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RETRACTED: The Impact of Geopolitical and Pandemic Risks on Tourist Inflows: Evidence From Asia-Pacific Region

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The aim of this research is to investigate the impact of major risks such as geopolitical and pandemic risks on tourism industry in selected countries of Asia-Pacific. The results were obtained using a sample of 10 neighboring countries in the period of 1996 to 2018. Diagnostic tests confirmed the existence of spatial interaction between model variables for these countries. According to the results, the economic growth, internally and in neighboring countries, leads to an increase in the influx of tourists. Whereas increased domestic prices will reduce the influx of domestic tourists, rising prices in neighboring countries intensify tourists' arrival of the country. Furthermore, results reveal that domestic geopolitical and pandemic risks lead to a decrease in tourist arrivals. In addition, whereas pandemic risks in neighboring countries do not have a significant effect on tourist arrivals, geopolitical risks in neighboring countries lead to more domestic tourists' arrival.

Keywords: tourism, geopolitical risks, pandemic risks, spatial panel data L83, E02, O43, Z30

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RETRACTED

INTRODUCTION

For the past few decades, the tourist industry in host countries is one of the main factors for economic development and has become a key sector of the economy and has direct and indirect economic benefits, which can be analyzed from the following perspectives: tourism's inflow has a critical role in increasing the economic growth in many developing and developed countries; improving social welfare and important sources of government revenue and tax; attracting foreign direct investment inflow and international investment; creating new jobs and employment opportunities, and income transfer from developed countries to developing countries; has a positive impact on the income inequality; and reducing poverty (Stynes, 1997; Brida et al., 2008; Lee, 2009; Deller, 2010; Scheyvens and Russell, 2012; Fereidouni and Al-Mulali, 2014; Incera and Fernández, 2015; Parida et al., 2015). Therefore, tourism development has a significant positive impact on economic growth so that policymakers among countries can use tourism as an instrument for welfare, economic growth, and development.

According to Roehl and Fesenmaier (1992), tourism is a risk-sensitive and very fragile industry. The demand for leisure and travel among countries is highly susceptible to disaster and risk in countries and region. We can classify tourist risk as the natural disasters such as hurricanes, pandemics, earthquakes, floods, and tsunamis and as human-caused disasters such as terrorist, political instability, and pandemics diseases, which can significantly impact the flow of international tourists among countries. The threat of danger that accompanies terrorism tends to intimidate potential tourists more severely. Besides, Glaesser (2006) shows that human-based disasters such as political conflicts, geopolitical risks (GPRs), and terrorist attacks tend to have more profound effects than natural base disasters on tourism development, and GPRs refer to a measure of political tensions in a country and the economy as they serve as an important factor in tourism development as well. In addition, because of the increasing political conflicts, the effect of GPRs on the tourism sector has received much attention in recent years. Moreover, as GPRs have been experienced by many countries and nations in two decades, so the study in this topic is important and has been more concern by scholars (Snowberg et al., 2007; Caldara and Iacoviello, 2018; Blattman and Miguel, 2010; Aghion et al., 2019).

The impact of country risk on tourism decisions has been an area of research concern on-demand side of tourism, and the element of travel risk as a component of tourist decisions has received limited attention. However, in the past few years, numerous tourist risks (natural disasters and human-caused disasters) have occurred around the world and have had effects on some tourist destinations, which we have seen a significant rise of risk or tourist among countries in the world. More ambiguous and complicated aspects of the impacts posed by politics on tourism are increasingly studied in the literature. Such aspects include political stability and security, institutions, and peace (Goeldner and Ritchie, 2003; Edgell et al., 2013; Balli et al., 2018; Demir and Gozgor, 2018; Kim et al., 2018; Ghalia et al., 2019). In the same line, because of the increasing frequency of political conflicts events, civil wars, international wars, terrorist attacks, and several diseases and pandemics such as coronavirus (COVID-19), SARS, Malaria, Yellow Fever, Dengue, and Ebola, the study of the effect of these two important risks, which are pandemic risks and GPRs, on the economy and tourist inflows around the world has received much attention. The prevalence of epidemics like SARS and Swine Flu led to a ban on the international movement of people and a reduction in international travel (Ala'a and Albattat, 2019), and there is a high risk of transmitting the disease through travel in the community (Freedman and Leder, 2005; MacIntyre, 2020). According to UNWTO (2020), because of pandemics and increase of coronavirus, tourist inflows in the world are declined around 20%–30%, which is worth of 300 to 450 US$ billion. In other words, it is worth examining how they can affect the tourism development because pandemics and geopolitical uncertainties have been stressed as an important driver of tourist development. However, there arises a question of whether pandemics and GPR contribute to tourism development.

