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Is Globalization in Retreat? Cross-Country Evidence from a Spatial Analysis of Tourist Flows

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Abstract

In recent years, international tourism has grappled with various impediments to cross-border activities triggered by geopolitical shifts. This study examines whether globalization is in retreat through the lens of international tourism. We employed spatial autoregressive models, in which several connectivity mechanisms are embedded, to analyze a global dataset of tourist flows. Our findings reveal that spatial dependence in tourism flows significantly weakened during the 2008 Global Financial Crisis and became increasingly driven by institutional factors, while the effects of trade links and geographical proximity diminished. This study contributes to the literature on tourism globalization by providing empirical evidence of the megatrends of deglobalization. For tourism firms operating under the assumption of ongoing globalization, these megatrends signal a significant change in the business environment. Firms should be prepared to reorient their market focus and reallocate their resources toward institutionally aligned regions in an evolving global landscape. Also available in Chinese. See Supplemental Material for details.

Keywords

international tourist flows, globalization, global business environment, trilemma of world economy, connectivity, spatial autoregressive model

Introduction

Globalization encapsulates many contemporary influential trends characterized by the growing interconnection of regions and nations through cross-border flows of trade, capital, labor, technology, and information (Song et al., 2018; Turok et al., 2017). For decades, international tourism has been a key engine of globalization, contributing to social exchanges, physical movements, and economic globalization (Titievskaia et al., 2020). The tourism industry represents a major export service for many economies, accounting for approximately 10% of global GDP and employment in 2019 (World Travel & Tourism Council, 2023).

Despite a long period of economic booms, signs of a retreat in globalization emerged following the Global Financial Crisis of 2008, which is widely regarded as the turning point of hyperglobalization (Goldberg & Reed, 2023). Since then, the world has witnessed a slowdown in trade, foreign direct investment, and financial flows. During the same period, major protests have erupted across Europe and the United States against the rising cost of living, increasing inequality, and the erosion of democracy.

Amid this anti-globalization backlash, many countries have seen voters and parties shift toward protectionism and isolationism (Colantone et al., 2021), accompanied by a rise in populism. A typical aspect of populism is anti-immigration discourse. In some countries, concerns about cultural threats and reduced social cohesion have fueled public resistance to immigration (Freeman, 2006). Resonating with this discourse, the anti-tourism sentiment has framed tourism in terms of cultural, economic, and environmental conflicts, sparking a series of protests

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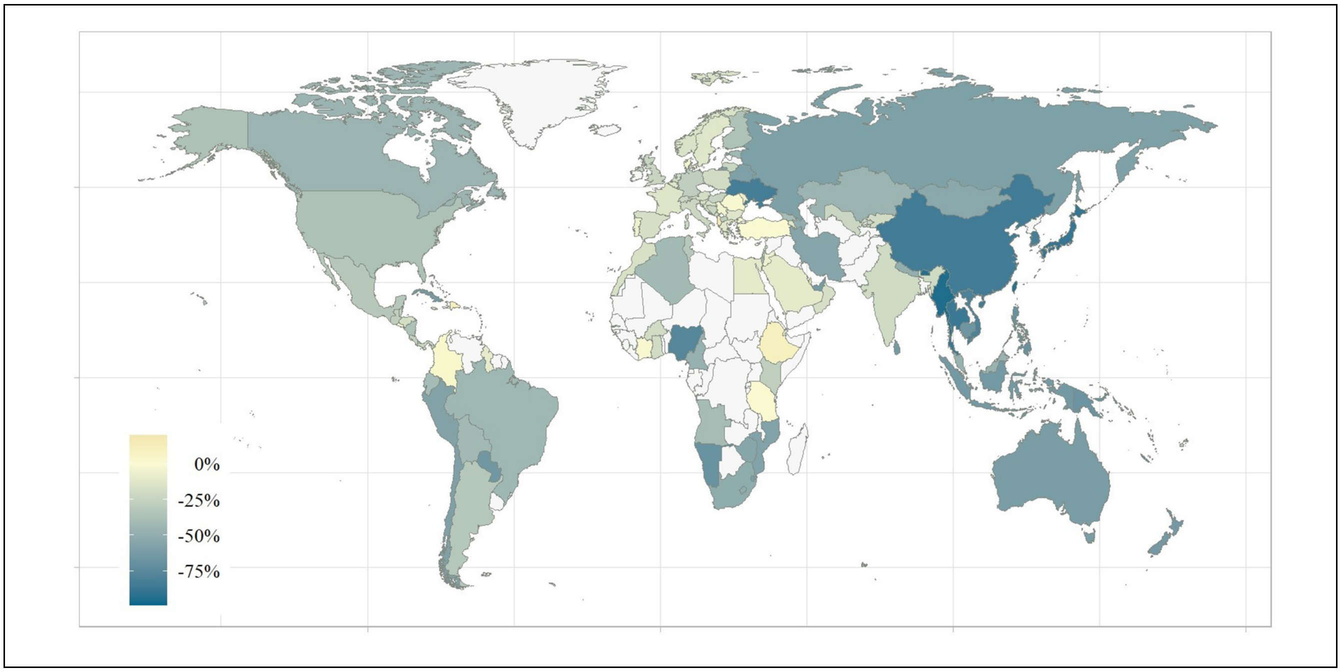

Figure 1. Percentage change of country-level tourist flows, 2022 versus 2019.
Source. Authors' calculations based on data from the Compendium of Tourism Statistics, World Tourism Organization.
Note. Data on country-level total arrivals are used. Wherever this metric is unavailable, overnight visitor data are used instead. Light gray indicates no data.

against overtourism in popular destinations, such as Barcelona, Venice, and Athens.

The slowdown in globalization was exacerbated by the COVID-19 pandemic. In 2020, many countries were forced to close their borders to foreign visitors or impose stringent restrictions such as quarantine measures to deter inbound visitors. Airlines around the world grounded their planes and significantly reduced the volume of passengers carried. International tourism effectively ground to a halt as cross-border tourist flows plummeted. The resulting sharp decline in international mobility, alongside supply-chain disruptions, led some commentators to proclaim the onset of "deglobalization" (Titievskaia et al., 2020). Even in 2022 when health risks had reduced significantly, tourism levels remained markedly below those of 2019 in most countries (see Figure 1). In rare cases, the decline exceeded 90%. Although the slow recovery of international tourism is likely due to a host of operational factors inherent to the industry, the decline or lack of social exchange through tourism activities has undoubtedly intensified the risks of deglobalization.

More recently, shifts in the global risk landscape, such as geopolitical tensions and the war in Ukraine that broke out in February 2022, have further disrupted international connectivity. Sanctions, restricted travel routes, tightened visa policies, and surging fuel costs have all compounded the fragmentation of global mobility.

Against this backdrop of mounting disruptions, in the tourism globalization literature, there has been an increased focus on understanding the interconnectedness of tourism markets. The latter is typically examined from the perspective of spatial dependence or co-movement patterns (e.g., Cao et al., 2017; Kuok et al., 2023; McKercher et al., 2008; Yang et al., 2023), which are shaped by the strength of connectivity or "distance" between the markets. Empirical evidence tends to support the existence of such close connections.

However, the ongoing trend of global disconnection raises critical questions: Has the interconnectedness of tourism markets weakened? If so, which forms of connectivity or "distance" remain crucial to tourism markets? A positive answer would imply that tourism activities are becoming less globalized and less proactive, casting doubt on the growth prospects of tourism markets worldwide. On the theoretical level, a positive answer would prompt a new line of investigation into the mechanisms behind and implications of the change of course.

The present study engages with these emerging questions and contributes to the tourism globalization literature with new insights for the evolving debate on global reversal, where empirical evidence is still scarce and limited to a few exceptions (Giammetti et al., 2022). International tourism, despite being a vital facilitator of cultural exchange, knowledge diffusion, long-term migration, and investment, remains underrepresented in the mainstream discourse on globalization. Hence, incorporating the perspective of international tourism is essential to debating whether deglobalization is in fact occurring.

This study also advances the tourism globalization literature by developing a line of theoretical reasoning drawn from the trilemma of the world economy model (Rodrik, 2000) in international political economy. The model explains the inherent tensions interfering with cross-country interconnectedness and the mechanisms behind potential deglobalization. The evolution of global interconnectedness carries important implications for businesses. As Witt (2019) argues, for firms that operate under the implicit assumption of continuous globalization, deglobalization would mark a significant turn of events.

Our results point to a general decline in interconnectedness at the global level since the 2008 Global Financial Crisis, accompanied by a gradual rise at the regional level driven by institutional proximity. In this environment, tourism firms reliant on overseas tourists will find their demand patterns increasingly shaped by regional institutional structures: their customer base will be swayed toward coming from institutionally similar markets, and their ability to attract tourists from distant markets will be significantly constrained. Our results highlight the significance of regional links, which may have stronger spatial spillovers than global ones. Thus, tourism firms should reconfigure their global strategies, notably by reorienting their market focus and reallocating overseas resources toward institutionally proximate regions.

Literature Review

Globalization is a multifaceted phenomenon that encompasses almost all spheres of human activity. This study interprets tourism globalization from the perspective of spatial dependence, which weakens if the global economy experiences a reversal, or deglobalization.

Globalization and International Tourism

Globalization is generally defined as a set of processes involving the compression of space and time and the intensification of economic, political, social, and cultural interdependence on a global scale (Song et al., 2018). Falling transport costs, heightened human mobility, and new communication technologies have prompted many economists to predict the death of distance and the demise of cities and regions (Turok et al., 2017). Thus, globalization is closely associated with the notion that distances are now less of a barrier than before.

The degree of globalization can be measured using the KOF Globalization Index (Gygli et al., 2019), a composite indicator that captures the key dimensions of globalization. Figure 2 depicts the development of globalization since 1980, which has been increasing, although the trend started to slow down in the late 2000s. As shown in panel (b), stagnant growth in *economic globalization* is a notable contributor to this slowdown.

International tourism is deeply intertwined with globalization processes. Over the past half-century, rapid growth in international tourism has mirrored the rise in globalization. Figure 3 illustrates the growth trends of global arrivals since 1995. By and large, the global tourism industry enjoyed a steady rise before the 2008 Global Financial Crisis. During the harshest years of the financial crisis, the growth trajectory shifted downwards, although the industry quickly recovered after 2010 and returned to a growth rate similar to that before the crisis. Then came the pandemic, which practically invalidated the lifeline of the industry—face-to-face communication—and caused global tourism numbers to plummet almost overnight.

In the tourism literature, empirical quantitative studies of tourism globalization have proliferated in recent years and tend to agree on the existence of a certain degree of economic integration among tourism markets. Cao et al. (2017) found evidence that tourism demand co-moves among developed economies and among developing economies separately, while Kuok et al. (2023) demonstrated that these global co-movements create mechanisms of transmission of policy uncertainty shocks across tourism markets. Focusing on specific dimensions of globalization, Shao et al. (2023) reported that a country's degree of economic globalization directly influences its prominence in the international tourist flow network, while Gozgor et al. (2022) and Haini et al. (2024) affirmed that social globalization plays a moderating role in tourism investment and economic growth, respectively.

However, economic integration is never static and can oscillate over time. As mentioned in Section The Retreat of Globalization, inherent forces hamper progress toward complete global integration. Whether the interconnection of tourism markets is weakening and through which mechanisms remains undetermined.

Spatial Dependence, Connectivity Mechanism, and Distance

Spatial Dependence Between Tourism Markets. Spatial dependence describes a phenomenon in which the economic outcomes of a spatial unit are influenced by outcomes in nearby units due to interactions through trade, information, movement of people, or other forms of economic activity. In tourism, these interactions are often studied using gravity models of tourist flows between an origin and a destination. However, as Yang and Wong (2012) argue, interactions can also occur between destinations, exerting unintended effects or externalities, the extent of which depends on the distribution of spatial units. When these externalities persist across locations and adjust the spatial distribution of activities, they cause spatial

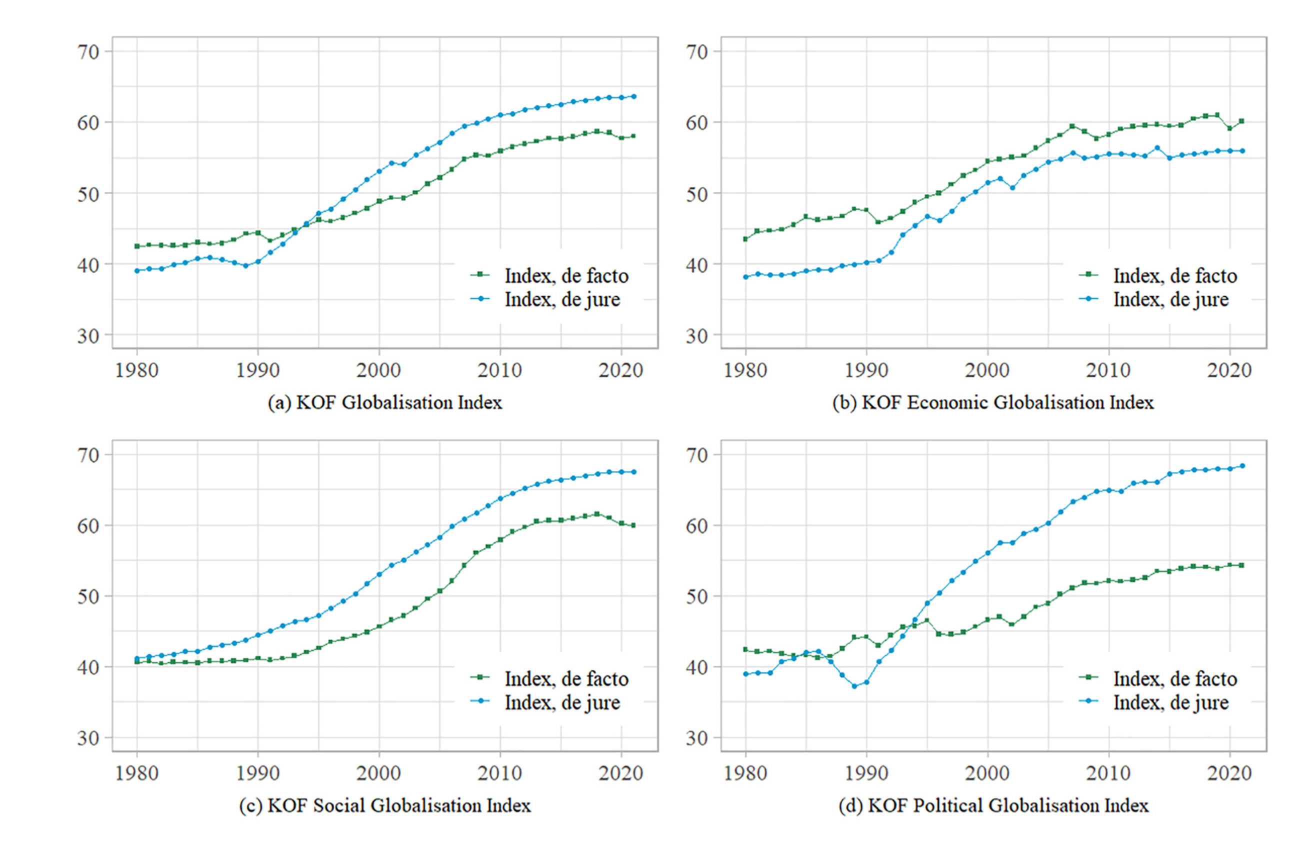

Figure 2. Trends of the KOF Globalization Indices (range 0–100).
Source. The KOF Swiss Economic Institute. The data are simple averages of individual country KOF index.
Note. de facto indices capture actual international flows and activities, whereas de jure indices measure policies and conditions that enable, facilitate and foster international flows and activities.

