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Interconnectedness of international tourism demand in Europe: A cross-quantilogram network approach

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HIGHLIGHTS

- We study directional interconnectedness in quantiles of tourism demands in Europe.
- Networks are dense when tourism demand growth is small.
- Networks are sparse when tourism demand growth is larger.
- Most of the directional dependence is capture in first three months.
- Using ERGM, we identify reciprocity as a common feature of tourism demand networks.

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ABSTRACT

We study the interconnectedness of international tourism demand changes among 30 European countries. Using cross-quantilogram analysis, we estimate the strength of the directional (lead/lag) relationships of the international tourism demand of European countries in percentiles (10th, 50th, 90th). The complex interconnectedness of international tourism demand is studied within networks, where a fixed number of vertices represent countries, and oriented edges represent the presence of a directional relationship between the international tourism demand of two countries. A comparison of these networks reveals the following regularities. First, we find obvious asymmetry across percentiles, where demand behaves much more similarly during times of crisis (10th percentile) compared to tranquil periods (50th percentile). The interconnectedness of these networks almost diminishes when the international demand for tourism increases sharply (90th percentile). Second, we observe that the interconnectedness does not change much among the short- (within 3 months), mid- (up to 6 months) and long-term (up to 9 months) lead/lag relationships, which leads us to conclude that much of the interconnectedness of international tourism demand is driven by dependence during the first three months. On the basis of these findings, we review the possible forces that may drive the formation of the resulting complex structures using exponential random graph models. Our third finding is that there is a tendency for the relationships of the international tourism demand among the various countries to be bidirectional. Finally, our fourth new finding is that the interconnectedness of markets during sharp declines in tourism demand tends to increase for Central and Eastern European (*CEE*) countries, and those that are less developed in terms of their relative sector size to the size of the economy.

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1. Introduction

Since the early work of Barabási and Albert [1], networks have been found, created and studied in many socioeconomic areas. As is documented in the recent review of Martí et al. [2], in the past few years, networks have been particularly used in finance [3–5], business and trade [6–10], supply chain networks [11–13], transportation [14–19], social relationships [20–22] and also in tourism [22–39].

In this study, we contribute to the latter strand of the literature. The tourism sector includes many agents such as visitors; accommodation providers; food and beverage services; recreation and entertainment; transportation companies; and travel services, such as travel agencies, travel guides, tour operators and insurance companies, and it is therefore believed that the tourism sector consists of a complex system of relationships [23]. Motivated by this idea, in this paper, we study how the international demand for tourism is related among 30 European countries. We take a macro-level perspective, where countries represent tourism destinations, and international tourist arrivals at a given country represent the international demand for tourism services in a given country. Therefore, among the many agents that operate in the tourism sector, we specifically consider international visitors. At the macro-level, we aggregate international demand across the whole country. We acknowledge that each country can influence local tourism sectors through tourism policies, however, it is likely that these, in turn, are manifested into the overall level of international tourism demand for the whole country.

We create a real-world network, where nodes represent countries, and edges are created according to the dependence measured between the numbers of arrivals of non-residents (demand) to a given country. Such complex networks are of interest to a wide range of agents. For example, a dense network suggests that the international demand of different countries is interrelated, and tourism policies, at a country level, could be collaborative (for an example of cross-country regional collaboration, see [40,41]). Out- and in-degrees can be interpreted as measures of relatedness of among the tourism policies of countries. Put differently, in-degrees measure the sensitivity of international tourism demand to the development of international tourism in foreign countries. On the other hand, out-degrees indicate whether the international tourism demand of a given country could be used to forecast development of international tourism demand in foreign countries (for example, by including past observations of tourism demand into the forecasting equation of tourism development of foreign countries).

Real-world networks have already been used to describe the tourism sector [42]. The websites of tourism destinations on Elba Island showed little interconnectedness in a study conducted by de Fontoura and Baggio [26]. Hernandez and González-Martel [27] modeled a supply network and the interrelationship among lodging, services and tourist behavior in the tourism destination of Gran Canaria Island. There was a positive correlation among the degree of substitutability, closeness centrality, and betweenness centrality for tourism flows in China in a study conducted by Hong and Tao [28]. The binary and value network of tour operators and travel agencies, which are entities of a distribution channel, was illustrated by Tran et al. [22] in a case study of Hanoi, Vietnam. Networks can be used to help policy makers and tourism service providers improve their planning of a given destination development [29–35,39].

Our study is most closely related to one conducted by Miguéns and Mendes [36], who created an oriented network of international tourism arrivals in 2004, with 208 nodes representing both countries and territories. Oriented edges were created if tourists traveled from node i to node j. The resulting network led to 5775 weights, a dense topological structure with small shortest paths and exponentially decaying in- and out-degrees. The weights followed a scale-free power-law distribution. Provenzano et al. [43] created and studied a network of bilateral tourism flows within European countries using data from the United Nations World Tourism Organization (UNWTO) over the period from 1995 to 2012. They reveal that the network's density increased, the average path length decreased, while also tourism evolved towards higher concentration in a lower number of areas. Our approach differs in several ways. First, compared to Miguéns and Mendes [36] we use a more homogeneous sample that includes 30 European countries, and each country represents a node in the network. Our sample selection is motivated by the fact that these countries are in the same region, and almost all of the countries in our sample are members of the European Union and subject to similar regulations at the European level. Second, an oriented edge is created if Granger causality in quantiles is confirmed from international tourism demand of country i to country j. Third, using monthly data from January 2004 to May 2018, we study the determinants of international tourism demand.

The remainder of this paper is structured as follows. Section 2 presents the data and describes the methodology. In Section 3, we discuss the results, and Section 4 concludes.

2. Data and methodology

2.1. Data

Tourism demand is, in many cases, measured and represented by data on arrivals [36–38]. In this paper, to proxy for the international tourism demand, we use data on the arrivals of non-residents at tourist accommodation establishments in a given country, retrieved from Eurostat. For 30 countries, we obtain monthly data from January 2004 to May 2018. Let $A_{i,t}$ denote the arrival, where i is a given country, and t is a given month ($t = 13, 14, \ldots, T$ and is the time index).

Table 1
Characteristics of changes in arrivals — international tourism demand.