In this context, this study analyzes tourism development and GPR relationship in Asian and Pacific countries. These selected countries represent the sample of the current study that seeks to obtain a better understanding of the role of GPR in tourism inflows by using a spatial panel data approach for the years 1996–2018.

This study contributes to the literature in two ways:

I. Scholars employ different econometric models to verify the relationship between important variables on tourism development. To get more reliable results, this study may definitely be the pioneer to use a spatial panel data method for exploring the impacts of geopolitical and pandemic risks on tourism inbound. Traditional analysis frameworks commonly fail to incorporate spatial characteristics. As a result, they cannot consider spatial dependence, i.e., the dependence of a cross-sectional observation on the other ones. In addition, they cannot capture the indirect effects (induced by the neighbors) and spatial spillover influences of geopolitical and pandemic risks in one country and a region to tourism development in other countries. Thus, spatial econometric models are more advantageous and provide higher efficiency and effectiveness (Meng et al., 2017; You and Lv, 2018). In fact, to the best of our knowledge, our study is the first to estimate spatial econometric models in the impact of risks on tourism.

II. For the first-time GPR as a country risk employed in this study with new indicators, in the previous studies, the measurement of the GPR is used by dummy variables for countries, but we have chosen a new and developed GPR index that was first time introduced by Caldara and Iacoviello, (2018), which represent the risks associated with the various global geopolitical by automated text searches of newspapers. Meanwhile, to show the impact of natural disaster risk, the World Economic Uncertainty Index that is developed by Ahir et al. (2018) is used, whereas the previous scholars and researchers use the number of infected/death and dummy variables. These two indicators help to measure the intensity of the GPR and natural risk events in selected countries.

The remaining of this study is organized as follows. Section *Brief Literature Reviews* revises the literature on GPR and tourism development. Section *Methods and Materials* describes the data and methodology. Section *Empirical Results and Discussion* presents the results of our analysis. Section *Conclusion and Policy Implication* provides conclusions and policy implications.

BRIEF LITERATURE REVIEWS

In recent years, the tourism industries have experienced some natural disasters and human-caused disaster risks, and the literature in this area tries to explore how they can affect tourism flows among countries. Given the increasing frequency of terrorist and rapid increase in terrorist attacks and regional conflict incidents around the world, most literature in the politics and economics literature try to find the impact of them on tourist industry by case study and a group of country and modify some econometric methods based on time series, cross-sectional, or panel data (Wahab, 1996; Kliot and Mansfield, 1997; Llorca-Vivero, 2008; Buigut, 2018; Bassil et al., 2019). These studies confirmed that terrorism, conflicts, political instability, natural disaster, and pandemics have significant impact and decline tourist arrivals. In particular, it remains unknown whether and how geopolitical and pandemic risks in neighboring countries and regions can affect the tourism among countries, and there is a lack of literature to explore the role of these two key risks on tourism inflows in a region. Most of the important studies in this subject are as follows.