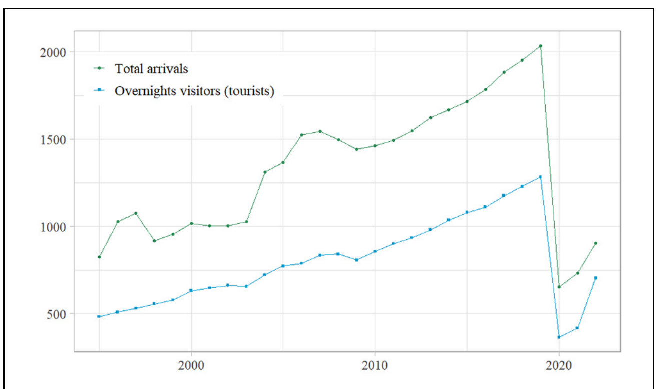

Figure 3. Trends of global tourist flows (million persons).
Source. Authors' calculation based on the Compendium of Tourism Statistics—Basic data and indicators, World Tourism Organization. Not all countries have available data.

dependence. A key consequence of spatial dependence in tourism is the spatial spillover effect, in which the success or growth of a region's tourism industry indirectly affects tourist flows to nearby regions.

Yang and Wong (2012) and Marrocu and Paci (2013) synthesized both supply and demand perspectives that justify the existence of spatial dependence between destinations. The supply-side argument revolves around the economies of agglomeration, which can stem from Marshallian and Jacobian externalities. Marshallian externalities capture increasing returns to scale at the intra-industry level and explain intra-industry agglomeration. In the context of tourism, the attractiveness of a region may lie in the natural or anthropogenic features that provide the product core to support various specialized tourism forms. Endowments such as natural scenery and cultural attractions will likely cluster in a particular region, along with shared large-scale infrastructures (e.g., airports, conference centers, and museums). At the firm level, tourism-related firms that cluster together benefit from productivity spillovers. Because the productivity of the tourism industry is strongly dependent on the knowledge and skills of humans, labor movement between destinations contributes to tourism growth in host regions. Productivity spillovers can also be associated with knowledge diffusion processes and demonstration effects between tourism-related firms or local and regional authorities. In addition, as Loungani et al. (2002) point out, agglomeration can be reinforced by information networks owing to the paucity of private information, enhancing trade and investment flows between regions by reducing the costs of intra-industry trade. Meanwhile, Jacobian externalities capture the benefits of the diversification of economic activities at the inter-industry level. The heterogeneity and diversity of tourism supply (e.g., natural landscapes, resort facilities, and cultural/sporting venues) observed in agglomerated regions enhances their attractiveness because tourism products are composite and require groups of service providers to aggregate to offer an integrated product.

The demand-side argument is based on travelers' multi-destination travel plans and the word-of-mouth effect (Yang & Wong, 2012). Spatial spillovers can be theorized as the result of *learning* (at the destination) and *communication* (at the origin) processes (Marrocu & Paci, 2013). International tourism often involves visiting multiple adjacent destinations during a single trip. This may be due to destinations being bundled in a holiday package or a cost-effective method of tourism. Multi-destination travel plans can be facilitated by a common visa policy (e.g., the Schengen Agreement) or a regional visa waiver program. Therefore, visits to a destination present opportunities to *learn* information about neighboring countries, which can then result in future visits. Once travelers return from their destinations, they share their experiences with their families, friends, and business partners as well as on local social media. The exchange of knowledge and information about different destinations serves as a *communication* process (i.e., word of mouth), thereby decreasing the perceived risks for potential visitors and increasing their propensity to travel to a new destination. Occasionally, spatial spillovers between destinations may also be triggered by regional shocks, typically negative events (e.g., threats of disease, terrorist incidents, and political unrest) that deter visitors because of heightened perceived risks.

Foreign direct investment can be a catalyst for the abovementioned mechanisms of spatial dependence. Multinational firms' overseas presence can boost the visibility of their home countries as tourism destinations through co-branding or promotional campaigns. More importantly, investments in transportation infrastructure can improve connectivity in host countries, indirectly benefiting firms' home countries by making them more accessible to those residing in or visiting the host countries.

Connectivity and Distance. The magnitude of spatial dependence is explained by distance decay theory (see, e.g., Conley & Ligon, 2002; J. P. Elhorst et al., 2024; McKercher et al., 2008). As Conley and Ligon (2002) and Jovanović (2020) argue, "distance" should be understood in its broad sense, referring to obstacles to goods, services, factors, and knowledge passing through space. Underlying these obstacles are the transaction costs of interactions, such as transport, tariffs, contract enforcement, exchange and banking, and differences in language, culture, and, political systems.

In international tourism, transaction costs range from visa-free status to national price-level differences, shared language, and proximity (Chung et al., 2020). They constitute mechanisms that regulate cross-country connectivity (Hennart, 2010) by acting as impediments. Specifically, these connectivity mechanisms can be economic, institutional, cultural, or geographical (Song et al., 2018; Yang et al., 2023).

Economic linkages. The proliferation of regional trade agreements over the past 30 years helps explain the increasing significance of economic linkages. The formation of the European Union and the ratification of the North American Free Trade Agreement (replaced by the United States-Mexico-Canada Agreement in 2020) have enabled goods to flow more easily across borders (Cooke et al., 2015). This often entails free movement of people (including visa-free travel). Strong trade ties between countries constantly lead to increased business travel, such as exhibitions and conferences, which can extend to meetings with clients or suppliers along global value chains.

Institutional and cultural proximities. Noonan et al. (2020) revealed that in agglomeration economies, institutional proximity can improve firm-level productivity, possibly due to knowledge sharing between firms from similar backgrounds. In the same vein, institutional proximity between destinations can facilitate knowledge sharing, thus boosting the productivity and attractiveness of tourism supply in neighboring regions. In addition, harmonized visa policies between institutions can make multi-destination trips seamless. Borderless common travel areas are more likely to emerge in countries with similar institutional frameworks. Even in the absence of a common visa policy, institutional and cultural proximities between destinations can still lead to faster information flows, which can encourage travelers who intend to visit multiple places to take a further trip. Moreover, cultural proximity can reduce barriers to communication and interaction (Yang et al., 2023). When negative events invalidate a traveler's original plan, they can comfortably shift to culturally similar destinations without significantly compromising their enjoyment.

Geographical proximity. As Balli and Tsui (2016) point out, geographical proximity and a liberalized regional aviation regime that allows frequent flight services can contribute to spatial spillovers. Geographical proximity has implications for tourists' financial and time costs and thus regulates tourist flows. Low-cost carriers and high-

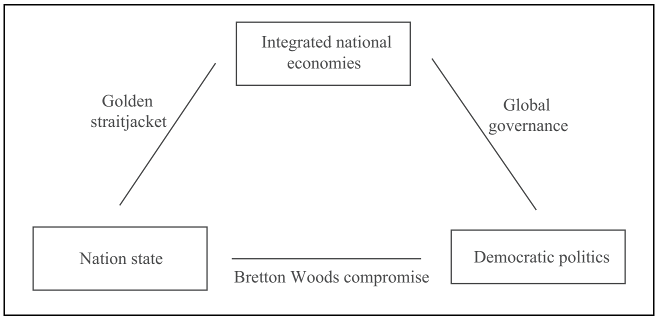

Figure 4. Trilemma of the world economy.
Source. Adapted from Rodrik (2000). Used with permission from Rodrik and the American Economic Association.

speed rail networks have significantly strengthened cross-border travel and made isolated markets more accessible. Accordingly, the availability of efficient transportation infrastructure amplifies the effects of trade and institutional ties, reinforcing spatial dependence by reducing both the physical and economic barriers to travel.

The Retreat of Globalization

Researchers have long noted the rise of discontent with globalization, including the anti-globalization and alter-globalization movements in the late 1990s and early 2000s. In recent years, "slowbalization" and "deglobalization" have become salient in the literature (McGrew, 2020). Reflecting on how far international economic integration would go, Rodrik (2000) developed the trilemma of the world economy model (depicted in Figure 4), which was inspired by the "impossible trinity" in international economics.

In an open economy setting, countries face choices between *international economic integration*, the *nation-state*, and *democratic politics*. The trilemma model predicts that an open economy can, at best, accommodate two mechanisms out of three. The model aptly explains why we are far from complete international economic integration (i.e., a perfectly globalized world): achieving it would entail either a significant diminution of national sovereignty or a shrinkage of democratic politics. The existence of national borders has a significant depressive effect on commerce, even in the absence of obstacles such as formal tariffs, non-tariff barriers, and linguistic and cultural differences. Similar restrictive effects of national borders also apply to the international mobility of people (Rodrik, 2000).

If the *nation-state* cannot be abandoned, then we must confront the inherent tensions between *economic integration* and *democratic politics*. Rodrik (2021) outlines a causal framework that highlights several pathways through which globalization may drive support for populism. The general idea is that globalization shocks (e.g., trade, finance, and immigration) enter a country's system through their impact on economic conditions, particularly economic dislocation, which subsequently influences political outcomes—that is, the electoral success of populist politicians.

In the context of the movement of people, one pathway is *culture, racial attitudes*, and *social identity* (Rodrik, 2021). It is suggested that economic shocks can heighten feelings of insecurity, causing voters to make sharper distinctions between insiders ("us") and ethnic, religious, or racial outsiders ("them"). A sudden influx of foreigners may generate a cultural backlash that has nothing to do with economics, such as xenophobia or anti-immigrant sentiments that emerge purely from psychological and identity-related processes. Alternatively, the influx may generate a backlash because it creates economic dislocation. Such dislocations arise from competition in local labor markets (e.g., by driving down local wages) or public goods provision (e.g., by reducing the availability of public services). A similar dynamic is observed in the case of mass tourism. A thriving tourism industry can lead to the commercialization or dilution of local cultures and traditions. Apart from feeling a loss of cultural identity, local residents may also perceive luxurious facilities (e.g., resorts, yachts) as symbols of capitalism as the economic benefits of tourism are often channeled to large corporations and foreign investors. Moreover, the influx of foreign tourists can strain local infrastructure and drive up housing costs. All of this fuels resentment among locals, as evidenced by various recent overtourism protests in popular European destinations such as Barcelona, Venice, and Athens. In time, these economic factors can boost support for populist anti-immigrant parties either because these parties allay voters' economic anxieties or because economic dislocation activates the affirmation of traditional dominant identities and hostility toward perceived out-groups on cultural grounds. Hence, tourism, like immigration, may catalyze populist backlash and political movements, reinforcing the departure from global integration.

The trilemma model's prediction presents a reasonably accurate depiction of reality that is broadly compatible with *liberalism*'s approach (Witt, 2019) to the question of deglobalization. In contrast, the theoretical school of *realism* (Witt, 2019) attributes deglobalization to geostrategic rivalry. It argues that periods of globalization occur when a hegemon creates and maintains a set of international institutions that govern aspects such as trade and investments. The hegemon keeps this system in place as long as it remains strong enough to do so and the benefits exceed the costs. However, there is no guarantee that other states will benefit from the system. Once a shock to the system, such as an economic crisis, reveals that the hegemon has lost its power relative to other countries to the point that it is no longer overwhelmingly powerful, the system becomes unstable, which may lead to deglobalization.

International tourism, an integral part of international economic integration, is also affected by the aforementioned mechanisms, such as populism, anti-immigrant sentiment, and geostrategic shifts. The resulting retreat of globalization would imply that the previously compressed "distance" is being stretched again, increasing the transaction costs of international tourism and diminishing the prosperity of businesses and regions dependent on tourists' spending.

Therefore, we can hypothesize that spatial dependence between tourism markets on a global scale would decline in the wake of the retreat but would strengthen for markets in close "proximity" to each other. Further, the connectivity mechanisms involved in such a shift in spatial dependence would likely differ in size, and institutional factors could stand out as the forces that reshape tourism market connections. As geopolitical risks loom over the global economy, with protectionist policies and nationalistic sentiments gaining traction, governments may introduce more stringent visa restrictions that could segment the global travel system. Reduced airline connectivity due to geopolitical tensions, sanctions, and rising fuel costs may particularly weaken long-haul travel flows. Consequently, established international travel routes could face a reconfiguration, alongside a shift in tourists' preference for destinations that minimize regulatory frictions and have a greater cultural affinity with their home countries.

In this paper, we seek empirical evidence to evaluate these hypotheses. In doing so, we identify the megatrends in the business environment for the tourism industry and the types of markets (e.g., institutionally similar, culturally similar) whose growth will be most strongly correlated. This will help firms formulate business strategies of market focus.