Country	Mean	SD	Skew.	Kurt.	Min.	Max.	AC(1)	KPSS
Spain	0.05	0.08	−0.31	4.41	−0.20	0.32	0.84	0.02
Portugal	0.07	0.09	−0.36	4.21	−0.26	0.29	0.56	0.29
Denmark	0.03	0.08	0.25	3.66	−0.20	0.30	0.61	0.19
Germany	0.05	0.05	−0.29	4.96	−0.11	0.25	0.51	0.05
Greece	0.07	0.11	−0.19	2.82	−0.24	0.39	0.60	0.13
Austria	0.04	0.08	0.28	5.49	−0.25	0.35	−0.41	0.24
Finland	0.04	0.09	−0.20	3.07	−0.22	0.29	0.75	0.04
Sweden	0.05	0.06	−0.18	3.39	−0.15	0.22	0.56	0.29
Switzerland	0.02	0.06	−0.21	2.74	−0.14	0.16	0.63	0.06
France	0.01	0.08	−0.17	4.03	−0.28	0.28	0.37	0.37
Italy	0.03	0.06	0.08	4.80	−0.20	0.27	0.01	0.06
Netherlands	0.05	0.08	−0.37	3.49	−0.16	0.24	0.66	0.32
Norway	0.05	0.09	0.00	3.09	−0.18	0.28	0.59	0.18
United Kingdom	0.03	0.12	0.10	4.93	−0.50	0.42	0.42	0.07
Island	0.17	0.18	1.48	6.69	−0.11	1.03	0.63	0.74
Belgium	0.02	0.08	−0.71	5.34	−0.24	0.28	0.75	0.03
Luxembourg	0.03	0.11	1.42	7.75	−0.26	0.57	0.71	0.09
Slovenia	0.06	0.09	0.06	3.84	−0.17	0.37	0.37	0.14
Cyprus	0.03	0.12	0.53	4.77	−0.32	0.44	0.64	0.54
Hungary	0.05	0.08	−0.29	3.57	−0.23	0.23	0.66	0.23
Romania	0.06	0.10	−0.73	3.12	−0.21	0.27	0.70	0.40
Czech Republic	0.05	0.07	−0.52	4.55	−0.21	0.22	0.49	0.25
Bulgaria	0.07	0.12	0.14	3.94	−0.29	0.45	0.44	0.16
Poland	0.05	0.08	−0.75	3.58	−0.18	0.21	0.68	0.16
Slovakia	0.05	0.13	−1.00	4.12	−0.35	0.28	0.89	0.05
Croatia	0.07	0.11	−0.12	3.82	−0.31	0.37	0.05	0.38
Latvia	0.11	0.14	0.27	3.74	−0.24	0.54	0.76	0.09
Malta	0.05	0.11	−0.19	3.41	−0.25	0.33	0.71	0.25
Estonia	0.04	0.09	0.27	3.07	−0.17	0.31	0.56	0.05
Lithuania	0.09	0.12	0.35	4.91	−0.24	0.52	0.78	0.07

Note: AC(1) denotes the size of the first-order autocorrelation coefficient. KPSS denotes the Sul et al. [44] *version of the unit-root test proposed by* Kwiatkovski et al. [45]. *Values higher than 0.580 suggest the rejection of the null hypothesis that there is no unit-root.*

The cross-quantilogram analysis is based on changes in tourism demand. However, as is usual for tourism activity indicators, the series of arrivals exhibits a 12-month seasonal pattern. We, therefore, calculate changes in the tourism demand as:

$$r_{i,t} = \frac{A_{i,t} - A_{i,t-12}}{A_{i,t-12}} \tag{1}$$

Two percent of the data on arrivals ($A_{i,t}$) contained missing observations that were imputed via interpolation techniques. For example, if for a given country, i arrivals for January 2006 were missing, we selected only arrivals from January (to account for the 12-month seasonality), and using these data, we performed a cubic spline interpolation of the given missing data points. However, if the missing data were at the beginning or at the end of the series, we used a simple linear time trend interpolation.

The summary characteristics of the changes in international tourism demand (Eq. (1)) are presented in Table 1, which follows. Several interesting observations can be drawn from these summary statistics. For example, the positive average change in international tourism demand suggests that in Europe, international tourism demand has increased. The highest increase was observed for Iceland and Latvia, smaller countries within our sample. In contrast, the smallest increase was observed for France, which is a large and well-developed tourism destination, where tourism growth might already be limited. Finally, a common feature of almost all the series is that tourism demand changes are characterized by a mild persistence, in form of a positive autocorrelation coefficient (0.55 in average), with the exception of Austria.

2.2. Directional predictability in quantiles

Let $r_{i,t}$ denote changes in international tourism demand (Eq. (1)), while in this case $i = 1, 2$ represents two different countries. The time series of changes in international tourism demand ($r_{i,t}$) is assumed to be strictly stationary. Its unconditional distribution function is denoted by $Fi(.)$, the unconditional density function as $fi(.)$ and the unconditional quantile function as $q_i(\tau_i) = inf\{\nu : F_i(\nu) \leq \tau_i\}$ for $\tau_i \in (0, 1)$.

We are interested in estimating dependence between the event $\{r_{1,t} \leq q_{1,t}(\tau_1)\}$ and $\{r_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$ given integer $k = \pm 1, \pm 2, \ldots$, where in general $\tau = (\tau_1, \tau_2)$ is an arbitrary pair of quantiles. However, in our analysis, we study only cases where $\tau_1 = \tau_2$. Next, we define a hit function $\Psi_\alpha(u) = I[u < 0] - \alpha$, and then the cross-quantilogram is defined as:

$$\rho(k) = \frac{E[\Psi_{\tau_1}(r_{1,t} - q_{1,t}(\tau_1))\Psi_{\tau_2}(r_{2,t-k} - q_{2,t-k}(\tau_2))]}{\sqrt{E[\Psi^2_{\tau_1}(r_{1,t} - q_{1,t}(\tau_1))]}\sqrt{E[\Psi^2_{\tau_2}(r_{2,t-k} - q_{2,t-k}(\tau_2))]}} \quad (2)$$

The cross-quantilogram in Eq. (2) can be understood as a cross-correlation of quantile-hit processes. In a special case, where the two series are identical, Eq. (2) corresponds to the quantilogram proposed by Linton and Whang [46]. Next, given the unconditional estimate of quantiles $\hat{q}_i(\tau_i)$, the sample cross-quantilogram is defined as:

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^{T} \Psi_{\tau_1}(r_{1,t} - \hat{q}_{1,t}(\tau_1))\Psi_{\tau_2}(r_{2,t-k} - \hat{q}_{2,t-k}(\tau_2))}{\sqrt{\sum_{t=k}^{T} \Psi^2_{\tau_1}(r_{1,t} - \hat{q}_{1,t}(\tau_1))}\sqrt{\sum_{t=k}^{T} \Psi^2_{\tau_2}(r_{2,t-k} - \hat{q}_{2,t-k}(\tau_2))}} \quad (3)$$

The value of Eq. (3) is by construction limited to $\hat{\rho}_\tau(k) \in [-1, 1]$. We use Eq. (3) to describe the magnitude of the directional dependence in quantiles of two time series. For example, $\hat{\rho}_\tau(1) = 0$ implies that if the international tourism demand of country 2 is lower (higher) than a given quantile $q_2(\tau_2)$ at time $t-1$, then it does not help in predicting whether the international tourism demand of country 1 is lower (higher) than a given quantile $q_1(\tau_1)$ at time t. In our setting, the lead/lag parameter k controls the delay in the predictability from one time series to another in terms of months.