For instance, Seddighi et al. (2001) examined the effect of political instability on tourism demand and they confirmed that political risks and terrorist attacks result in turning down in arrivals in some tourist destination in word. Fletcher and Morakabati (2008) explored the influences of terrorism and political instability on tourism inflow in Kenya and Fiji. They concluded no stable association. However, a number of political events (e.g., international conflicts and coups) were demonstrated to pose much more significant influences than low-to-medium on-off terrorist attacks. Eryiğit et al. (2010) utilized a gravity model and found that tourism climate was a prominent factor for the explanation of tourist flow between Turkey and other countries.

Furthermore, Kuo et al. (2008) tried to find effects of two pandemic diseases, namely, SARS and Avian Flu, on tourist inflows in Asian countries, they found that SARS has a negative and significant effect on tourist inflow in Asian countries, but Avian Flu has no significant effect on tourism in this region.

Alsarayreh et al. (2010) employed questionnaire techniques and explored the impacts of terrorism on tourism inbound within 42 countries. The respondents mostly believed terrorism to have diminished international tourism activities. Saha and Yap (2013) utilized panel data estimation and studied the effects of political instability on tourism in 139 countries from 1999 to 2009. Political instability was concluded to negatively affect tourism at any terrorist threat levels.

In the case of Turkey, Gozgor et al. (2017) investigated the effects of the military in politics on the inbound tourism on tourism inflows from 71 countries to Turkey for a period from 1984 to 2014, and they utilize dynamic panel data (GMM) and simple panel data with fixed and random effect by a military in politics proxy that is a component of the political risk and they found a negative and significant impact of the military in politics on tourism inflows in turkey, where 1% of the reduction in index of the military politics leads to around 7% increase in the tourism inflows in turkey.

Samitas et al. (2018) investigated the role of political risk and terrorism on tourism inflows in Greece over the period of 1977 to 2012. Terrorism proxies that they use are drawn from the Global Terrorism Database to extract a common factor applying PCA method and they utilized a long-run Granger causality test to find the two-way direction of proxies, and the results confirm the negative effect of terrorism on tourism inflow in Greece with a unidirectional causality from terror to tourism in the short-run, but there is a causality direction from terrorism to tourism.

Moreover, Ghalia et al. (2019) employed a gravity model to the impacts of political risks, institutional quality, distance, and socio-economic factors on tourist inbound for top 34 destination countries over the period of 2005 to 2014, and they find that institutional quality and absence of conflict are significant factors in tourism inflows and that lower levels of political risk in the destination countries contribute to increasing tourism flows.

Then, Demir et al. (2019) utilized panel data fixed-effects methods to analyze the impact of GPRs on tourism arrivals in 18 countries for the period from 1995 to 2016. As the first research in the literature, they use a GPR index and found that GPR has significant a negative impact, and it is the most significant factor in tourism development.

In a more recent study, Demir et al. (2020), in the case of Turkey, employed the NARDL model to examine the asymmetric impact of GPRs on tourist inflows from January 1990 to December 2018 and used monthly data used on the basis of the GPR index, which was developed by Caldara and Iacoviello (2018), to measure GPR. They found an asymmetric and significant effect of the GPR index in the short run where an increase in GPR index reduces tourist arrivals; meanwhile, a decrease in proxy has no effect in the short run. Moreover, they could not confirm evidence of asymmetry for variables in the long run. In addition, Karabulut et al. (2020) explored the effects of a pandemic on tourism development for 129 countries over the period of 1996 to 2018; they modify the GMM panel data method and found a negative and significant effect of pandemics on tourist arrivals only in low-income economies, where a 10% increase in pandemic proxy leads to a 2.1% decrease in tourist inflows in these countries. Moreover, in high- income countries, the impact of pandemics on tourist arrivals is very slow and insignificant.

In their recent study, Li et al. (2020) expressed that tourism is a risk-prone industry so they attempted to systematically identify the risk exposures of tourism companies from a holistic perspective during 2006–2019 by utilizing the Sentence Latent Dirichlet Allocation (Sent-LDA) model where they found 30 risk exposures of the tourism sector, which include new natural and human-based risks where epidemic risk, information technology risk, safety risk, seasonal risk, and tax risk have high average fluctuation rate beside other risks.