Methodology

Empirically verifying spatial dependence and measuring its strength would require specifying and estimating spatial interaction models, which are well suited for describing geographic flows, including travels from one location to another (Marrocu & Paci, 2013; Yang et al., 2017). A common type of spatial interaction model is the spatial autoregressive model, in which spatial dependence between countries is captured by an explanatory variable representing the influence of neighboring or partner countries, and this influence can be attributed to different forms of connectivity mechanisms.

Spatial Autoregressive Model

In this study, our main models use the spatial autoregressive specification, which augments traditional linear models by including a spatially lagged dependent variable. The model's fixed-effect panel data variant takes the following basic form (J. P. Elhorst, 2003):

$$\boldsymbol{Y_t} = \rho \boldsymbol{W_t} \boldsymbol{Y_t} + \boldsymbol{X_t}\boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\varepsilon_t}\,(t = 1, 2, \ldots, \mathrm{T}) \tag{1}$$

where $\boldsymbol{Y_t}$ is a vector of N observations on a dependent variable, with N being the number of spatial units (in this study, countries), $\boldsymbol{X_t}$ is an $N \times K$ matrix of observations on K exogenous (explanatory) variables with an associated $K \times 1$ vector of coefficients $\boldsymbol{\beta}$, $\boldsymbol{\mu}$ is an $N \times 1$ vector of time-invariant individual effects, $\boldsymbol{\varepsilon_t}$ is an $N \times 1$ vector of idiosyncratic errors with its element $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$, $\boldsymbol{W_t}$ is an $N \times N$ spatial weight matrix representing connectivity between spatial units, and ρ is the spatial lag coefficient. We allow the spatial weight matrix to be time variant, and this can be accommodated in the estimation by using the procedure developed by Grieser et al. (2022)—a mix of Maximum Likelihood Estimation and Markov Chain Monte Carlo sampling.

Spatial dependence occurs when tourism trends in one country are influenced by those in neighboring countries. It is modeled through the spatial lag term $\boldsymbol{W_t Y_t}$, with connectivity mechanisms embedded in the spatial weight matrix $\boldsymbol{W_t}$. Hence, ρ, the spatial lag coefficient, is our parameter of interest. The varying size of this coefficient captures the strength of spatial dependence associated with a particular connectivity mechanism. At first sight, this influence carries the interpretation that the value of the dependent variable Y at i ($\forall i = 1, 2, \ldots, N$) only depends on the weighted average of its counterparts. However, as Anselin (2003) showed, any economic interpretation of the spatial correlation of Y between spatial units also works through the spatial patterns in X and the other terms. This can be illustrated using the reduced form of Equation 1:

$$\boldsymbol{Y_t} = (\boldsymbol{I} - \rho \boldsymbol{W_t})^{-1}\boldsymbol{X_t}\boldsymbol{\beta} + (\boldsymbol{I} - \rho \boldsymbol{W_t})^{-1}\boldsymbol{\mu} + (\boldsymbol{I} - \rho \boldsymbol{W_t})^{-1}\boldsymbol{\varepsilon_t} \tag{2}$$

The infinite series expansion of the matrix inverse in Equation 2 is:

$$(\boldsymbol{I} - \rho \boldsymbol{W_t})^{-1} = \boldsymbol{I} + \rho \boldsymbol{W_t} + \rho^2 \boldsymbol{W_t^2} + \rho^3 \boldsymbol{W_t^3} + \ldots \tag{3}$$

The first matrix term on the right-hand side, the identity matrix $\boldsymbol{I}$, represents a direct effect of a change in $\boldsymbol{X}$, while the second term $\rho \boldsymbol{W_t}$ represents an indirect effect of a change in $\boldsymbol{X}$. All other terms on the right-hand side represent second- and higher-order direct and spillover effects (Vega & Elhorst, 2015). A shock to the k^{th} variable in $\boldsymbol{X}$ for a spatial unit i will propagate to its neighbors, then to the neighbors of its neighbors, and so on, creating bands of ever more extensive reach and implying the existence of a spatial multiplier process. Hence, the spatial autoregressive model of Equation 1 captures both the unmodeled effects (i.e., spatial externalities via error terms) and the modeled effects (i.e., spatial externalities via the included explanatory variables).

Variable Selection and Data

Dependent and Independent Variables. For the dependent variable $\boldsymbol{Y_t}$, we use the number of tourist arrivals at the country level to capture the flow of international visitors. It represents a real—instead of nominal—measure of tourism demand as the variable is valued in terms of quantity rather than absolute money amounts.

With respect to the explanatory variables $\boldsymbol{X_t}$, we consider an array of economic and political factors, drawing from the literature on the modeling and forecasting of tourism demand. In particular, we primarily refer to the globalization studies by Chung et al. (2020), Dees et al. (2007), Haini et al. (2024), Kuok et al. (2023), and Shao et al. (2023) and the spatial econometric applications by Karimi et al. (2022), Ouchen and Montargot (2022), and Yang and Wong (2012). Furthermore, considering that international tourism is a subcategory of trade in services, we also follow the reviews by Morley et al. (2014) and Rosselló Nadal and Santana Gallego (2022) on the gravity model, whose "spatial thinking" is similar to the spatial autoregressive model despite differences in model specification.

Our review suggests that the following explanatory variables are appropriate for modeling global tourist flows. Economic indicators—*real GDP index* and *price level index* (adjusted by exchange rates) at destination levels—are essential for modeling tourist flows because they reflect the size of an economy and the economic conditions that affect tourism activities. To capture global shocks, such as the shifts in the geopolitical environment identified as a cause of deglobalization in the literature review, we utilize *oil prices* and the composite *country risk index* compiled by the PRS group. Furthermore, we incorporate the globalization indices developed by the KOF Swiss Economic Institute (Gygli et al., 2019). This dataset provides measures of the degree of globalization for every country in three broad dimensions: *economic globalization*, *social globalization*, and *political globalization*. The specific data we use are the de jure measures of KOF indices, which capture the policies and conditions that (in principle) enable, facilitate, and foster tourist flows and activities. These include, for example, tariffs, capital account openness, freedom to visit, internet access, civil liberties, and international treaties. This allows us to account for the conditions that may correlate with populism and geopolitical shifts and determine a country's inflow of international visitors.

Spatial Weight Matrices. A spatial weight matrix describes the structure of the connectivity between spatial units. In the literature review, we delineated four broad mechanisms of distance decay, which regulate the level of spatial externalities. Accordingly, we construct our spatial weight matrices based on those four mechanisms and as continuous metrics, which are typically defined by inverse distance measures. Operationally, we calculate *distance* as the Euclidean distance:

$$d_{ij} = \sqrt{\sum_{l=1}^{L} (i_l - j_l)^2} \tag{4}$$

where d_{ij} is the distance between spatial units i and j, with each unit being described by L dimensions, and i_l and j_l are the values of the l^{th} dimension for i and j, respectively. It should be noted that there are other commonly used alternatives, such as the Kogut and Singh index (KSIndex). However, as Beugelsdijk et al. (2018) show, the correlations between the KSIndex and the Euclidean distance index are very high, above 0.90. Both measures yield similar regression results. Hence, we opt to use one measure.

Regarding the elements of a spatial weight matrix, the inverse distance is defined as $w_{ij} = d_{ij}^{-2}$, reflecting a distance decay pattern similar to a gravity function (Ertur & Koch, 2007). w_{ij} then constitutes the i^{th} row and j^{th} column element of an $N \times N$ spatial weight matrix $\boldsymbol{W}$ (N is the number of spatial units), with zeros on the diagonal (i.e., $w_{ii} = 0$). Next, $\boldsymbol{W}$ is row standardized. Thus, each row i corresponds to the weights of unit i's partners and the row sums to unity (i.e., $\sum_{j=1}^{N} w_{ij} = 1, \forall i = 1, 2, \ldots, N$). Following the discussion in the literature review, we define *distance* as institutional, cultural, and geographical distance, with the former two calculated as the Euclidean distance and the last one as physical distance. Three spatial weight matrices, $\boldsymbol{W_{inst}}$, $\boldsymbol{W_{cult}}$, and $\boldsymbol{W_{geog}}$, are compiled accordingly.

The fourth spatial weight matrix, $\boldsymbol{W_{trad}}$, captures cross-country economic linkages. We use bilateral trade shares in lieu of inverse distance measures. Trade share represents the value of trade between country i and country j relative to the total trade of country i with all partners. In $\boldsymbol{W_{trad}}$, its elements $w_{ij} = \frac{export_{ij} + import_{ij}}{\sum_{n=1}^{N} (export_{in} + import_{in})}$, where $export_{ij}$ and $import_{ij}$ are the nominal values of i's exports to and imports from j. Similar to the distance-based matrices above, the elements in row i of $\boldsymbol{W_{trad}}$ also sum to unity.

We refer to all N spatial units accommodated in the spatial weight matrices as *global partners*. If we limit our scope to regional partners, we can apply a selection matrix $\boldsymbol{W}^S$ that denotes the k-nearest neighbors of unit i. $\boldsymbol{W}^S$ is a binary matrix, with elements $w^s_{ij} = 1$ if unit j belongs to the k geographically nearest unit for i (and 0 otherwise).

Table 1. Sampled Countries in the Global Tourism System.

Region	Countries				
Africa	Ethiopia	South Africa			
Americas	Argentina	Brazil	Canada	Chile	Mexico
	Peru	United States			
East Asia and the Pacific	Australia	China	Indonesia	Japan	Korea
	Malaysia	New Zealand	Philippines	Singapore	Thailand
Europe	Austria	France	Germany	Greece	Israel
	Italy	Netherlands	Norway	Poland	Portugal
	Russian Federation	Spain	Sweden	Turkey	United Kingdom
Middle East	Egypt	Saudi Arabia	United Arab Emirates		
South Asia	India	Iran			

Note. Region category is defined as per the World Tourism Organization's Compendium of Tourism Statistics.

The Hadamard product of $\boldsymbol{W}^S$ and the global partners spatial weight matrix $\boldsymbol{W}$, that is, $\boldsymbol{W}^S \odot \boldsymbol{W}$, after row-standardization, captures the spatial externalities of the *k-nearest partners*. In Section Empirical Results, we report estimates of spatial dependence among both *global* and *k-nearest partners*.

Data Description. Annual data for the variables described above were collected from various international macroeconomic databases. The sample period is 1995 to 2022. We constructed a global system of tourism markets by including in our sample 39 countries (see Table 1) that meet the following criteria: (1) there is a geographical spread of countries, (2) the countries are major destinations in their regions, and (3) there is good availability of data. Overall, these 39 countries accounted for approximately 76% of total tourist arrivals worldwide in 2022. In line with the core–periphery view of the world system, our use of major destinations should be sufficient to capture global tourism trends, which are driven by core influential actors in the system. This approach is also consistent with the practices in similar cross-country spatial studies (e.g., Asgharian et al., 2013; P. Elhorst et al., 2013; Ouchen & Montargot, 2022; Ragoubi & El Harbi, 2018).

Tables 2 and 3 summarize the dependent and independent variables, including their operational definitions, data sources, and descriptive statistics. Wherever multiple sources are available for certain variables, we chose the source that offered the most data points.

Regarding the spatial weight matrices, $\boldsymbol{W}_{trad}$, $\boldsymbol{W}_{inst}$, $\boldsymbol{W}_{cult}$, and $\boldsymbol{W}_{geog}$, we resorted to a variety of sources. It should be noted that $\boldsymbol{W}_{inst}$ and $\boldsymbol{W}_{trad}$ are time-varying, whereas $\boldsymbol{W}_{cult}$ and $\boldsymbol{W}_{geog}$ are time-invariant.

$\boldsymbol{W}_{trad}$ (bilateral trade share): Trade shares were calculated as described in Section Spatial Weight Matrices. Annual nominal values of exports and imports were collected from the Direction of Trade Statistics of the International Monetary Fund.

$\boldsymbol{W}_{inst}$ (institutional proximity): We gathered annual data on the 12 components of political risk ratings published in the PRS Group's International Country Risk Guide. These data are country specific and cover 12 dimensions of political risk, ranging from government stability, corruption, law and order, and democratic accountability to bureaucracy quality. Institutional distance was calculated as the Euclidean distance of the 12 dimensions between two countries.

$\boldsymbol{W}_{cult}$ (cultural proximity): Data on Hofstede's cultural dimensions were taken from Geert Hofstede's research site (https://geerthofstede.com/). There are six dimensions: individualism, power distance, masculinity, uncertainty avoidance, long-term orientation, and indulgence. We calculated cultural distance as the Euclidean distance of the six dimensions between two countries.

$\boldsymbol{W}_{geog}$ (geographical proximity): We computed the geographical distance between two countries using the information in the R statistical package *cepiigeodist* provided by the Centre d'Études Prospectives et d'Informations Internationales.

Figure A1 visualizes these distance/proximity measures through matrices of gradient colors, where each cell represents the degree of distance/proximity between two countries.

Subsetting the Sample

Because we are interested in tracking the varying degrees of spatial dependence over the sample period, we divided the sample into multiple sub-periods. To this end, we conducted the panel data structural break test, developed by Ditzen et al. (2021), on the tourist arrivals variable. This test can detect an unknown number of breaks and identify break dates.

The results are presented in Table 4. The test returned a series of *F*-statistics, which suggest that the highest number of breaks in the sample was four. In addition, the

Table 2. Definitions and Sources of Variables.