Given $k = 1, 2, \ldots, p$, we are interested in the following hypothesis, $H_0 : \rho_\tau(1) = \cdots = \rho_\tau(p) = 0$, $H_1 : \exists k, \rho_\tau(k) \neq 0$, $k = 1, 2, \ldots, p$. Han et al. [47] suggested using a Ljung–Box type of test statistics, as given by:

$$\hat{Q}_\tau(p) = T(T+1)\sum_{k=1}^{p} \frac{\hat{q}^2_\tau(k)}{T-k} \quad (4)$$

where the critical values are obtained via the stationary bootstrap procedure proposed by Politis and Romano [48], in which pseudo samples are constructed from blocks of data with random block length. The expected block size has been identified by Politis and White [49] and Patton et al. [50].

2.3. Cross-quantilogram networks

Let $G_{p,\tau} = (V, E)$ be a graph where the elements of the vertex set $V \subset C$ correspond to individual countries; the elements of the set of edges $E \subset V \times V$ contains all edges (i, j) between countries $i, j \in V$; and $i \neq j$, $i, j = 1, 2, \ldots, N$. A directed edge from country j to country i is constructed if the test statistics (Eq. (4)) for a given p and τ suggests significance at the given significance level. This procedure leads to a Granger causality-type network [5,51–53]. For a given country j, the testing procedure for a given p and τ, is repeated 29 times; i.e. if $j = 2$, then we perform the test for $i = 1, 3, 4, 5, \ldots, 30$. This may lead to an excessive overall type I error in the tests. We therefore calculate the level of significance as $0.05/(29 - 1)$.

In our empirical application, we consider $p = 3, 6$ and 9. For smaller values of p, for example, 3 (months), we are estimating short-term lead relationships from one series to another; for higher values of p (6 and 9) we are estimating mid- and long-term relationships. Finally, the cross-quantilogram analysis is performed for three percentiles, $\tau = 0.10, 0.50, 0.90$. This approach allows us to study the asymmetric dependence among the international tourism demand of various countries. The combinations of p and τ lead to the estimation of short- ($p = 3$), mid- ($p = 6$), and long-term ($p = 9$) directional relationships in the left ($\tau = 0.10$) tail, center ($\tau = 0.50$), and right ($\tau = 0.90$) tail of the distribution of tourism demand changes; i.e., overall, there are 9 networks.

2.4. Measures of connectedness

First, we use a simple measure of connectedness, the degree of the vertex. As we create and study directed networks, we consider both in-degree, $\deg^{in}(i)$, and out-degree $\deg^{out}(i)$, vertex measures:

$$\deg^{in}(i) = |\{(j, i) \in E; j \in V\}| \quad (5)$$

$$\deg^{out}(i) = |\{(i, j) \in E; j \in V\}| \quad (6)$$

The $|\cdot|$ denotes the cardinality of the given set. Countries with higher in-degree are more likely to be influenced by the development of international tourism activity in other countries (in Granger sense).[1] Similarly, countries with high

[1] When we refer to 'influence', we mean in the Granger sense [55].

Table 2
Centrality measures for cross-quantilogram networks with $p = 3$.

Country	Cross-quantilogram networks, $p = 3$								
	10th percentile			50th percentile			90th percentile		
	out-d.	in-d.	harmo.	out-d.	in-d.	harmo.	out-d.	in-d.	harmo.
Spain	14	18	18.70	8	3	11.18	0	0	0.00
Portugal	12	12	16.40	3	3	7.59	0	0	0.00
Denmark	8	7	13.41	2	0	7.02	0	1	0.00
Germany	15	5	17.27	1	1	1.92	0	0	0.00
Greece	0	1	0.00	5	6	9.48	0	0	0.00
Austria	0	0	0.00	0	0	0.00	0	0	0.00
Finland	4	14	11.30	1	9	1.56	0	0	0.00
Sweden	4	1	11.23	3	0	9.09	0	0	0.00
Switzerland	1	0	9.14	3	1	8.30	0	0	0.00
France	3	3	10.69	4	2	8.06	0	0	0.00
Italy	2	0	10.76	2	2	6.54	1	0	1.48
Netherlands	12	4	16.32	4	6	8.80	0	0	0.00
Norway	6	4	12.02	8	2	11.09	1	0	1.49
United Kingdom	0	0	0.00	2	4	7.33	0	0	0.00
Island	0	0	0.00	2	4	7.26	1	1	1.49
Belgium	0	1	0.00	3	3	7.47	0	0	0.00
Luxembourg	0	0	0.00	1	0	1.98	0	0	0.00
Slovenia	4	4	10.72	1	2	6.15	0	0	0.00
Cyprus	0	0	0.00	1	3	1.72	0	0	0.00
Hungary	14	16	17.36	2	1	7.13	0	0	0.00
Romania	18	15	19.26	5	6	9.17	0	0	0.00
Czech Republic	9	8	14.15	1	1	5.32	0	0	0.00
Bulgaria	6	8	12.22	2	1	1.99	0	0	0.00
Poland	13	5	17.05	2	2	2.04	0	0	0.00
Slovakia	6	13	12.70	4	4	8.75	1	2	1.05
Croatia	4	4	11.02	2	0	7.27	0	0	0.00
Latvia	5	12	12.26	1	4	5.44	0	0	0.00
Malta	11	6	14.89	6	4	9.32	1	1	0.89
Estonia	0	0	0.00	2	3	6.27	0	0	0.00
Lithuania	9	19	14.39	2	6	2.04	0	0	0.00
Average	6.00		10.11	2.77		6.24	0.17		0.21

Notes: out-d. denotes the out-degree of the vertex, in-d. denotes the in-degree of the vertex, and harmo denotes the harmonic centrality of the vertex, as in Boldi and Vigna [54].

out-degree are more likely to influence other markets in the network. The vertex degree is a simple measure that identifies the most influential countries within the network.