According to Rosselló et al. (2020), natural disasters and unexpected events are determining factors for the tourism sector; they examined the effects of natural disasters on international tourism for 171 countries and estimated by panel data with destination fixed effects, and, using yearly data for the period of 1995–2013, they found that, in the short run, disasters generally affect international tourism arrivals negatively and, in the long run, it is insignificant, which means disaster damage seems to prevent tourists to visit the affected destination as well.

To sum up the literature review in this area, we concluded that there are several studies that show the impact and the determinants of tourism inflows by natural and human-based disaster and risks. We claim that previous research simply considers the direct impact of geopolitical and pandemic risks on tourist inflows because, when examining natural and human-based risks on tourist, there is likely spatial dependency, thus neglecting its spillover effect on risks, where the spillover effect (i.e., indirect effect) relates to the influence generated by the tourist development of neighboring countries. There is spatial dependence in essence in many subjects related to geopolitical and pandemic risks problems (Lv and Li., 2021), as most of the studies in this topic use a conventional and basic panel data analysis that has ignored spatial dependence within the data, so we anticipated that results are in partial or even biased estimation.

METHODS AND MATERIALS

Empirical Model

The tourism arrivals using a conventional log-linear functional form can be expressed as a function of the logarithm of gross domestic product (GDP) per capita (*lnGDP*), the logarithm of the level of prices in the destination country (*lnPRICE*), the logarithm of world pandemic uncertainty index (*lnWPUI*), and the logarithm of GPR index (*lnGPR*). We have divided the tourist arrival data by the population to get the amount per capita to control for the size of the destination country. We consider the logarithm of the real GDP per capita as a proxy for the development level at each destination (Saha and Yap 2013; Rosselló et al., 2020).

$$\begin{aligned} ln\,TOUR_{it} &= \beta_1 + \beta_2\, ln\,GDP_{it} + \beta_3\, ln\,PRICE_{2it} + \beta_4\, ln\,WPUI_{it} \\ &\quad + \beta_5\, ln\,GPR_{it} + c_i\,(optional) + \alpha_t\,(optional) + v_{it} \end{aligned} \tag{1}$$

The model used while studying the possibility of examining the effects of a particular country's political risks on its tourism inputs also allows us to examine the effects of neighboring countries' political risks. The effects of the variables of neighboring countries on the variables of a particular country are called spatial effects. To take into account such spatial effects, three different models can be used. A spatial panel data model can include a lagged dependent variable or follow a spatially autoregressive process in the error term (Anselin et al., 2008). The spatial lag model considers the effects of a neighboring country's dependent variable on the dependent variable in a particular country. The dependent variable of the present study is tourist arrivals to the countries, so this model allows the study of the effects of the inbound of tourists of the neighboring country on the tourism industry of a particular country. The spatial lag model is formulated as follows:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, y_{jt} + \varphi + x_{it}\beta + c_i\,(optional) + \alpha_t\,(optional) + v_{it} \tag{2}$$

where x_{it} is a $1 \times K$ vector of independent variables for cross-sectional countries $i = 1, \ldots, N$ at periods $t = 1, \ldots, T$. In addition, β is a $K \times 1$ vector of parameters. y_{it} is the dependent variable. $\sum_{j=1}^{N} w_{ij}\, y_{jt}$ denotes the interaction effect of the dependent variables y_{jt} in neighboring countries on the dependent variable y_{it} in a specific country, and λ is the corresponding parameter. w_{ij} is the i, j–th element of a $N \times N$ spatial weights matrix w. Before the standardization of the matrix, the value of the i, j–th element will be one of the two neighboring countries and zero if they are not neighbors. c_i are spatial-specific intercepts that capture heterogeneities across countries, and α_t are time period–specific intercepts that capture heterogeneities across time periods. The omission of these two latter variables could bias the estimates in a cross-sectional and time-series study, respectively (Baltagi, 2005). v_{it} is the random error term that is assumed to be normally distributed with zero mean value and constant variance (Elahi et al., 2021a; Elahi et al. 2021b; Elahi et al. 2022a; Elahi et al. 2022b).