Variable	Measurement	Unit	Data source
Tourist arrivals	Arrivals of non-resident tourists	Thousand persons	Compendium of Tourism Statistics, World Tourism Organization
Real GDP index	GDP in constant 2015 US$ converted to index	Index, 2015 = 100	World Development Indicators, World Bank
Price level (adjusted by US$)	Calculated as $\frac{\text{consumer price index}}{\text{exchange rate index}} \times 100$ (base year: 2015). Where CPI data is not available, the GDP deflator measure is used in lieu. Exchange rate index is derived by converting local currency per US$ (period average) measure to an index with the base year as 100.	Index, 2015 = 100	International Financial Statistics, International Monetary Fund
Country risk index	Composite index reflecting political, economic, and financial risks	Index, range 0–100	International Country Risk Guide, The PRS Group
Oil price	Brent crude oil spot price (free-on-board) in constant 2015 US$	Dollars per barrel	The U.S. Energy Information Administration
KOF Globalization index de jure	Composite index reflecting economic, social, and political globalization	Index, range 0–100	KOF Globalization Index, KOF Swiss Economic Institute
KOF Economic Globalization index de jure	Composite index characterizing policies and conditions behind long distance flows of goods, capital, and services	Index, range 0–100	KOF Globalization Index, KOF Swiss Economic Institute
KOF Social Globalization index de jure	Composite index characterizing policies and conditions facilitating the spread of ideas, information, images, and people	Index, range 0–100	KOF Globalization Index, KOF Swiss Economic Institute
KOF Political Globalization index de jure	Composite index characterizing conditions enabling the diffusion of government policies	Index, range 0–100	KOF Globalization Index, KOF Swiss Economic Institute

Note. Kalman smoothing and state space models are used to impute missing values in the dataset.

associated four break dates were identified, together with their 95% confidence intervals. Considering the actual events, we defined these five sub-periods as (1) 1995 to 2000, (2) 2001 to 2006, (3) 2007 to 2011, (4) 2012 to 2019, and (5) 2020 to 2022. Periods 1 and 2 were characterized by macroeconomic stability. The macro policy environment in Period 2 was even more relaxed than in Period 1 (e.g., lax monetary policy in the developed world) in view of the September 11 attacks, which substantially disrupted international tourism, and the dot-com crash, which caused a mild recession. Period 3 marked the turning point of hyperglobalization as the financial crisis hit the world markets. Period 4 saw economies recover from the financial crisis and, for some, from their sovereign debt crisis. In this period, growing discontent with globalization was brewing. In Period 5, geopolitical tensions were heightened, compounded by the devastating impact of the pandemic.

Empirical Results

Our modeling strategy involved implementing the spatial autoregressive model across several specifications, with independent variables and spatial weight matrices being replaced alternately.

Spatial Dependence Among Global and k-Nearest Partners

As mentioned in Section Spatial Weight Matrices, we used spatial weight matrices constructed based on all global partners and k-nearest partners. To determine the value of k, we experimented alternately with 5, 7, 9, and 11. Our preliminary analysis suggested that the model fit (in terms of R-squared) was best when $k = 9$. Hence, we opted to use this value for the regressions.

Tables 5 to 8 report the estimation results capturing spatial dependence among both global partners (i.e., all 39 countries in the sample) and each country's nine nearest partners. Each table corresponds to one connectivity mechanism. Overall, the results suggest that the size of an economy (captured by the *real GDP index*) was positively associated with the volume of tourist inflows, with the coefficient ranging from 0.216 to 1.047. The effect of the general *price level* tended to be statistically insignificant. These findings are consistent with the existing literature (for a review, see Rosselló Nadal & Santana Gallego, 2022).

When it comes to the geopolitical and globalization factors, there was agreement across model specifications that globalization indices predict tourist inflows. The composite *KOF Globalization index* was unequivocally significant, with its coefficient constantly above 1, higher

Table 3. Descriptive Statistics and Variable Correlations.

Variable	Obs	Min	Max	Median	Mean	Standard deviation	Tourist arrivals	Real GDP index	Price level (adjusted by US$)	Country risk index	Oil price	KOF globalization index de jure	KOF economic globalization index de jure	KOF social globalization index de jure	KOF political globalization index de jure
Tourist arrivals	1,092	103.3	162,537.9	8,264.9	16,609.8	21,211.5	1.000								
Real GDP index	1,092	16.6	165.5	88.6	84.0	22.9	0.117	1.000							
Price level (adjusted by US$)	1,092	27.9	313.2	96.2	91.1	24.0	0.058	0.657	1.000						
Country risk index	1,092	45.0	92.4	75.3	74.8	8.0	0.071	0.083	0.080	1.000					
Oil price	1,092	18.6	117.2	56.1	60.9	29.3	0.119	0.404	0.585	−0.024	1.000				
KOF globalization index de jure	1,092	25.5	93.2	76.2	74.4	12.9	0.176	0.487	0.330	0.549	0.182	1.000			
KOF economic globalization index de jure	1,092	13.1	94.5	72.5	68.6	17.4	0.106	0.260	0.142	0.630	0.032	0.869	1.000		
KOF social globalization index de jure	1,092	12.2	92.1	72.5	69.4	16.3	0.075	0.517	0.406	0.579	0.241	0.917	0.721	1.000	
KOF political globalization index de jure	1,092	44.0	100.0	88.6	85.2	12.0	0.310	0.484	0.302	0.065	0.211	0.706	0.364	0.542	1.000

than all other variables included. This strong effect stems from the conditions that facilitate *social* and *political globalization*, as evidenced by the statistically significant coefficients on these two variables in Models (5) and (10). This makes sense given that international tourism is perceived primarily as a form of globalization of social interactions (Titievskaia et al., 2020). The KOF index framework also conceptualizes international tourism as a component of social globalization, facilitated by infrastructure such as the freedom to visit and international airports. In addition, the social globalization index also embeds the conditions that drive trade in cultural goods and recreational services. Regarding political globalization, the index measures the availability of international organizations and bilateral investment treaties. It provides an indication of how favorable a country's political environment is to international connections. The *country risk index* also proved to be a positive factor in pulling in visitors, although its statistical significance was ambiguous: the higher the index rating, the lower the risk associated with a country and the more visitors are attracted. This result corroborates the literature, such as Ghalia et al. (2019) and Tang (2018). Meanwhile, *oil price*, a factor sensitive to geopolitical shifts, tends to be statistically insignificant.

Further, the value of the spatial lag coefficient ρ was unanimously significant and, in each table, highly robust across model specifications. Focusing on Models (1) to (5), which depict the spatial dependence among all partners in the sample, we observe that institutional proximity ($\boldsymbol{W_{inst}}$) exerted stronger spatial externalities (ρ ranging from 0.530 to 0.669) than other mechanisms (ρ predominantly between 0.400 and 0.500). This finding suggests that at the global level, the spatial spillovers of tourist flows are stronger between countries that are institutionally close than between countries linked through economic, cultural, and geographical mechanisms. A plausible explanation is that close institutional proximity produces similar visa arrangements and, as Wang and Heinonen (2015) found, opens up the possibility of air transport liberalization, thus supporting travelers' multi-destination travel plans. In addition, as per the supply-side argument in Section Spatial Dependence Between Tourism Markets, close institutional proximity enhances the productivity and attractiveness of tourism supply in agglomeration economies, helping destinations pull in spillovers of tourist flows. Furthermore, close institutional proximity can influence countries' decisions to form trade agreements (Liu et al., 2024), providing another channel of spatial interactions on a global scale. Our estimates of ρ from Models (1) to (5) are consistent with those obtained in a similar global context, for example, by Ouchen and Montargot (2022).

Next, we turn to Models (6) to (10), where the spatial interactions were limited to the nine nearest partners. The

Table 4. Structural Break Test for Panel Data.

Test	Test statistic	Bai and Perron critical values		
		1% Critical value	5% Critical value	10% Critical value
$F(1\|0)$	42.99	7.68	5.74	4.91
$F(2\|1)$	18.10	8.42	6.47	5.70
$F(3\|2)$	17.41	8.86	7.01	6.14
$F(4\|3)$	10.16	9.34	7.42	6.45
$F(5\|4)$	7.33	9.59	7.64	6.74
Detected number of breaks:		4	4	5
Break point number		Date	95% Confidence interval	
1		1999	1998	2000
2		2005	2003	2007
3		2013	2012	2014
4		2018	2017	2019

Note. The detected number of breaks indicates the highest number of breaks for which the null hypothesis is rejected.

degree of spatial dependence (ρ) was typically smaller than that of global partners, indicating that the total spatial spillover effects of regional partners were weaker. The results exhibit a similar pattern to Models (1) to (5) in that the regional-level spatial influence exerted via the institutional connectivity mechanism was the strongest (ρ ranging from 0.469 to 0.600), followed by geographical and then other mechanisms. Our findings highlight the relevance of non-geographical connectivity mechanisms to international tourism. Notably, we reveal that as globalization weakens, institutional proximity will play an increasingly dominant role in shaping tourism flows.

The results in Tables 5 to 8 cover the period 1995 to 2019, which is shorter than the entire sample (1995–2022). In our preliminary analysis, which used the entire sample, we found the spatial lag coefficient ρ to be exceptionally large. In most cases, it was revised to between 0.700 and 0.900, implying extraordinary spatial effects. As we will see in the next section, these unusually high values are likely due to the period 2020 to 2022 being an outlier because of the pandemic. Given this abnormality, in the final version of Tables 5 to 8, we limited the data to 1995 to 2019 to obtain estimates that reflect "normal" conditions.

Spatial Dependence Over Time

We then estimated the spatial autoregressive model using sub-period samples to determine how the degree of spatial dependence evolved from one period to another. This exercise produced one set of spatial lag coefficients for each of the five sub-periods. Figures 5 to 8 present the estimates of ρ for each sub-period, which were derived from the regressions of models similar to those in Tables 5 to 8. Each figure corresponds to a single connectivity mechanism.

In each figure, the estimates are generally consistent across the model specifications. A common pattern to all four figures is that ρ tended to be the smallest and least significant for Period 3, when the global financial crisis broke out, indicating weakened spatial dependence regardless of the geographic scale levels. This corroborates the consensus that the 2008 Global Financial Crisis marked the turning point of hyperglobalization. The financial crisis disrupted the growth of international tourism in 2007 to 2009, and it was not until 2010 that the level of global tourist flows returned to pre-crisis levels (Figure 3). After the crisis (Period 4), the general pattern saw the degree of *global* spatial interactions (captured by the green circles in the figures) decline. Spatial influence via trade links (Figure 5), cultural proximity (Figure 7), and geographical proximity (Figure 8) only resumed to a level close to or slightly below the pre-crisis level (Period 2). In contrast, connectivity via institutional mechanisms (Figure 6) was strengthened relative to Period 2. This may be explained by recent shifts in how countries are interconnected, with rising trade protectionism, heightened cultural conflicts, and the growth convergence effects of institutional proximity, as documented by Ahmad and Hall (2023).

The picture becomes more nuanced when we turn to *regional* (*k-nearest*) partners. Post crisis (Period 4), the degree of spatial dependence (represented by the blue squares) via trade links (Figure 5) and geographical proximity (Figure 8) failed to recover fully, but it exceeded the pre-crisis level (Period 2) via institutional (Figure 6) and cultural (Figure 7) mechanisms. The rising importance of institutional connectivity confirms our finding in the previous section that close institutional proximity facilitates spatial spillovers. The diverging patterns for the cultural mechanism, where ρ declines for global partners and rises for regional partners in Period 4 relative to Period 2, may

Table 5. Estimation Models of Spatial Dependence Via $\boldsymbol{W_{trad}}$ (Bilateral Trade), 1995 to 2019.

	Global partners					k-Nearest partners				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals
Real GDP index	1.018***	0.970***	1.018***	0.453***	0.304***	1.027***	0.978***	1.029***	0.519***	0.378***
	(0.046)	(0.047)	(0.047)	(0.058)	(0.059)	(0.047)	(0.048)	(0.047)	(0.059)	(0.059)
Price level	−0.024	−0.141**	−0.025	0.026	−0.018	0.014	−0.101	0.015	0.074	0.030
	(0.047)	(0.053)	(0.047)	(0.043)	(0.043)	(0.047)	(0.053)	(0.047)	(0.043)	(0.044)
Oil price		0.093***					0.093***			
		(0.022)					(0.022)			
Country risk index			0.013					−0.090		
			(0.161)					(0.161)		
KOF globalization index				2.102***					1.950***	
				(0.150)					(0.152)	
KOF economic globalization index					0.032					−0.007
					(0.067)					(0.069)
KOF social globalization index					1.056***					1.028***
					(0.095)					(0.097)
KOF political globalization index					1.253***					1.160***
					(0.170)					(0.176)
W matrix: $\boldsymbol{W_{trad}}$										
ρ (spatial lag coefficient)	0.408***	0.426***	0.410***	0.488***	0.457***	0.305***	0.321***	0.304***	0.339***	0.306***
	(0.041)	(0.041)	(0.042)	(0.038)	(0.036)	(0.034)	(0.034)	(0.035)	(0.032)	(0.031)
R-squared	.696	.702	.696	.749	.766	.692	.698	.692	.738	.754
Adjusted R-squared	.696	.701	.695	.749	.765	.691	.697	.691	.737	.752
Number of groups	39	39	39	39	39	39	39	39	39	39
Number of time periods	25	25	25	25	25	25	25	25	25	25

Note. $k = 9$ nearest partners; all variables are log-transformed; standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 6. Estimation Models of Spatial Dependence Via $\boldsymbol{W_{inst}}$ (Institutional Proximity), 1995 to 2019.

	Global partners					k-Nearest partners				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals
Real GDP index	0.602***	0.599***	0.576***	0.293***	0.216***	0.552***	0.545***	0.539***	0.316***	0.253***
	(0.052)	(0.053)	(0.052)	(0.059)	(0.060)	(0.053)	(0.054)	(0.053)	(0.059)	(0.059)
Price level	−0.027	−0.047	−0.038	0.038	0.019	0.019	−0.019	0.014	0.076	0.046
	(0.042)	(0.047)	(0.042)	(0.041)	(0.042)	(0.041)	(0.046)	(0.041)	(0.040)	(0.041)
Oil price		0.016					0.033			
		(0.020)					(0.020)			
Country risk index			0.422**					0.254		
			(0.151)					(0.147)		
KOF globalization index				1.457***					1.259***	
				(0.145)					(0.148)	
KOF economic globalization index					0.037					−0.002
					(0.067)					(0.066)
KOF social globalization index					0.659***					0.765***
					(0.097)					(0.096)
KOF political globalization index					1.065***					0.649***
					(0.170)					(0.177)
W matrix: $\boldsymbol{W_{inst}}$										
ρ (spatial lag coefficient)	0.642***	0.638***	0.669***	0.587***	0.530***	0.588***	0.583***	0.600***	0.521***	0.469***
	(0.036)	(0.038)	(0.037)	(0.038)	(0.038)	(0.033)	(0.033)	(0.033)	(0.035)	(0.036)
R-squared	.740	.740	.743	.764	.770	.750	.750	.751	.764	.770
Adjusted *R*-squared	.740	.740	.743	.763	.769	.750	.750	.751	.764	.769
Number of groups	39	39	39	39	39	39	39	39	39	39
Number of time periods	25	25	25	25	25	25	25	25	25	25

Note. $k = 9$ nearest partners; all variables are log-transformed; standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 7. Estimation Models of Spatial Dependence Via $\boldsymbol{W_{cult}}$ (Cultural Proximity), 1995 to 2019.