Second, we use a global measure of connectedness that attempts to measure the importance of a country within the whole network of countries. We use harmonic centrality [54] as it is suitable even for networks that are not strongly connected. Let $d(i,j)$ be the shortest path from vertex i to vertex j. Next, assume that if there is no path between the two vertices, then $d(i,j) = \infty$. We conveniently define that $1/\infty = 0$. Next, the harmonic centrality of vertex i is defined as:

$$H(i) = \sum_{d(i,j)<\infty, i\neq j} \frac{1}{d(i,j)} \tag{7}$$

Higher harmonic centrality of a given country implies that the given country is more highly interconnected in the network; i.e., this country is more important than a country with lower harmonic centrality. When calculating harmonic centrality, we weight each edge based on the ultrametric distance [56] $d(i,j) = [2(1-\rho_{\tau(i,j)}(k))]^{0.5}$, where $\rho_{\tau(i,j)}(k)$ is the strength of the relationship of country i to county j, as estimated in Eq. (3).

2.5. Exponential random graph model

We study the mechanics behind the formation of cross-quantilogram networks of international tourism demand. It is likely that two or more specific countries are more likely to be connected in terms of their international tourism demand. The reasons might be very complex, from attracting tourists with similar preferences to geographical or cultural proximity. We are also interested in whether some network configurations are more likely than others, i.e., whether specific network configurations (i.e., the reciprocity of edges) are more likely than they would be in a random graph. In addition to network characteristics, we are also interested in the role of vertex attributes in forming the network.

Let $\mathbf{Y}$ be a random network with a fixed number of vertices, N, and oriented edges, where $Y_{i,j} = 1$ denotes a presence of an oriented edge from i ($i = 1, 2, \ldots, N$) to j ($j = 1, 2, \ldots, N$), $i \neq j$, which is denoted by $i \longrightarrow j$. The absence of an edge is denoted by $Y_{i,j} = 0$. The observed network is denoted by $\mathbf{y}$. Both the random and observed networks can

Table 3
Centrality measures for cross-quantilogram networks with $p = 6$.

Country	Cross-quantilogram networks, $p = 6$								
	10th percentile			50th percentile			90th percentile		
	out-d.	in-d.	harmo.	out-d.	in-d.	harmo.	out-d.	in-d.	harmo.
Spain	14	17	16.87	8	3	11.95	0	0	0.00
Portugal	12	11	15.03	4	4	8.73	0	0	0.00
Denmark	7	6	12.22	1	1	6.72	0	1	0.00
Germany	12	7	14.91	1	2	1.51	2	0	1.69
Greece	2	1	9.62	5	5	10.11	0	0	0.00
Austria	0	0	0.00	0	0	0.00	0	0	0.00
Finland	3	17	8.47	2	9	1.63	0	0	0.00
Sweden	11	1	13.53	3	1	9.65	0	0	0.00
Switzerland	0	0	0.00	2	1	8.51	0	0	0.00
France	5	3	10.53	2	1	7.02	1	0	1.20
Italy	7	0	12.06	3	2	2.77	0	0	0.00
Netherlands	16	3	17.79	5	4	10.00	0	0	0.00
Norway	8	4	12.20	9	2	12.20	0	0	0.00
United Kingdom	0	0	0.00	4	0	9.67	0	0	0.00
Island	0	0	0.00	2	3	8.05	2	0	2.22
Belgium	0	0	0.00	2	2	2.82	1	2	0.67
Luxembourg	0	0	0.00	2	1	6.08	0	0	0.00
Slovenia	4	3	9.70	2	3	7.19	0	0	0.00
Cyprus	0	0	0.00	1	4	1.23	1	1	1.28
Hungary	10	15	14.25	2	1	7.93	0	0	0.00
Romania	18	15	18.25	4	6	9.42	0	0	0.00
Czech Republic	8	7	12.68	2	1	7.83	0	0	0.00
Bulgaria	5	6	10.43	2	2	1.97	0	0	0.00
Poland	15	3	17.37	2	1	2.26	0	0	0.00
Slovakia	5	20	10.84	5	5	10.11	0	1	0.00
Croatia	7	3	11.43	2	0	7.68	0	0	0.00
Latvia	3	17	8.68	1	8	2.47	0	1	0.00
Malta	8	8	12.71	5	3	9.52	1	0	0.87
Estonia	0	0	0.00	3	4	7.36	0	0	0.00
Lithuania	6	19	11.50	1	8	1.19	0	2	0.00
Average	6.20		9.37	2.90		6.45	0.27		0.26

Notes: out-d. denotes the out-degree of the vertex, in-d. denotes the in-degree of the vertex, and harmo denotes the harmonic centrality of the vertex, as in Boldi and Vigna [54].

be understood as adjacency matrices. The observed vertex attributes are denoted by $\mathbf{x}$. In general, we are interested in the estimation of parameters that relate the network and vertex attributes to the probability of observing an edge. We use an exponential random graph model (ERGM) to estimate the parameters related to the formation of a graph: $P(\mathbf{X} = \mathbf{x}|\mathbf{Y} = \mathbf{y}) = 1/\kappa(\theta, \mathbf{y}, \mathbf{x})\exp(\theta_E Z_E(\mathbf{y}) + \theta_R Z_R(\mathbf{y}) + \sum_{c=3}^{C} \theta_c Z_c(\mathbf{y}, \mathbf{x}))$. The parameters of interest are denoted by θ. The $Z(.)$ is a function of network statistics. For example, we include the number of edges as network characteristics ($Z_E(\mathbf{y})$) and the number of reciprocal edges ($Z_R(\mathbf{y})$). Next, we include four vertex characteristics ($Z_c(\mathbf{y}, \mathbf{x})$).

The numerator should be normalized across all possible networks for a given number of vertices. This is accomplished by the normalizing constant $\kappa(\theta, \mathbf{y}, \mathbf{x})$ that ensures that the resulting distribution function is a probability distribution function. More specifically, $\kappa(\theta, \mathbf{y}, \mathbf{x}) = \sum_{y \in Y} \exp\left(\theta_E Z_E(\mathbf{y}) + \theta_R Z_R(\mathbf{y}) + \sum_{c=3}^{C} \theta_c Z_c(\mathbf{y}, \mathbf{x})\right)$. As the number of possible networks $2^{(N(N-1))/2}$ is large even for moderately sized networks, it is not possible to estimate the normalizing constant in a straightforward way. A Markov Chain Monte Carlo maximum likelihood estimation is carried out to estimate the sample of graphs. More specifically, we rely on the Metropolis–Hastings algorithm to guide the creation of the sample of graphs (see [57] for detailed information on the implementation of this algorithm).