The spatial error model is introduced below as the second model. In this model, the error term of unit i, u_{it}, depends on the error terms of neighboring countries j, u_{jt}, the spatial weights matrix W, and an idiosyncratic component, v_{it}:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, y_{jt} + \varphi + x_{it}\beta + c_i\,(optional) + \alpha_t\,(optional) + u_{it}$$

$$u_{it} = \rho \sum_{j=1}^{N} w_{ij}\, u_{jt} + v_{it} \tag{3}$$

The spatial Durbin model also extends the spatial lag model with spatially lagged independent variables. This model allows the study of the effects of independent variables of neighboring countries on the independent variable of a particular country (LeSage and Pace, 2009, Ch. 6):

$$\begin{aligned} y_{it} &= \lambda \sum_{j=1}^{N} w_{ij}\, y_{jt} + \varphi + x_{it}\beta + \sum_{j=1}^{N} w_{ij}\, x_{jt}\theta + c_i\,(optional) \\ &\quad + \alpha_t\,(optional) + v_{it} \end{aligned} \tag{4}$$

where $\sum_{j=1}^{N} w_{ij}\, x_{jt}$ investigates the interaction effect of the independent variables x_{jt} in neighboring countries on the dependent variable y_{it} in a specific country. In addition, θ is a $K \times 1$ vector of parameters.

Data

The data set used for the empirical analysis consists of annual observations on 10 neighboring countries over the period of 1996 to 2018 so that most countries are located in the Asia-Pacific region. The availability of data on GPRs is the main criteria for selecting the countries. The index is available for 19 countries, but to investigate the interaction spatial effects, we must consider the countries that are neighbors with each other. **Figure 1** shows the amount of the GPRs index in the countries under study. In **Table 1**, a summary of the constructed variables is presented. All the variables are converted into logarithmic forms. Taking natural logarithms leads to estimates of elasticity.

EMPIRICAL RESULTS AND DISCUSSION

The hypothesis and diagnostic tests are used to select the optimal models. The Lagrange Multiplier (LM) and robust LM tests consider the possibility of the presence of spatial interaction effects in the different models using the residuals of a non-spatial model, with or without the spatial fixed effects. The test examines the presence of the spatial lag or spatial error in the model and is a measure to confirm the spatial effects and the necessity to use spatial econometrics. The alternative hypotheses in the test verify the spatially lagged dependent variable or the spatial error autoregressive, whereas the null hypotheses confirm the non-spatial model. As presented in **Table 2**, on the basis of the results, the presence of spatial lag effects and spatial error effects in the spatial fixed effect models is approved.