	Global partners					*k*-nearest partners				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals
Real GDP index	0.851***	0.847***	0.832***	0.439***	0.307***	1.047***	1.035***	1.043***	0.606***	0.440***
	(0.051)	(0.051)	(0.052)	(0.060)	(0.060)	(0.049)	(0.050)	(0.050)	(0.060)	(0.061)
Price level	−0.034	−0.065	−0.046	0.036	0.003	0.029	−0.026	0.025	0.099*	0.054
	(0.046)	(0.051)	(0.046)	(0.043)	(0.043)	(0.048)	(0.053)	(0.048)	(0.045)	(0.045)
Oil price		0.028					0.050*			
		(0.021)					(0.022)			
Country risk index			0.329*					0.097		
			(0.162)					(0.170)		
KOF globalization index				1.727***					1.804***	
				(0.149)					(0.156)	
KOF economic globalization index					−0.038					−0.089
					(0.068)					(0.070)
KOF social globalization index					0.845***					0.935***
					(0.097)					(0.101)
KOF political globalization index					1.274***					1.341***
					(0.173)					(0.179)
W matrix: $\boldsymbol{W_{cult}}$										
ρ (spatial lag coefficient)	0.449***	0.442***	0.473***	0.429***	0.388***	0.217***	0.208***	0.223***	0.207***	0.183***
	(0.037)	(0.038)	(0.039)	(0.036)	(0.035)	(0.031)	(0.032)	(0.032)	(0.030)	(0.028)
R-squared	.710	.710	.712	.745	.759	.682	.683	.682	.721	.740
Adjusted *R*-squared	.710	.710	.711	.745	.758	.682	.683	.682	.720	.739
Number of groups	39	39	39	39	39	39	39	39	39	39
Number of time periods	25	25	25	25	25	25	25	25	25	25

Note. $k = 9$ nearest partners; all variables are log-transformed; standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 8. Estimation Models of Spatial Dependence Via $\boldsymbol{W_{geog}}$ (Geographical Proximity), 1995 to 2019.

	Global partners					*k*-nearest partners				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals
Real GDP index	0.697***	0.694***	0.688***	0.444***	0.334***	0.706***	0.701***	0.700***	0.482***	0.370***
	(0.050)	(0.051)	(0.051)	(0.057)	(0.058)	(0.049)	(0.050)	(0.050)	(0.056)	(0.058)
Price level	−0.009	−0.033	−0.014	0.056	0.020	0.014	−0.018	0.011	0.074	0.036
	(0.042)	(0.047)	(0.042)	(0.041)	(0.042)	(0.042)	(0.047)	(0.042)	(0.041)	(0.042)
Oil price		0.021					0.028			
		(0.020)					(0.020)			
Country risk index			0.221					0.159		
			(0.149)					(0.148)		
KOF globalization index				1.302***					1.214***	
				(0.151)					(0.154)	
KOF economic globalization index					−0.070					−0.094
					(0.066)					(0.066)
KOF social globalization index					0.832***					0.826***
					(0.096)					(0.096)
KOF political globalization index					0.783***					0.721***
					(0.176)					(0.179)
W matrix: $\boldsymbol{W_{geog}}$										
ρ (spatial lag coefficient)	0.514***	0.510***	0.525***	0.446***	0.405***	0.476***	0.472***	0.483***	0.406***	0.368***
	(0.032)	(0.033)	(0.033)	(0.034)	(0.034)	(0.029)	(0.030)	(0.030)	(0.032)	(0.032)
R-squared	.742	.742	.744	.757	.767	.745	.745	.745	.755	.766
Adjusted *R*-squared	.742	.742	.743	.756	.766	.744	.744	.745	.755	.765
Number of groups	39	39	39	39	39	39	39	39	39	39
Number of time periods	25	25	25	25	25	25	25	25	25	25

Note. $k = 9$ nearest partners; all variables are log-transformed; standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

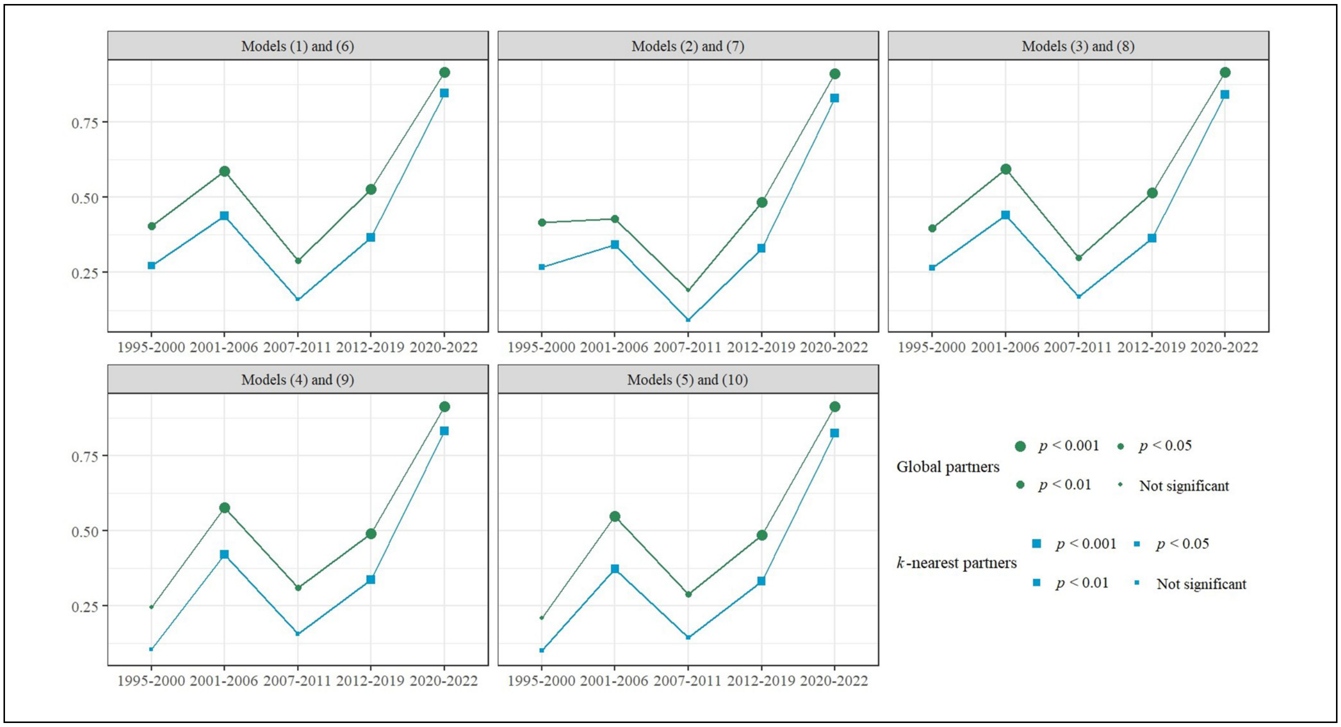

Figure 5. Estimates of spatial lag coefficient ρ for sub-periods (W matrix: bilateral trade $\boldsymbol{W_{trad}}$).
Note. $k = 9$ nearest partners; models have the same specifications as those presented in Table 5; the size of symbols reflects the significance level.

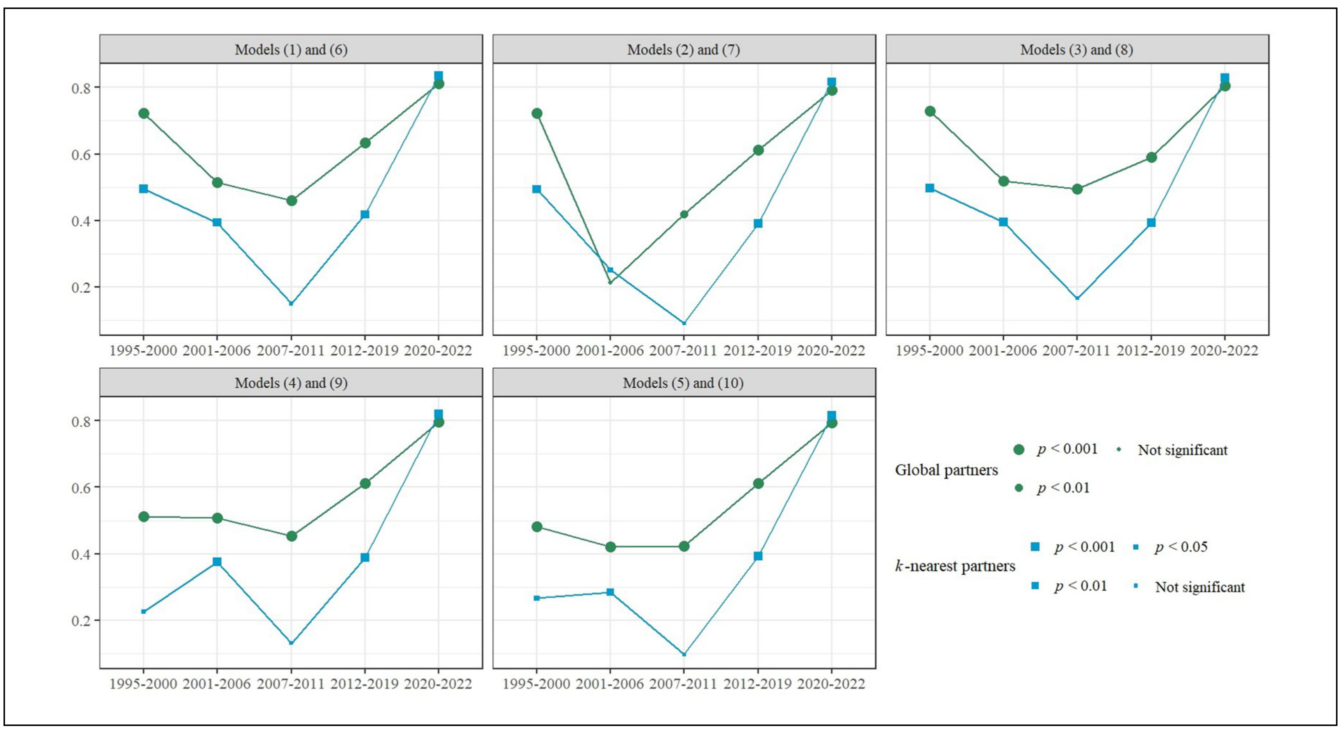

Figure 6. Estimates of spatial lag coefficient ρ for sub-periods (W matrix: institutional proximity $\boldsymbol{W_{inst}}$).
Note. $k = 9$ nearest partners; models have the same specifications as those presented in Table 6; the size of symbols reflects the significance level.

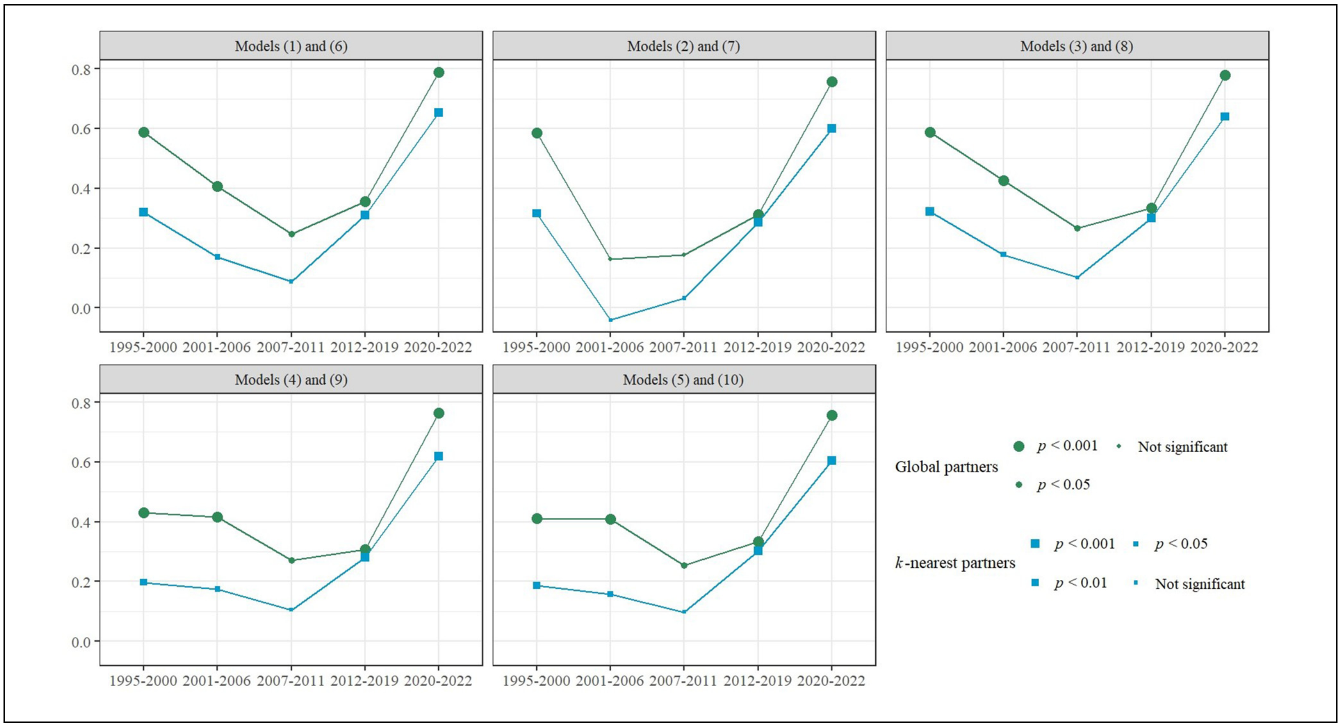

Figure 7. Estimates of spatial lag coefficient ρ for sub-periods (W matrix: cultural proximity $\boldsymbol{W_{cult}}$).
Note. $k = 9$ nearest partners; models have the same specifications as those presented in Table 7; the size of symbols reflects the significance level.