3. Results

3.1. Topological properties of the cross-quantilogram tourism demand networks

Tables 2–4 report the in- and out-degrees along with the harmonic centrality. There are several new findings that the networks revealed. First, we observe that irrespective of whether the networks are created by using only short-term information (up to three months, $p = 3$) or long-term (up to nine months, $p = 9$), the networks at the same percentile change only negligibly. This suggests that interconnectedness between international tourism demand is created mostly during the first three months (i.e., for $p = 3$), as these relationships are subsumed in $p = 6$ and $p = 9$.

Second, and our most important finding in this section is that with respect to the given percentiles there is an obvious asymmetry in the interconnectedness of international tourism demand. For example, for short-term (3 month or quarterly)

Table 4
Centrality measures for cross-quantilogram networks with $p = 9$.

Country	Cross-quantilogram networks, $p = 9$								
	10th percentile			50th percentile			90th percentile		
	out-d.	in-d.	harmo.	out-d.	in-d.	harmo.	out-d.	in-d.	harmo.
Spain	10	13	13.48	6	4	11.26	0	0	0.00
Portugal	10	9	12.98	6	4	10.59	0	0	0.00
Denmark	7	6	11.26	2	1	6.39	1	1	0.77
Germany	12	4	13.88	2	1	8.57	3	0	2.74
Greece	1	1	2.19	5	5	10.25	0	0	0.00
Austria	0	0	0.00	0	0	0.00	0	0	0.00
Finland	3	18	2.61	2	8	6.85	0	0	0.00
Sweden	11	1	12.93	3	2	9.73	0	0	0.00
Switzerland	0	0	0.00	3	1	9.08	0	0	0.00
France	4	2	9.46	2	4	7.35	1	1	0.82
Italy	8	0	11.68	2	0	6.68	0	0	0.00
Netherlands	17	1	18.23	8	4	12.32	0	0	0.00
Norway	8	2	11.57	8	1	12.35	0	0	0.00
United Kingdom	0	0	0.00	4	0	9.93	0	0	0.00
Island	0	0	0.00	2	2	8.42	1	0	1.28
Belgium	0	0	0.00	1	2	5.58	0	2	0.00
Luxembourg	0	0	0.00	2	1	7.58	0	1	0.00
Slovenia	2	3	2.54	2	4	7.32	0	0	0.00
Cyprus	0	0	0.00	2	2	6.40	1	2	0.95
Hungary	7	14	11.65	2	2	7.51	0	0	0.00
Romania	16	14	16.53	5	8	9.61	0	0	0.00
Czech Republic	7	5	11.31	2	3	7.44	0	0	0.00
Bulgaria	4	6	3.46	4	2	8.62	0	0	0.00
Poland	17	2	17.93	2	1	7.41	0	0	0.00
Slovakia	3	20	2.86	4	4	9.75	1	0	1.26
Croatia	8	3	11.13	2	1	7.47	0	0	0.00
Latvia	3	18	2.72	1	11	4.85	0	1	0.00
Malta	8	7	11.66	5	3	10.23	1	0	1.24
Estonia	0	0	0.00	3	4	7.53	0	0	0.00
Lithuania	3	20	2.76	1	8	7.08	0	1	0.00
Average	5.63		7.16	3.10		8.14	0.30		0.30

Notes: out-d. denotes the out-degree of the vertex, in-d. denotes the in-degree of the vertex, and harmo denotes the harmonic centrality of the vertex, as in Boldi and Vigna [54].

interconnectedness, at the 10th percentile, international tourism demand is strongly interconnected. The average degree is 6.00, and harmonic centrality is 10.11. At the 50th percentile, international tourism demand is less interconnected; the average degree is halved at 2.77, and harmonic centrality is 6.24. At the 90th percentile, the interconnectedness almost disappears, as the network has an average degree of just 0.17, and harmonic centrality is 0.21. This obvious asymmetry is also observed in Fig. 1. Therefore, during declines, international tourism demand appears to be quite similar across countries, as it shows strong signs of interconnectedness, while during good times, international tourism demand is more segmented. This asymmetry is also observed for networks created when considering possible mid- ($p = 6$, Fig. 2) and long-term ($p = 9$, Fig. 3) relationships.

Third, we identified that the most important 'hubs' in the 10th percentile networks are represented by countries as Spain, Romania, Hungary, Germany, Lithuania and Portugal. Interestingly, the most influential (in Granger sense) is the international tourism demand of Romania that influences international tourism demand of 18 countries, followed by Germany (15), Spain and Hungary (both 14). Therefore, for these countries, international tourism demand is most informative with respect to next month's international tourism demand of other markets. On the other hand, the most sensitive is the market of Lithuania with 19 in-degrees of international tourism demand, followed by Spain (18), and Hungary (16). Results in Tables 2–4 also reveal a general tendency, where international tourism demand of *CEE* countries is more likely to be interconnected in the left-tail (higher in- and out-degrees) compared to *non-CEE* countries.

3.2. Mechanics behind the cross-quantilogram tourism demand networks: ERGM approach

It is unlikely that the structures identified in the cross-quantilogram network could appear by chance. In this section, we review the possible forces that are likely to drive the formation of the resulting complex structure of relationships. We rely on the ERGM framework. We consider two network statistics, the number of edges and the number of reciprocal relationships, and four vertex (country) attributes.