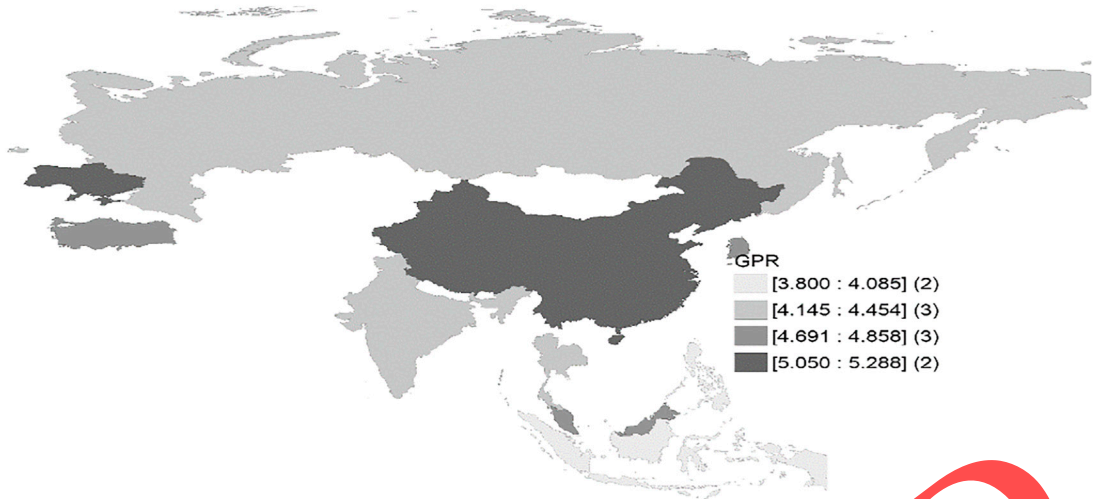

FIGURE 1 | Geopolitical risks index in the countries.

TABLE 1 | Variables constructed.

Variable	Variable constructed	Source
$lnTOUR_{it}$	$\ln TOURISM_{it} = \log(TOURISM_{it})$ $RENEW_{it}$ = Tourist arrivals per capita	UNWTO
$lnGDP_{it}$	$\ln GDPP_{it} = \log(GDPP_{it})$ GDP_{it} = GDP per capita in 2010 prices $ in the country *i* in period *t*	WDI
$lnPRICE_{it}$	$\ln PRICE_{it} = \log(PRICE_{it})$ $PRICE_{it}$ = the ratio of PPP conversion factor to market exchange rate	WDI
$lnWPUI_{it}$	$\ln WPUI_{it} = \log(1 + 100 \times WPUI_{it})$ $WPUI_{it}$ = World Pandemic Uncertainty Index (WPUI)	Ahir and et al. (2018)
$lnGPR_{it}$	$\ln GPR_{it} = \log(GPR_{it})$ GER_{it} = Geopolitical Risk (GPR)	Caldara and Iacoviello (2018)

UNWTO: United Nations World Tourism Organization; https://www.unwto.org/data.
WDI: World Development Indicator; https://datacatalog.worldbank.org/dataset/world-development-indicators.
"World Pandemic Uncertainty Index" by Ahir and et al. (2018) at https://worlduncertaintyindex.com/data/
"Measuring Geopolitical Risk" by Caldara and Iacoviello (2018) at https://matteoiacoviello.com/gpr.htm.

TABLE 2 | The spatial lag or the spatial error in the spatial and time period fixed-effects model.

		Pooled OLS		Spatial fixed effects		Time period fixed effects	
Model 1	LM spatial lag	0.369	(0.544)	28.394	(0.000***)	0.194	(0.66)
	LM spatial error	0.453	(0.501)	6.248	(0.012**)	0.792	(0.373)
	robust LM spatial lag	4.798	(0.028**)	28.303	(0.000***)	0.432	(0.511)
	robust LM spatial error	4.882	(0.027**)	6.157	(0.013**)	1.031	(0.31)
Model 2	LM spatial lag	0.214	(0.644)	28.837	(0.000***)	0.293	(0.589)
	LM spatial error	0.688	(0.407)	7.406	(0.007***)	1.11	(0.292)
	robust LM spatial lag	4.732	(0.03**)	26.264	(0.000***)	0.556	(0.456)
	robust LM spatial error	5.207	(0.022**)	4.833	(0.028**)	1.373	(0.241)
Model 3	LM spatial lag	0.22	(0.639)	29.558	(0.000***)	0.263	(0.608)
	LM spatial error	0.727	(0.394)	7.388	(0.007***)	1.488	(0.223)
	robust LM spatial lag	4.981	(0.026**)	28.027	(0.000***)	1.23	(0.267)
	robust LM spatial error	5.488	(0.019)	5.857	(0.016**)	2.455	(0.117)

*Note: p-value, ***, **, and * show significance at 1%, 5%, and 10% level, respectively.*
Source: Authors' estimations.