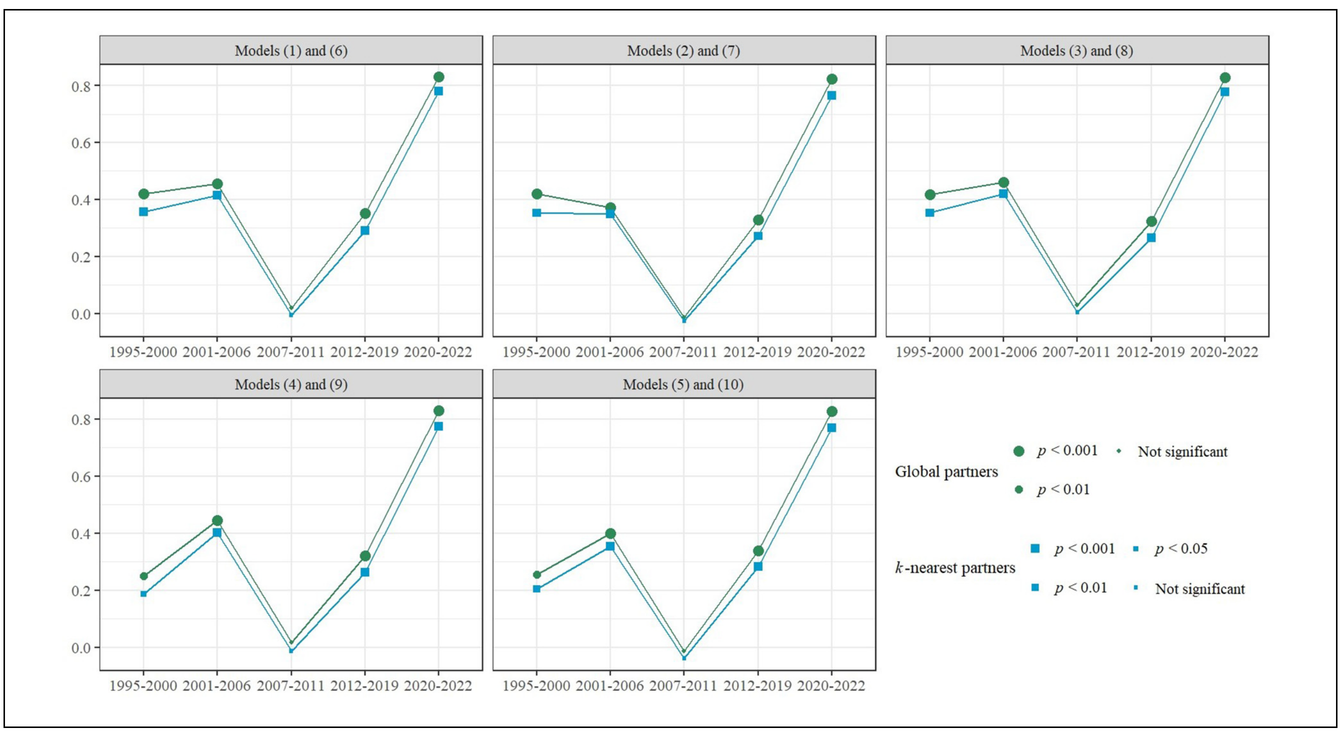

Figure 8. Estimates of spatial lag coefficient ρ for sub-periods (W matrix: geographical proximity $\boldsymbol{W_{geog}}$).
Note. $k = 9$ nearest partners; models have the same specifications as those presented in Table 8; the size of symbols reflects the significance level.

be due to the greater cultural affinity achieved at regional levels than at global levels.

In the previous section, we alluded to Period 5 being an outlier, as evidenced by the significant increase in ρ for the last period in the four figures. In Figure 6, which depicts the institutional mechanism, the spatial lag coefficient is even higher for global partners than for regional partners, although only to a minimal extent. As suggested by Vega and Elhorst (2015), common factors such as policy changes and health warnings can contribute to a large ρ. Synchronized health measures in response to the pandemic certainly support this line of explanation. The rapid spread of the virus across borders forced most governments to simultaneously adopt social restrictions and quarantine measures for incoming visitors. This was particularly true at the regional level because new variants often spread regionally first. Regional tourism markets then co-moved, prompted by the closure and reopening of national borders.

Caution should be exercised when interpreting the difference between ρ for global partners and for k-nearest partners, that is, the gap between the green circle and blue square for each period in the figures. From a statistical perspective, there is no guarantee that the gap is significant. To assert whether there is indeed a difference, we carried out a z-test on the equality between a green circle and a blue square. The test results are presented in Table A1 in the Appendices. The null hypothesis of the test in each period was that ρ for k-nearest partners (blue squares) was equal to ρ for global partners (green circles). In general, if both coefficients are significant on their own, then the z-test tends to reject the null hypothesis, suggesting no equality between them. However, if either coefficient is insignificant, the z-test often accepts the null hypothesis of equality. On quite a number of occasions where equality was detected, we found that regional spatial interactions largely accounted for a country's global interactions, meaning that the extensity of spatial interactions may not be truly global.

Robustness Checks

Before the main models presented above, we explored a range of alternatives during the preliminary analysis stage. In particular, we experimented with the spatial Durbin model, which augments the spatial autoregressive model Equation 1 by including spatially lagged explanatory variables, $\boldsymbol{W_t X_t}$, which are cross-country weighted averages of real GDP, price level, country risk, and KOF indices. This form of spatial lag is a way of capturing global common correlated effects (see Dees et al., 2007; Kuok et al., 2023). Unfortunately, the results turned out to be far from satisfactory, with the spatial lag coefficients on $\boldsymbol{W_t X_t}$ being inconsistent across specifications and, on several occasions, explosive. Therefore, we did not pursue the spatial Durbin model as a viable alternative.

Regarding the main models, we conducted a series of Lagrange Multiplier tests for spatial dependence (Anselin et al., 1996) to confirm our model specification. The tests examine the possibility of a spatial lag or spatial error in the residuals against the null hypothesis of no such spatial effect. If the null hypothesis is rejected, then a spatial autoregressive or spatial error model is preferred. The test results are presented in Table A2 in the Appendices. On several occasions, the p-values for the error and robust error tests were greater than 0.05, whereas those for the lag and robust lag tests were all below 0.001. These results confirmed the existence of spatial lag effects and suggested that the spatial autoregressive model was appropriate. We also conducted the Hausman test for the spatial panel data model to confirm the fixed-effects estimator. The test results are also reported in Table A2. They were not unanimous across models but leaned toward the rejection of the null hypothesis, favoring the fixed-effects estimator.

We also experimented with additional spatial weight matrices. Instead of using distance-based continuous measures, we attempted two binary matrices, $\boldsymbol{W_{bloc}}$ and $\boldsymbol{W_{regn}}$, the former denoting membership in a trade bloc and the latter signifying membership in a geographical region. That is, the elements $W_{bloc ij} = 1$ if country i and j are connected through their membership in the same trade bloc (and 0 otherwise), while the elements $W_{regn_{ij}} = 1$ if country i and j belong in the same geographical region (and 0 otherwise). Both $\boldsymbol{W_{bloc}}$ and $\boldsymbol{W_{regn}}$ were then row standardized so that the weights in row i ($\forall i = 1, 2, \ldots, N$) sum to unity. The two spatial weight matrices and their spatial lag terms were intended to capture the spatial influence of alternative forms of regions. The trade blocs considered were the 21 large established ones listed on the globalEDGE portal (https://globaledge.msu.edu/global-insights/by/trade-bloc). Meanwhile, the geographical regions were defined as per the World Tourism Organization's Compendium of Tourism Statistics (see Table 1). The results are presented in Tables A3 and A4 in the Appendices. The coefficients were consistent with those of Models (6) to (10) in Table 5 (bilateral trade) and Table 8 (geographical proximity) for the k-nearest partners. This is not surprising given that the alternative matrices capture connectivity mechanisms similar to those of the main models.

Based on these checks, we can conclude that our choice of spatial autoregressive models and the estimates from the main models were robust.

Discussions

A Trend Toward Regionalization?

Our results revealed that spatial dependence was exceptionally strong during the pandemic. As discussed in Section Spatial Dependence over Time, one possible contributor was common responses such as health measures, vaccine strategies, and border controls, which regulated the flow of international visitors in a coordinated manner. However, this does not preclude other underlying, structural changes in international institutions that may also have driven shifts in spatial influence patterns. Jones and Giacomin (2022) argue that regionalization intensified following the outbreak of the pandemic. They point out that multinational enterprises now face “structural breaks” in their value chains, and intra-regional trade flows have increased markedly, with the inauguration of Asia’s 15-member Regional and Comprehensive Economic Partnership in January 2022 being the landmark step in this trend.

Put the pandemic aside, though our results uncovered signs of weakened global spatial dependence but growing regional spatial dependence via institutional and cultural mechanisms, this does not mean that regionalization is set in stone. Our post-pandemic sample was not large enough to draw this conclusion yet. Moreover, the evolution of globalization processes is neither linear nor unidirectional (Song et al., 2018). While the liberalism and realism approaches reviewed in Section The Retreat of Globalization both predict a reversal of globalization, they offer different prospects: liberalism suggests a patchwork of economic linkages, whereas realism predicts the emergence of economic blocs around major countries (Witt, 2019). Therefore, various future scenarios are possible, and more time and data are needed to assess how the dynamics will unfold.

Institutional Proximity and Regionalization

If, over time, regionalization comes to dominate the global economy, it should not be defined solely in geographical terms. Instead, non-geographical mechanisms such as the global distribution of institutional classifications can also drive this trend. Regionalization can manifest as trade blocs (as in Table A3) or other intergovernmental arrangements. Nations may cluster into blocs that share governance models, regulatory frameworks, and cultural affinity to reinforce integration through institutional compatibility rather than pure market logic.

As concerns the tourism industry, if travel patterns are increasingly shaped by institutional factors, the global travel regime may undergo some form of fragmentation. One of the visible ways in which institutional factors are reinforced in the tourism industry is through visa policies. Visa restrictions, which traditionally serve as a line of defense against unwanted foreigners or *personae non-gratae* for national and economic security reasons, have increasingly become a geopolitical instrument, signaling strategic alliances, or institutional decoupling (García-Herrero & Tan, 2022). In recent years, countries have selectively relaxed visa policies for institutionally similar partners while tightening restrictions for those deemed geopolitically or institutionally distant (Czaika et al., 2018). An example is the United States Trump administration’s 2017 travel bans on immigration from seven predominantly Muslim countries. This form of institutional segmentation of travel access is likely to push tourists to gravitate toward destinations where visa procedures are simpler and entry requirements are less restrictive.

Practical Implications

For tourism firms, the shift toward a more fragmented global business environment requires a reorientation of the market focus and a reconfiguration of resources. From the demand management perspective, firms should be prepared to reorient their market focus from a culturally diverse customer base to a more regionally concentrated one. Firms may prioritize attracting tourists from institutionally aligned regions. A thriving tourism market there could generate healthy spatial spillovers of tourist flows, making joint efforts such as collaborative marketing campaigns and partnerships with businesses in politically aligned regions an effective strategy for boosting tourism demand. Panel (b) of Figure A1 can serve as a guide for identifying the institutional structure of major economies worldwide.

On the supply side, firms, especially multinationals, should reconfigure market portfolios to mitigate the risks associated with geopolitical volatility. This reconfiguration could involve prioritizing or reallocating investments toward institutionally aligned regions, forging partnerships with local businesses there, and expanding presence to raise awareness of the home market. Firms and regional tourism boards can also develop multi-destination itineraries to direct tourist flows. To facilitate seamless travel experiences, firms and regional tourism boards should advocate for reciprocal visa agreements, streamlined travel procedures, and, more importantly, enhanced infrastructure linkages within institutionally proximate networks. A recent example is the Grand Tours Visa, a Schengen-style unified visa offering access to six Gulf countries, to be launched by the Gulf Cooperation Council to boost regional tourism.

At the macro level, one implication is the increasing synchronicity of business cycles in institutionally similar countries, which might be driven by common shocks to all countries (e.g., oil price shocks that increase or decrease the price of oil for everyone), shocks to countries in the same region (e.g., weather disruptions or regional conflicts), or shocks originating in one country being propagated rapidly to nearby locations (Cooke et al., 2015). As discussed in Section Connectivity and

Distance, the extent to which business cycles synchronize across countries depends on factors such as physical distance, trade volume, and similarities in institutional frameworks or language. If global integration continues to be constrained by geopolitical shifts, leading to a more regionalized structure, then economic shocks will likely propagate faster in institutionally aligned clusters than in the global market. Hence, tourism firms must closely monitor developments in institutionally similar markets that may cause spillover effects in the future.

Conclusion

This study examines the retreat of globalization through the lens of international tourism. We hypothesized that the inherent conflict between economic integration and democratic politics and the shifts in the geopolitical landscape would cause spatial dependence between tourism markets on a global scale to decline, but it would strengthen for those markets that are proximate to each other. Evidence regarding this hypothesis will prompt a theoretical reflection on the direction in which the global business environment will evolve and how "distance" will continue to shape the global travel regime.

We applied a spatial autoregressive model to cross-country tourist flow statistics and estimated the degree of spatial dependence. Our empirical results revealed nuanced findings. First, spatial dependence was considerably weakened during the Global Financial Crisis of 2008. Second, after the crisis, the interconnectedness between tourism markets has increasingly been driven by institutional proximity, while the influence of trade links and pure geographical distance has diminished. Third, the importance of cultural affinity is mixed, declining at the global level but strengthening at the regional level. Lastly, global and regional spatial dependence was exceptionally strong during the pandemic, likely due to coordinated health policy responses.