Because of economic transformation, the tourism industry in *CEE* countries is still underdeveloped. To account for the presence of these markets, we included a variable that should capture the likelihood of an edge forming *from* and *to* the

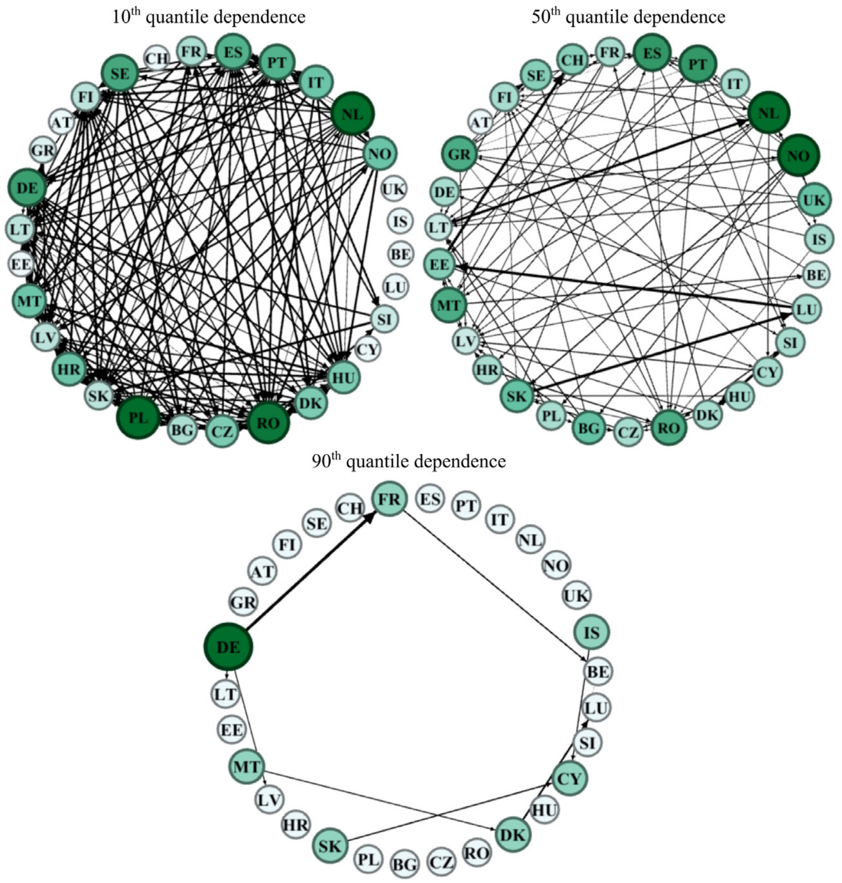

Fig. 1. Cross-quantilogram networks of international tourism demand, $p = 3$. *Notes: The thickness of the edges corresponds to the size of the directed relationship. A darker vertex indicates a stronger weighted out-degree (weighted by the strength of the directional relationships), and a larger vertex indicates a stronger weighted in-degree.*

CEE market. More specifically, the first vertex attribute is an indicator variable that assumes the value of 1 if the given country is from the *CEE* and 0 otherwise.

The tourism sector in countries that have not adopted the Euro currency might be subject to more foreign exchange risks, which in turn could make them more vulnerable to swings in international tourism demand. We therefore study whether the adoption of the Euro currency is associated with increased or decreased interconnectedness of international tourism demand. The second vertex attribute is also an indicator variable that assumes the value of 1 if the given country adopted the Euro currency and 0 otherwise.

The descriptive statistics (see Table 6) also suggest that more developed countries, with respect to tourism, might have more segmented international tourism demand behavior; i.e., they are less interconnected with other countries in Europe. The overall development of the tourism sector is measured by the average ratio of the total international tourism receipts (revenues from international tourists) to the GDP of the country in nominal terms over the observed time interval. The third vertex attribute, in our empirical model, is based on this ratio in a following way. We set the value of this attribute for a given country to 1 if the value of this measure of tourism development is above the median (across countries) and 0 otherwise.

Finally, we also include a broad index of tourism competitiveness as the fourth vertex attribute. This index is published by the World Economic Forum [58–61] and captures a broad view on the possibilities of a developing tourism sector in a given country. More specifically, it evaluates the level of human, cultural and natural resources of a country, its legal framework (with respect to tourism), its business environment and its infrastructure. Higher values indicate that the given country has greater potential to develop tourism. Similarly as before, in our empirical model, we use a simplified version of this variable by setting the vertex attribute to 1 if the value of the index is above the median and 0 otherwise. The descriptive statistics of the four vertex attributes can be found in Appendix.

In Table 5, we report the estimated coefficients obtained from the ERGM estimated for networks created for $p = 3, 6, 9$ and at the 10th and 50th percentile respectively. We do not report results for the 90th networks that are very sparse, and

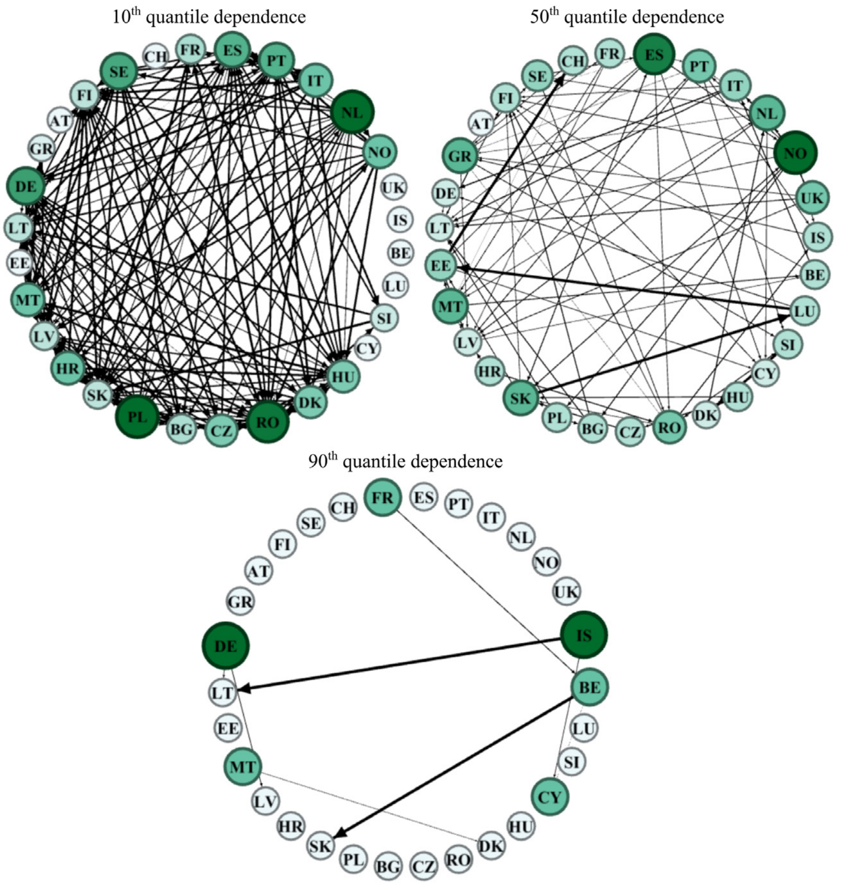

Fig. 2. Cross-quantilogram networks of international tourism demand, $p = 6$. *Notes: The thickness of the edges corresponds to the size of the directed relationship. A darker vertex indicates a stronger weighted out-degree (weighted by the strength of the directional relationships), and a larger vertex indicates a stronger weighted in-degree.*