TABLE 3 | The spatial Durbin model and Hausman test results.

	Model 1		Model 2		Model 3	
Hausman test statistics	9.096	(0.059*)	919.897	(0.000***)	812.954	(0.000***)
Hausman test statistics	330.353	(0.000***)	388.007	(0.000***)	370.606	(0.000***)
Fixed effects estimator						
Wald test for spatial Durbin model against spatial lag model	37.975	(0.000***)	37.603	(0.000***)	53.528	(0.000***)
Wald test for spatial Durbin model against spatial error model	76.381	(0.000***)	73.664	(0.000***)	87.078	(0.000***)
LR test spatial Durbin model against spatial lag model	38.863	(0.000***)	38.531	(0.000***)	52	(0.000***)
LR test spatial Durbin model against spatial error model	79.009	(0.000***)	76.93	(0.000***)	92.884	(0.000***)
Random effects estimator						
Wald test for spatial Durbin model against spatial lag model	36.086	(0.000***)	35.842	(0.000***)	53.028	(0.000***)
Wald test for spatial Durbin model against spatial error model	83.848	(0.000***)	81.987	(0.000***)	95.741	(0.000***)
LR test spatial Durbin model against spatial lag model	35.699	(0.000***)	35.295	(0.000***)	50	(0.000***)
LR test spatial Durbin model against spatial error model	79.702	(0.000***)	79.092	(0.000***)	92.632	(0.000***)

*Note: p-value, ***, **, and * show significance at 1%, 5%, and 10% level, respectively.*
Source: Authors' estimations.

TABLE 4 | The parameter estimation results for Models 1–3.

	Model 1		Model 2		Model 3	
lnGDP	0.606	(0.000***)	0.622	(0.000***)	0.528	(0.000***)
lnPRICE	–0.296	(0.001***)	–0.311	(0.001***)	–0.354	(0.000***)
lnWPUI			-0.031	(0.055*)	–0.028	(0.071*)
lnGER					–0.14	(0.021**)
W × lnGDP	0.033	(0.73)	0.019	(0.841)	0.024	(0.802)
W × lnPRICE	0.582	(0.000***)	0.578	(0.000***)	0.681	(0.000***)
W × lnWPUI			0.021	(0.301)	0.015	(0.452)
W × lnGER					0.262	(0.000***)
W × lnTOU	0.355	(0.000***)	0.357	(0.000***)	0.39	(0.000***)

*Note: p-value, ***, **, and * show significance at 1%, 5%, and 10% level, respectively.*
Source: Authors' estimations.

Table 3 investigates the probability of choosing a random-effects model instead of a fixed-effects model using Hausman test statistics. The test results of the Hausman test for both the spatial Durbin and the spatial lag models are significant at the 1% level. Because the null hypothesis emphasizes the existence of a random-effects model, the existence of random effects in the model is rejected.

Two separate hypotheses H_0: $\theta = 0$ and H_0: $\theta + \lambda\beta = 0$ are also implemented to investigate the probability of the existence of the spatially lagged independent using the LR test or the Wald test. The first hypothesis converts the spatial Durbin model to the spatial lagged model, and the second simplify the spatial Durbin model to a spatial error model. The LR test and the Wald test are significant at the level of 1% in **Table 3**, confirming the existence of the spatial lagged independent variables in the models. Therefore, the spatial Durbin model with the spatial fixed effects is selected as the final model.

Table 4 presents the estimation results for domestic and spatial variables in the form of three different models. In the first model, the effects of price levels and GDP per capita of domestic and neighboring countries are included in the model, whereas, in the second and third models, the two other variables, namely, world pandemic uncertainty index and GPR, are added to the models, respectively. To analyze the results, we use the estimated coefficients to calculate the direct and indirect effects of the dependent variables in **Table 5**. Direct effects estimate the effects of the domestic independent variables on the domestic dependent variable, whereas indirect effects measure the effects of the independent variables of neighboring countries on the domestic dependent variable.