Our results corroborate the notion that the 2008 Global Financial Crisis marked the turning point of globalization. This also applies to the international movement of people, with weakened interconnectedness characterizing the global tourism industry after the financial crisis relative to the pre-crisis era. Hence, distance is still ingrained in international tourism. Importantly, non-geographical mechanisms, especially institutional proximity, will play an especially important role in shaping tourism flows.

Given our findings, we caution that the tourism industry will navigate a less integrated global business environment, although the future of globalization remains uncertain at this point, and alternative scenarios are possible. Businesses and authorities in the industry should be prepared to reorient their market focus from a culturally diverse customer base to a more regionally concentrated one and should embrace a reconfiguration of their overseas investment portfolios toward institutionally aligned regions. Accordingly, there is greater scope than ever to engage in joint promotional campaigns, develop multi-destination itineraries, and strategically invest in infrastructure to direct tourist flows.

Regarding limitations, our paper focuses on global aggregate patterns, thus omitting micro-level details. Future research can explore the role of interconnectedness between countries in the international propagation of shocks. This will have important implications for understanding whether the impact of shocks is limited to regions or extends globally. Additional studies can also explore the extent to which transaction costs at the firm level have risen in recent years, adding empirical evidence to the question of deglobalization. Methodologically, researchers may exploit spatial econometric models that can simultaneously accommodate multiple spatially lagged dependent variables (resulting from different spatial weight matrices) in a panel data setting to control for different spatial connectivity mechanisms in a single model.

Appendices

Table A1. *Z*-tests for Equality of Spatial Lag Coefficient ρ Between Models.

W matrix	Sub-periods	*Z*-test	Models				
			(1)/(6)	(2)/(7)	(3)/(8)	(4)/(9)	(5)/(10)
W_{trad}	1995–2000	Statistics	0.830	0.854	0.802	0.859	0.713
		p-Value	0.407	0.393	0.423	0.390	0.476
	2001–2006	Statistics	1.123	0.510	1.136	1.150	1.385
		p-Value	0.261	0.610	0.256	0.250	0.166
	2007–2011	Statistics	0.743	0.480	0.735	0.882	0.869
		p-Value	0.457	0.631	0.462	0.378	0.385
	2012–2019	Statistics	1.362	1.218	1.296	1.255	1.271
		p-Value	0.173	0.223	0.195	0.209	0.204
	2020–2022	Statistics	1.182	1.276	1.209	1.282	1.426
		p-Value	0.237	0.202	0.227	0.200	0.154
W_{inst}	1995–2000	Statistics	1.858	1.835	1.833	1.579	1.259
		p-Value	0.063	0.066	0.067	0.114	0.208
	2001–2006	Statistics	0.827	−0.172	0.828	0.895	0.931
		p-Value	0.408	0.864	0.408	0.371	0.352
	2007–2011	Statistics	1.792	1.701	1.864	1.816	1.883
		P-Value	0.073	0.089	0.062	0.069	0.060
	2012–2019	Statistics	2.119	2.042	1.856	2.039	2.103
		p-Value	0.034	0.041	0.064	0.042	0.036
	2020–2022	Statistics	−0.276	−0.243	−0.268	−0.257	−0.227
		p-value	0.783	0.808	0.789	0.797	0.820
W_{cult}	1995–2000	Statistics	2.399	2.358	2.286	1.900	1.934
		p-Value	0.016	0.018	0.022	0.057	0.053
	2001–2006	Statistics	1.908	1.204	1.902	1.930	2.213
		p-Value	0.056	0.229	0.057	0.054	0.027
	2007–2011	Statistics	1.160	0.944	1.192	1.214	1.218
		p-value	0.246	0.345	0.233	0.225	0.223
	2012–2019	Statistics	0.405	0.248	0.284	0.230	0.274
		p-Value	0.685	0.804	0.776	0.818	0.785
	2020–2022	Statistics	1.243	1.281	1.249	1.262	1.360
		p-Value	0.214	0.200	0.212	0.207	0.174
W_{geog}	1995–2000	Statistics	0.590	0.577	0.576	0.495	0.441
		p-Value	0.555	0.564	0.564	0.621	0.659
	2001–2006	Statistics	0.433	0.209	0.414	0.419	0.477
		p-Value	0.665	0.834	0.679	0.675	0.633
	2007–2011	Statistics	0.185	0.085	0.197	0.213	0.195
		p-Value	0.853	0.933	0.844	0.831	0.845
	2012–2019	Statistics	0.656	0.603	0.603	0.606	0.616
		p-Value	0.512	0.547	0.547	0.544	0.538
	2020–2022	Statistics	1.186	1.125	1.141	1.133	1.174
		p-Value	0.236	0.261	0.254	0.257	0.240

Note. The tests are conducted based on Figures 5 to 8 estimates. Each score tests the equality of spatial lag coefficients between models using global partners and *k*-nearest partners as spatial weight matrices.

Table A2. Lagrange Multiplier (LM) Tests and Hausman Tests for Model Specifications.

			Global partners					k-Nearest partners				
			Model					Model				
W matrix	Test		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\boldsymbol{W_{trad}}$	LM error	Statistics	1.437	3.769	0.930	9.868	21.734	0.111	0.693	0.029	0.070	0.027
		p-Value	0.231	0.052	0.335	0.002	0.000	0.739	0.405	0.864	0.791	0.869
	Robust LM error	Statistics	97.189	97.108	106.570	57.093	29.694	148.076	144.466	152.856	131.682	113.827
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	LM lag	Statistics	185.398	196.709	183.160	182.832	156.603	132.523	136.192	129.428	100.375	66.546
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Robust LM lag	Statistics	281.150	290.048	288.800	230.058	164.563	280.489	279.965	282.255	231.987	180.346
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Hausman	Statistics	22.455	24.758	33.309	9.411	7.943	33.685	29.806	21.225	13.904	30.664
		p-Value	0.000	0.000	0.000	0.052	0.242	0.000	0.000	0.000	0.008	0.000
$\boldsymbol{W_{inst}}$	LM error	Statistics	72.107	115.837	66.377	151.909	222.104	22.033	36.238	20.840	29.095	35.751
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Robust LM error	Statistics	0.036	0.191	1.089	27.484	74.415	79.235	77.303	87.561	37.388	24.897
		p-Value	0.850	0.662	0.297	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	LM lag	Statistics	305.168	354.685	311.468	260.454	217.287	238.445	252.690	237.088	189.772	149.819
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Robust LM lag	Statistics	233.097	239.039	246.180	136.028	69.598	295.647	293.754	303.809	198.065	138.966
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Hausman	Statistics	14.918	11.839	12.168	17.250	8.791	52.349	15.917	3.757	1.427	5.607
		p-Value	0.002	0.019	0.016	0.002	0.186	0.000	0.003	0.440	0.840	0.469
$\boldsymbol{W_{cult}}$	LM error	Statistics	42.043	58.514	38.954	68.136	69.162	9.590	17.308	9.110	15.504	34.631
		p-Value	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.003	0.000	0.000
	Robust LM error	Statistics	23.688	26.926	36.560	0.001	6.954	114.369	111.107	126.805	66.693	19.418
		p-Value	0.000	0.000	0.000	0.970	0.008	0.000	0.000	0.000	0.000	0.000
	LM lag	Statistics	241.030	257.783	246.461	186.973	120.313	158.627	166.219	157.601	133.559	110.532
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Robust LM lag	Statistics	222.676	226.195	244.067	118.839	58.104	263.406	260.018	275.295	184.748	95.319
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Hausman	Statistics	1.998	1.139	1.369	0.571	9.994	2.958	3.825	5.136	0.744	4.330
		p-Value	0.573	0.888	0.850	0.966	0.125	0.398	0.430	0.274	0.946	0.632
$\boldsymbol{W_{geog}}$	LM error	Statistics	11.386	18.925	10.657	6.950	18.249	10.650	17.380	10.242	3.220	10.742
		p-Value	0.001	0.000	0.001	0.008	0.000	0.001	0.000	0.001	0.073	0.001
	Robust LM error	Statistics	101.759	100.733	109.931	84.256	47.759	128.571	126.689	136.501	121.838	88.565
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	LM lag	Statistics	159.123	162.316	157.037	120.230	105.964	155.209	157.586	153.485	106.652	93.459
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Robust LM lag	Statistics	249.496	244.124	256.311	197.536	135.474	273.130	266.895	279.744	225.270	171.282
		p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Hausman	Statistics	21.450	15.769	52.327	2.342	2.141	22.816	15.623	46.253	0.659	2.707
		p-Value	0.000	0.003	0.000	0.673	0.906	0.000	0.004	0.000	0.956	0.845

Note. $k = 9$ nearest partners; models take the same specifications as those in Tables 5 to 8.

Table A3. Estimation Models of Spatial Dependence Via $\boldsymbol{W_{bloc}}$ (trade bloc), 1995 to 2019.

	(1)	(2)	(3)	(4)	(5)
Variable	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals
Real GDP index	1.080*** (0.049)	1.066*** (0.049)	1.079*** (0.050)	0.675*** (0.059)	0.503*** (0.061)
Price level	0.054 (0.048)	−0.007 (0.053)	0.052 (0.048)	0.130** (0.045)	0.086 (0.045)
Oil price		0.054* (0.022)			
Country risk index			0.029 (0.170)		
KOF globalization index				1.751*** (0.159)	
KOF economic globalization index					−0.100 (0.071)
KOF social globalization index					0.915*** (0.104)
KOF political globalization index					1.363*** (0.182)
W matrix: $\boldsymbol{W_{bloc}}$					
ρ (spatial lag coefficient)	0.205*** (0.034)	0.195*** (0.034)	0.208*** (0.035)	0.164*** (0.033)	0.132*** (0.032)
R-squared	0.678	0.679	0.678	0.713	0.733
Adjusted R-squared	0.677	0.679	0.677	0.712	0.732
Number of groups	39	39	39	39	39
Number of time periods	25	25	25	25	25

Note. All variables are log-transformed; standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table A4. Estimation Models of Spatial Dependence Via $\boldsymbol{W_{regn}}$ (Geographical Region), 1995 to 2019.

	(1)	(2)	(3)	(4)	(5)
Variable	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals	Tourist arrivals
Real GDP index	0.770*** (0.048)	0.764*** (0.049)	0.755*** (0.049)	0.508*** (0.056)	0.412*** (0.058)
Price level	0.033 (0.042)	−0.001 (0.048)	0.027 (0.042)	0.093* (0.041)	0.065 (0.042)
Oil price		0.029 (0.020)			
Country risk index			0.314* (0.153)		
KOF globalization index				1.320*** (0.153)	
KOF economic globalization index					−0.048 (0.068)
KOF social globalization index					0.721*** (0.100)
KOF political globalization index					0.977*** (0.177)
W matrix: $\boldsymbol{W_{regn}}$					
ρ (spatial lag coefficient)	0.420*** (0.027)	0.415*** (0.028)	0.434*** (0.028)	0.359*** (0.029)	0.307*** (0.029)
R-squared	0.735	0.735	0.737	0.751	0.758
Adjusted R-squared	0.735	0.735	0.737	0.750	0.757
Number of groups	39	39	39	39	39
Number of time periods	25	25	25	25	25

Note. All variables are log-transformed; standard errors in parentheses.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$; geographical region is defined as per the World Tourism Organization's Compendium of Tourism Statistics.

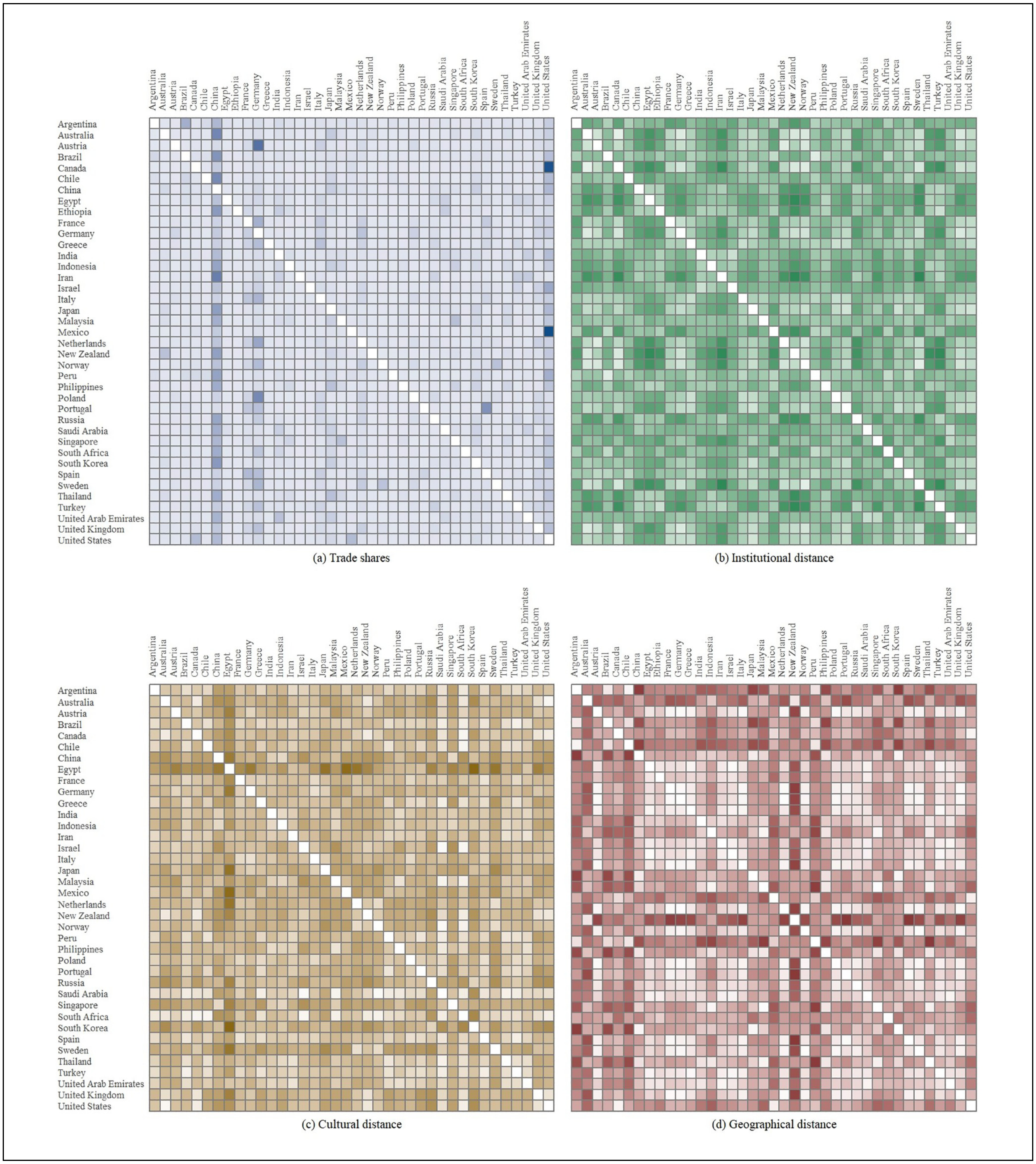

Figure A1. Matrix representation of country connectivity: distance and trade links, 2022.