do not lead to enough variability to perform a meaningful ERGM study. Given the results in Table 5, the corresponding probabilities can be derived in a straightforward way. For example, in the first model ($p = 3$ and 10th percentile), probability of observing an edge could be calculated as follows: $1/(1+\exp(-(-2.79+2.54\times 0-0.41\times 1-0.41\times 1+1.43\times 1+0.63\times 1)))=0.175$. In this particular example, we are considering only the significant coefficients, and a case with expected probability for forming an edge from a country that has adopted Euro (-0.41×1), that has higher level of international tourism receipts to GDP (-0.41×1) to a *CEE* country (1.43×1) that has also adopted the Euro currency (0.63×1). If we introduce mutuality, then the probability changes to $1/(1+\exp(-(-2.79+2.54\times 1-0.41\times 1-0.41\times 1+1.43\times 1+0.63\times 1)))=0.729$; i.e., the probability of a relationship increases from 0.175 to 0.73, which is an increase of 4.2 times. As is usual with multivariate non-linear models, the probabilities depend on the level of the other variables in the model. Therefore, instead of focusing on probabilities, we interpret significant coefficients (at the 10% significance level or lower), where positive coefficients suggest a positive association between the variable and the probability of an edge.

The results in Table 5 indicate several regularities within the tourism demand networks. Most of these regularities appear to have emerged for the 10th percentile networks. We also report the fit of the model (McFadden's R^2 [62]) and a set of goodness-of-fit test results where we compare the fit of the simulated networks' (from the estimated parameters of the ERGM) properties (out-degree, in-degree distributions and geodesic distance) with the observed networks. In most cases, the simulated networks appear to be similar to the observed network, which suggests a good fit.

Our first empirical result, which is provided in Table 5, indicates that when the tourism demand in one country influences the tourism demand in the other country (in Granger sense), it is likely that the latter is also influencing the former (significant and positive 'mutual' coefficient). This result holds for all the networks, and therefore, bi-directionality (reciprocity of mutuality) appears to be a common characteristic of international tourism demand interconnectedness.

Our second empirical result revealed by the ERGM shows that left-tail interconnectedness from countries that adopted Euro is less likely, as the coefficient is negative. On the other hand, adoption of Euro increased the probability that

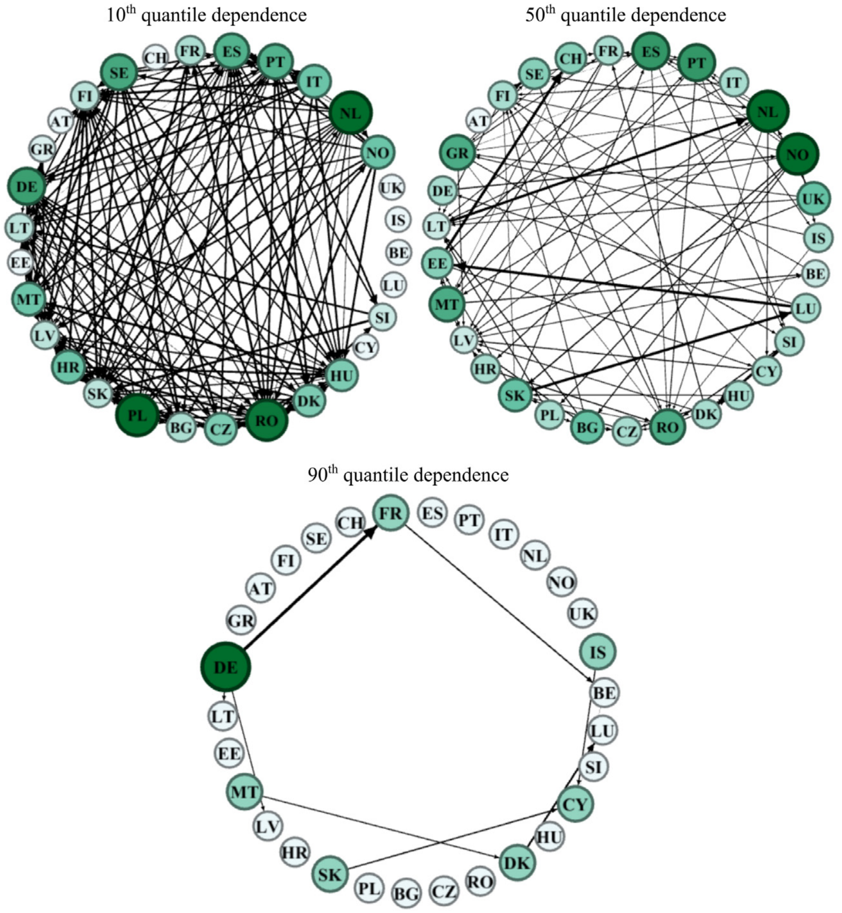

Fig. 3. Cross-quantilogram networks of international tourism demand, $p = 9$. *Notes: The thickness of the edges corresponds to the size of the directed relationship. A darker vertex indicates a stronger weighted out-degree (weighted by the strength of the directional relationships), and a larger vertex indicates a stronger weighted in-degree.*

a country is going to be influenced (in Granger sense) in the 10th and 50th percentiles. This has interesting policy implications, as it indicates that the adoption of the Euro has actually increased the sensitivity of international tourism demand with respect to the development on other markets.

Third, significant coefficients of the *CEE* variable in the Panel of 'Vertex level determinants of in-going edges' suggests that tourism sectors in *CEE* countries are more sensitive to the negative development (networks at the 10th percentile) of tourism in other countries.

Finally, our fourth empirical finding is that the development of the tourism sector, as measured by the ratio of the international tourism receipts to the GDP, is negatively associated with the probability of an out-going edge from a given country, i.e., a negative and significant coefficient. This result is partly surprising as we expected that countries with more developed tourism sectors (higher international receipts to GDP) will be more influential (in Granger sense) in the network, but the opposite is true as these countries tend to influence other markets less. At the same time, the more developed countries are also less influenced (negative significant coefficients for in-going edges). Overall it appears that the more developed countries have less interconnected international tourism demand.

