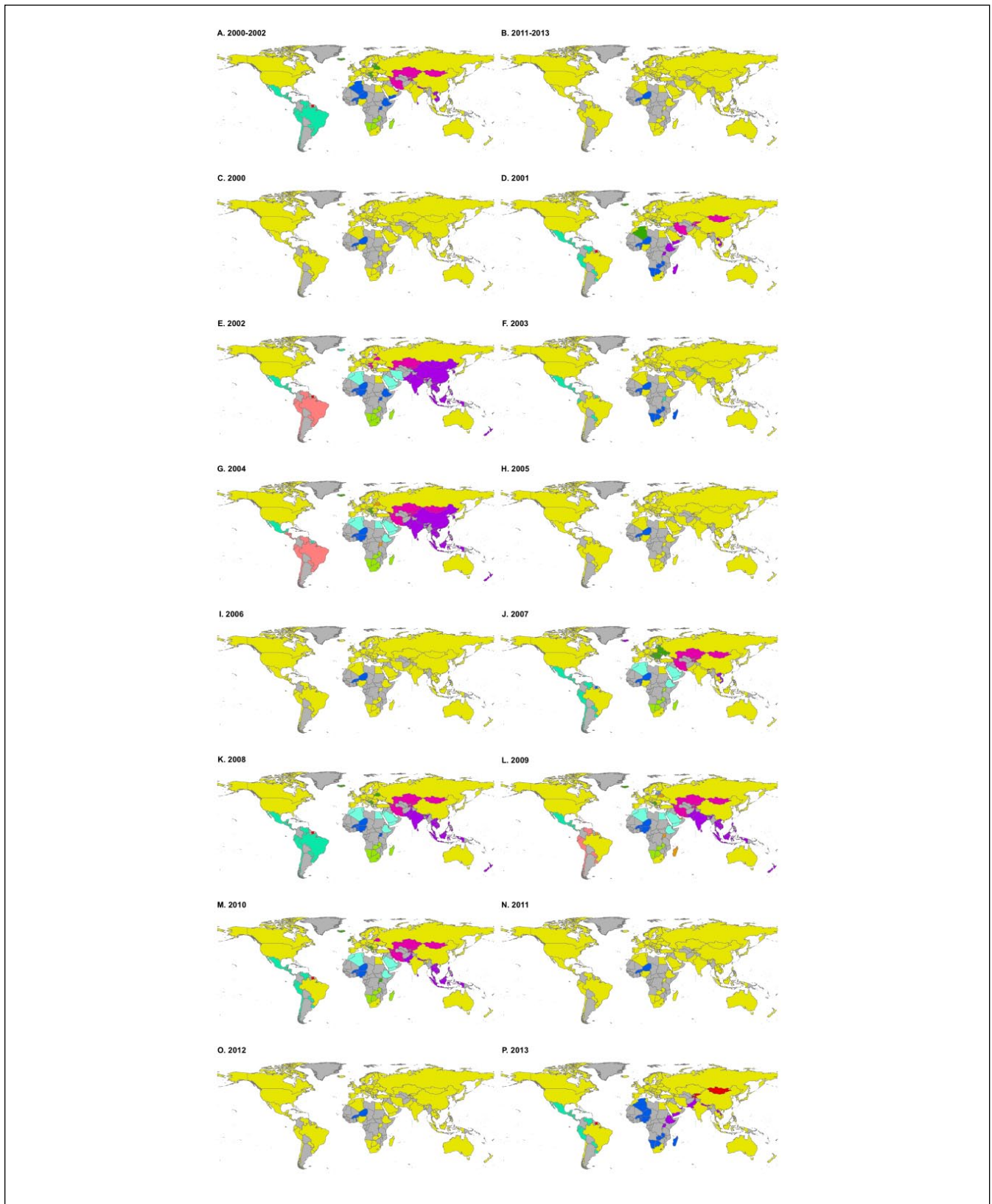
Appendix

Figure A1. Clusters of global tourism networks by country: (A) 2000–2002, (B) 2011–2013, (C) 2000, (D) 2001, (E) 2002, (F) 2003, (G) 2004, (H) 2005, (I) 2006, (J) 2007, (K) 2008, (L) 2009, (M) 2010, (N) 2011, (O) 2012, and (P) 2013.
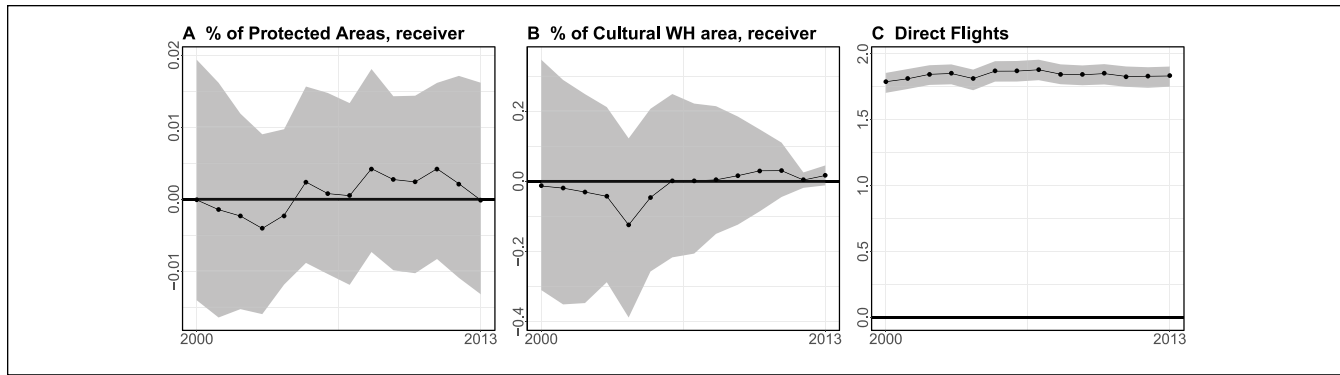
Figure A2. Mean and 95% highest posterior density (HPD) confidence intervals of the coefficients from 2000 to 2013 in the alternative model: (A) the proportion of protected areas in receiving countries, (B) the proportion of World Cultural Heritage sites in receiving countries, and (C) the number of direct flights between countries.

Table A1. Odds Ratios for Cluster Analysis and P-Value Based on Simulations Followed by Mean, Median, and 95% Quantile Interval of Simulations.

	n	Odds Ratio	P-Value	Mean	Median	2.5%	97.5%
2000	2	0.852	<0.001	0.592	0.604	0.346	0.638
2001	7	0.804	<0.001	0.594	0.604	0.345	0.641
2002	9	0.778	<0.001	0.598	0.608	0.351	0.640
2003	3	0.715	<0.001	0.597	0.609	0.348	0.641
2004	11	0.822	<0.001	0.600	0.604	0.546	0.642
2005	2	0.856	<0.001	0.592	0.598	0.539	0.629
2006	2	0.851	<0.001	0.588	0.599	0.347	0.630
2007	9	0.765	<0.001	0.588	0.597	0.344	0.626
2008	9	0.789	<0.001	0.586	0.585	0.555	0.617
2009	12	0.819	<0.001	0.579	0.586	0.370	0.615
2010	9	0.779	<0.001	0.571	0.579	0.357	0.605
2011	2	0.822	<0.001	0.561	0.568	0.466	0.591
2012	2	0.845	<0.001	0.567	0.570	0.537	0.597
2013	5	0.713	<0.001	0.566	0.569	0.533	0.598

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