Note. Panel (a) captures the trade shares of the partner countries (*x*-axis). The darker the color, the higher the trade share and the *tighter* the trade ties. Panels (b) to (d) capture various Euclidean distance measures. The darker the color, the *farther away* the countries are.

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Author Contributions

Zheng Cao: Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft, Writing - review & editing.

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References

Ahmad, M., & Hall, S. G. (2023). The growth effects of economic and political institutions: New evidence from spatial econometrics analysis using historical-based institutional matrix. *Economic Change and Restructuring*, *56*(2), 749–780. https://doi.org/10.1007/s10644-022-09440-1

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*, *26*(2), 153–166. https://doi.org/10.1177/0160017602250972

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*(1), 77–104. https://doi.org/10.1016/0166-0462(95)02111-6

Asgharian, H., Hess, W., & Liu, L.(2013). A spatial analysis of international stock market linkages. *Journal of Banking & Finance*, *37*(12), 4738–4754. https://doi.org/10.1016/j.jbankfin.2013.08.015

Balli, F., & Tsui, W. H. K. (2016). Tourism demand spillovers between Australia and New Zealand: Evidence from the partner countries. *Journal of Travel Research*, *55*(6), 804–812. https://doi.org/10.1177/0047287515569778

Beugelsdijk, S., Ambos, B., & Nell, P. C. (2018). Conceptualizing and measuring distance in international business research: Recurring questions and best practice guidelines. *Journal of International Business Studies*, *49*(9), 1113–1137. https://doi.org/10.1057/s41267-018-0182-4

Cao, Z., Li, G., & Song, H. (2017). Modelling the interdependence of tourism demand: The global vector autoregressive approach. *Annals of Tourism Research*, *67*, 1–13. https://doi.org/10.1016/j.annals.2017.07.019

Chung, M. G., Herzberger, A., Frank, K. A., & Liu, J. (2020). International tourism dynamics in a globalized world: A social network analysis approach. *Journal of Travel Research*, *59*(3), 387–403. https://doi.org/10.1177/0047287519844834

Colantone, I., Ottaviano, G. I., & Stanig, P. (2021). *The backlash of globalisation* (Discussion Paper No. 1800). London: Centre for Economic Performance. https://doi.org/10.2139/ssrn.3925321

Conley, T. G., & Ligon, E. (2002). Economic distance and cross-country spillovers. *Journal of Economic Growth*, *7*, 157–187. https://doi.org/10.1023/a:1015676113101

Cooke, D. A., Kose, M. A., Otrok, C., & Owyang, M. T. (2015, April). Regional vs. Global: How are countries' business cycles moving together these days? *The Regional Economist*. Retrieved November 6, 2024, from https://www.stlouisfed.org/˜/media/Publications/Regional%20Economist/2015/April/Regional_Global_business_cycles.pdf

Czaika, M., de Haas, H., & Villares-Varela, M. (2018). The global evolution of travel visa regimes. *Population and Development Review*, *44*(3), 589–622. https://doi.org/10.1111/padr.12166

Dees, S., Mauro, F. D., Pesaran, M. H., & Smith, L. V. (2007). Exploring the international linkages of the euro area: A global VAR analysis. *Journal of Applied Economics*, *22*(1), 1–38. https://doi.org/10.1002/jae.932

Ditzen, J., Karavias, Y., & Westerlund, J. (2021). Testing and estimating structural breaks in time series and panel data in Stata. *arXiv preprint arXiv:2110.14550*. https://doi.org/10.48550/arXiv.2110.14550

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review*, *26*(3), 244–268. https://doi.org/10.1177/0160017603253791

Elhorst, J. P., Tziolas, I., Tan, C., & Milionis, P. (2024). The distance decay effect and spatial reach of spillovers. *Journal of Geographical Systems*, *26*(2), 265–289. https://doi.org/10.1007/s10109-024-00440-5

Elhorst, P., Zandberg, E., & De Haan, J. (2013). The impact of interaction effects among neighbouring countries on financial liberalization and reform: A dynamic spatial panel data approach. *Spatial Economic Analysis*, *8*(3), 293–313. https://doi.org/10.1080/17421772.2012.760136

Ertur, C., & Koch, W. (2007). Growth, technological interdependence and spatial externalities: Theory and evidence. *Journal of Applied Economics*, *22*(6), 1033–1062. https://doi.org/10.1002/jae.963

Freeman, R. B. (2006). People flows in globalization. *Journal of Economic Perspectives*, *20*(2), 145–170. https://doi.org/10.1257/jep.20.2.145

García-Herrero, A., & Tan, J. (2022). Deglobalisation in the context of United States-China decoupling. *Bruegel*. Retrieved November 6, 2024, from https://www.bruegel.org/policy-brief/deglobalisation-context-united-states-china-decoupling

Ghalia, T., Fidrmuc, J., Samargandi, N., & Sohag, K. (2019). Institutional quality, political risk and tourism. *Tourism Management Perspectives*, *32*, 100576. https://doi.org/10.1016/j.tmp.2019.100576

Giammetti, R., Papi, L., Teobaldelli, D., & Ticchi, D. (2022). The network effect of deglobalisation on European regions. *Cambridge Journal of Regions Economy and Society*, *15*(2), 207–235. https://doi.org/10.1093/cjres/rsac006

Goldberg, P. K., & Reed, T. (2023). *Is the global economy deglobalizing? And if so, why? And what is next? No. w31115*. National Bureau of Economic Research. Retrieved November 6, 2024, from http://www.nber.org/papers/w31115.pdf

Gozgor, G., Lau, M. C. K., Zeng, Y., Yan, C., & Lin, Z. (2022). The impact of geopolitical risks on tourism supply in developing economies: The moderating role of social globalization. *Journal of Travel Research*, *61*(4), 872–886. https://doi.org/10.1177/00472875211004760

Grieser, W., Zekhnini, M., & Ditzen, J. (2022). nwxtregress: Network regressions in Stata, German Stata Users' Group Meetings 2022, Stata Users Group, 10 June. Retrieved November 6, 2024, from http://repec.org/dsug2022/germany22_ditzen.pdf

Gygli, S., Haelg, F., Potrafke, N., & Sturm, J.-E. (2019). The KOF Globalisation Index – revisited. *Review of International Organizations*, *14*(3), 543–574. https://doi.org/10.1007/s11558-019-09344-2

Haini, H., Wei Loon, P., Yong, S. K., & Husseini, S. (2024). Does social globalization affect the relationship between international tourism and economic growth? *Journal of Travel Research*, *63*(1), 252–269. https://doi.org/10.1177/00472875221146779

Hennart, J. F. (2010). Transaction cost theory and international business. *Journal of Retailing*, *86*(3), 257–269. https://doi.org/10.1016/j.jretai.2010.07.009

Jones, G., & Giacomin, V. (2022). Deglobalization and Alternative Futures. *Harvard Business School Technical Note 322-088*. Retrieved November 6, 2024, from https://www.hbs.edu/faculty/Pages/item.aspx?num = 61645

Jovanović, M. N. (2020). *Evolutionary spatial economics: Understanding economic geography and location over time*. Edward Elgar Publishing.

Karimi, M. S., Khezri, M., & Razzaghi, S. (2022). Impacts of regional conflicts on tourism in Africa and the Middle East: A spatial panel data approach. *Current Issues in Tourism*, *25*(10), 1649–1665. https://doi.org/10.1080/13683500.2021.1931054

Kuok, R. U. K., Koo, T. T. R., & Lim, C. (2023). Economic policy uncertainty and international tourism demand: A global vector autoregressive approach. *Journal of Travel Research*, *62*(3), 540–562. https://doi.org/10.1177/00472875211072551

Liu, R., Stengos, T., & Sun, Y. (2024). Spatial spillovers in trade agreement memberships: Does institutional proximity matter? *Review of International Economics*, *32*(3), 1398–1433. https://doi.org/10.1111/roie.12740

Loungani, P., Mody, A., & Razin, A. (2002). The global disconnect: The role of transactional distance and scale economies in gravity equations. *Scottish Journal of Political Economy*, *49*(5), 526–543. https://doi.org/10.1111/1467-9485.00246

Marrocu, E., & Paci, R. (2013). Different tourists to different destinations. Evidence from spatial interaction models. *Tourism Management*, *39*, 71–83. https://doi.org/10.1016/j.tourman.2012.10.009

McGrew, A. (2020). The logics of economic globalisation. In J. Ravenhill (Ed.), *Global political economy* (6th ed., pp. 249–281). Oxford University Press.

McKercher, B., Chan, A., & Lam, C. (2008). The impact of distance on international tourist movements. *Journal of Travel Research*, *47*(2), 208–224. https://doi.org/10.1177/0047287508321191

Morley, C., Rosselló, J., & Santana-Gallego, M. (2014). Gravity models for tourism demand: Theory and use. *Annals of Tourism Research*, *48*, 1–10. https://doi.org/10.1016/j.annals.2014.05.008

Noonan, L., O'Leary, E., & Doran, J. (2020). The impact of institutional proximity, cognitive proximity and agglomeration economies on firm-level productivity. *Journal of Economic Studies*, *48*(2), 257–274. https://doi.org/10.1108/jes-07-2019-0345

Ouchen, A., & Montargot, N. (2022). Non-spatial and spatial econometric analysis of tourism demand in a panel of countries around the world. *Spatial Economic Analysis*, *17*(2), 262–283. https://doi.org/10.1080/17421772.2021.1940256

Ragoubi, H., & El Harbi, S. (2018). Entrepreneurship and income inequality: A spatial panel data analysis. *International Review of Applied Economics*, *32*(3), 374–422. https://doi.org/10.1080/02692171.2017.1342776

Rodrik, D. (2000). How far will international economic integration go? *Journal of Economic Perspectives*, *14*(1), 177–186. https://doi.org/10.1257/jep.14.1.177

Rodrik, D. (2021). Why does globalization fuel populism? Economics, culture, and the rise of right-wing populism. *Annual Review of Economics*, *13*(1), 133–170. https://doi.org/10.1146/annurev-economics-070220-032416

Rosselló Nadal, J., & Santana Gallego, M. (2022). Gravity models for tourism demand modeling: Empirical review and outlook. *Journal of Economic Surveys*, *36*(5), 1358–1409. https://doi.org/10.1111/joes.12502

Shao, Y., Huo, T., Yang, Y., & Li, Z. (2023). Does economic globalization shape the international tourism structure? A cross-national panel data estimation. *Journal of Travel Research*, *62*(5), 1121–1139. https://doi.org/10.1177/00472875221119128

Song, H., Li, G., & Cao, Z. (2018). Tourism and economic globalization: An emerging research agenda. *Journal of Travel Research*, *57*(8), 999–1011. https://doi.org/10.1177/0047287517734943

Tang, C. F. (2018). The impacts of governance and institutions on inbound tourism demand: Evidence from a dynamic panel data study. *Asia Pacific Journal of Tourism Research*, *23*(10), 1000–1007. https://doi.org/10.1080/10941665.2018.1513052

Titievskaia, J., Kononenko, V., Navarra, C., Stamegna, C., & Zumer, K. (2020). *Slowing down or changing track? Understanding the dynamics of 'slowbalisation'*. European Union. https://www.europarl.europa.eu/thinktank/en/document/EPRS_IDA(2020)659383 Retrieved November 6, 2024 from.

Turok, I., Bailey, D., Clark, J., Du, J., Fratesi, U., Fritsch, M., Harrison, J., Kemeny, T., Kogler, D., Lagendijk, A., Mickiewicz, T., Miguelez, E., Usai, S., & Wishlade, F. (2017).

Global reversal, regional revival? *Regional Studies*, *51*(1), 1–8. https://doi.org/10.1080/00343404.2016.1255720

Vega, S. H., & Elhorst, J. P. (2015). The SLX model. *Journal of Regional Science*, *55*(3), 339–363. https://doi.org/10.1111/jors.12188

Wang, J. J., & Heinonen, T. H. (2015). Aeropolitics in East Asia: An institutional approach to air transport liberalisation. *Journal of Air Transport Management*, *42*, 176–183. https://doi.org/10.1016/j.jairtraman.2014.10.002

Witt, M. A. (2019). De-globalization: Theories, predictions, and opportunities for international business research. *Journal of International Business Studies*, *50*(7), 1053–1077. https://doi.org/10.1057/s41267-019-00219-7

World Travel & Tourism Council. (2023). Economic impact research. Retrieved June 17, 2024, from https://wttc.org/research/economic-impact

Yang, Y., Fik, T. J., & Zhang, H. L. (2017). Designing a tourism spillover index based on multidestination travel: A two-stage distance-based modeling approach. *Journal of Travel Research*, *56*(3), 317–333. https://doi.org/10.1177/0047287516641782

Yang, Y., & Wong, K. K. F. (2012). A spatial econometric approach to model spillover effects in tourism flows. *Journal of Travel Research*, *51*(6), 768–778. https://doi.org/10.1177/0047287512437855

Yang, Y., Zhang, L., Wu, L., & Li, Z. (2023). Does distance still matter? Moderating effects of distance measures on the relationship between pandemic severity and bilateral tourism demand. *Journal of Travel Research*, *62*(3), 610–625. https://doi.org/10.1177/00472875221077978

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