4. Conclusion

We study the interconnectedness of the development of international tourism demand in Europe. We create a directional network, where two countries (vertices) are interconnected if the international tourism demand of the first country leads (in Granger sense) international tourism demand in the second country within p months. In addition, we utilize the recently developed cross-quantilogram analysis, where directional relationships are determined for different

Table 5
Estimated coefficients from the ERGM.

	p=3		*p*=6		*p*=9	
	10th	50th	10th	50th	10th	50th
Edges	**−2.79**[d]	**−2.31**[d]	**−2.40**[d]	**−2.68**[d]	**−1.97**[d]	**−2.39**[d]
Mutual relationship	**2.54**[d]	**2.02**[d]	**1.36**[d]	**1.17**[c]	0.28	−0.47
Vertex level determinants of out-going edges						
Central and Eastern Europe	0.03	−0.61	0.33	−0.34	0.46	−0.36
Euro currency	**−0.41**[b]	−0.31	**−0.48**[b]	−0.19	**−0.42**[b]	−0.1
International tourism receipts to GDP	**−0.41**[a]	−0.04	**−0.48**[b]	0.01	**−0.87**[d]	−0.07
Tourism competitiveness index	−0.24	−0.17	0.20	0.12	0.08	−0.08
Vertex level determinants of in-going edges						
Central and Eastern Europe	**1.43**[d]	0.05	**1.40**[d]	0.32	**1.51**[d]	**0.67**[a]
Euro currency	**0.63**[c]	**0.86**[c]	**0.96**[d]	**1.18**[d]	**0.99**[d]	**0.98**[d]
International tourism receipts to GDP	0.08	**−0.45**[a]	**−0.38**[a]	**−0.42**[a]	**−0.59**[c]	**−0.41**[a]
Tourism competitiveness index	0.29	−0.36	−0.07	−0.54	−0.30	−0.37
Model fit (**McFadden's** R^2)						
Unrestricted model against the null model (no parameters)	0.39	0.58	0.34	0.56	0.39	0.53
Goodness-of-fit evaluation						
Out-degree	0.47	0.79	0.63	0.66	0.59	0.75
In-degree	0.49	0.71	0.61	0.83	0.66	0.65
Geodesic distance	0.81	0.73	0.79	0.77	0.77	0.76

Notes: Values in the table denote the estimated coefficients (CF). The superscripts a, b, c, and d, denote significance at the 10%, 5%, 1%, and 0.1%, respectively. McFadden's R^2 is calculated as $1-LL^{UR}/LL^{RM}$, where the fraction is the log-likelihood of the ratio of the unrestricted to the restricted model. Goodness-of-fit evaluates how the simulated network's distributions of characteristics (out-degree, in-degree, and geodesic distance) correspond to the observed network. The reported values in the table are average p-values, values above the significance level suggest that the distribution of the simulated network's characteristics correspond to the observed network. To improve readability, the significant coefficients are in boldface in the table.

percentile (10th, 50th, and 90th percentile) and different lead times ($p = 3, 6, 9$). We thus create 9 cross-quantilogram networks of international tourism demand and observe striking asymmetric interconnectedness.

It is found that when international tourism demand declines sharply (below the 10th percentile), it declines across almost all markets. On the other hand, when tourism demand increases sharply (above the 90th percentile), it increases in a segmented way. This asymmetry was found for all lags. In fact, increases are so segmented that, the average in- and out-degree among the 30 vertices is below 1. We identify, that during declines in international tourism demand, the most interconnected international tourism demand is that of Spain, and while also somewhat surprisingly that of Romania and Hungary.

We further explored determinants of the likelihood of a directed edge in cross-quantilogram international tourism demand networks using an ERGM framework. As before, we found that the results differ more for networks with different percentiles rather than those with different lead times. Our most notable results are as follows:

- Mutual interconnectedness is a typical feature of international tourism demand networks. Thus, it is more likely that two markets are interconnected in both directions rather than in just one direction.
- International tourism demand in *CEE* countries tends to be influenced more during sharp declines in international tourism demand (below the 10th percentile).
- Countries with lower development (importance) of the tourism sector within a country tend to be more interconnected with international tourism demand of other countries.

Most of our results are intuitive and support the meaningfulness of studying the complex interrelatedness of international tourism demand through network analysis. We believe that in the future, such an analysis can be helpful to enhance our understanding of how tourism sectors are related, who are the main propagators of shocks in tourism and what policy steps can be suggested to mitigate the propagation of negative shocks within such networks of international tourism demand.

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Appendix

Table 6
Descriptive statistics of the variables used in the ERGM model.

Country	Euro	CEE	ITR/GDP		Travel and tourism competitiveness index (TCI)	
	Adopted = 1	Member = 1	Mean	Above median	Mean	Above median
Spain	1	0	0.04	1	5.35	1
Portugal	1	0	0.05	1	4.85	0
Denmark	0	0	0.02	0	4.71	1
Germany	1	0	0.01	0	5.35	0
Greece	1	0	0.05	1	4.6	1
Austria	1	0	0.05	1	5.12	1
Finland	1	0	0.01	0	4.75	1
Sweden	0	0	0.02	0	4.9	1
Switzerland	0	0	0.02	0	5.32	1
France	1	0	0.02	0	5.32	1
Italy	1	0	0.02	0	4.49	1
Netherlands	1	0	0.02	0	4.9	1
Norway	0	0	0.01	0	4.77	1
United Kingdom	0	0	0.01	0	5.25	1
Iceland	0	0	0.04	1	4.83	1
Belgium	1	0	0.02	0	4.75	1
Luxembourg	1	0	0.08	1	4.72	0
Slovenia	1	1	0.05	1	4.39	0
Cyprus	1	0	0.09	1	4.5	0
Hungary	0	1	0.05	1	4.31	0
Romania	0	1	0.01	0	3.94	0
Czech Republic	0	1	0.04	1	4.5	0
Bulgaria	0	1	0.07	1	4.24	0
Poland	0	1	0.02	0	4.26	0
Slovakia	0	1	0.07	0	4.24	0
Croatia	0	1	0.02	1	4.26	0
Latvia	1	1	0.02	0	4.19	0
Malta	1	0	0.13	1	4.55	0
Estonia	1	1	0.06	1	4.54	0
Lithuania	1	1	0.03	1	4.13	0

Notes: Because of the skewness in the raw data, the reported ratios of international tourism receipts (ITR) to gross domestic product (GDP) are natural logarithms of the original ratio.

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