Because indirect effects include feedback effects that result from the effects of crossing neighboring states and returning to the states themselves, the effects are slightly different from the estimated parameter values in **Table 5**. Examination of the results of **Table 5** shows that each percentage increase in GDP per capita leads to a significant increase of about 0.6% in tourist arrivals, whereas the coefficient for GDP per capita of neighboring countries is about 0.34%. The growth of GDP per capita as an indicator of domestic development provides more tourist infrastructure and has positive and significant effects on tourist arrivals, whereas the growth of GDP per capita of neighboring countries through increasing demand for domestic tourism industries reveals the positive effects.

Each percent increase in the level of domestic prices leads to a decrease of about 0.2% in the entry of tourists, whereas an increase in the level of prices in the neighboring countries by a coefficient of 0.634 shows positive and significant effects. Therefore, if the level of prices in neighboring countries is higher compared to domestic prices, then the prices of goods and services in the country will be cheaper compared to neighboring countries, and as a result, we will have more tourists from neighboring countries or redirected tourists from other countries from neighboring countries to cheaper countries.

The world pandemic uncertainty index does not show spatial interaction effects, meaning that the increase in the index in neighboring countries does not have a significant effect on domestic tourist arrivals, whereas the effects of uncertainty resulting from domestic epidemics on the arrival of tourists are negative and lead to a significant reduction of 0.029% in tourist arrivals. However, the spatial effects of the GPR index are significant and profound. The increased domestic GPR leads to a significant decline in the number of tourists, and each percentage increase in the index leads to a decreased tourist arrival of about

TABLE 5 | Marginal effects of variables on tourist arrivals.

	Direct Effects		Indirect Effects		Total Effects	
	Coefficient	***p*-value**	**Coefficient**	***p*-value**	**Coefficient**	***p*-value**
Model 1						
$lnGDP_{it}$	0.653	(0.000***)	0.34	(0.006***)	0.993	(0.000***)
$lnPRICE_{it}$	−0.204	(0.035**)	0.643	(0.001***)	0.44	(0.016**)
Model 2						
lnGDP	0.667	(0.000***)	0.332	(0.005***)	0.999	(0.000***)
lnPRICE	−0.22	(0.027**)	0.634	(0.001***)	0.414	(0.021**)
lnWPUI	−0.029	(0.088*)	0.012	(0.609)	−0.017	(0.498)
Model 3						
lnGDP	0.572	(0.000***)	0.333	(0.01*)	0.905	(0.000***)
lnPRICE	−0.244	(0.028**)	0.777	(0.000***)	0.533	(0.017)
lnWPUI	−0.028	(0.09*)	0.005	(0.824)	−0.023	(0.368)
lnGER	−0.096	(0.149)	0.302	(0.025**)	0.206	(0.205)

*Note: p-value, *, **, and *** show significance at 1%, 5%, and 10% level, respectively.*
Source: Authors' estimations.

0.1%, which is high and significant. Besides, the increase in GPR index in neighboring countries promotes the domestic tourist arrivals, and each percentage increase gives rise to an increase of about 0.3%.

CONCLUSION AND POLICY IMPLICATION

In this study, data from 1996 to 2018 from 10 countries, including a number of Asia-Pacific countries, were used to investigate the effects of GPRs and pandemics on tourist arrivals as a case study. Diagnostic tests confirmed the spatial interaction between model variables and led to the selection of the spatial Durbin model with the spatial fixed effects. According to the results of the growth of GDP per capita domestically and in neighboring countries, it has led to a significant increase in tourist arrivals. Economic growth can pave the way for the expansion of industrial infrastructure. However, as economic growth in neighboring countries increases, two conflicting effects appear in the influx of domestic tourists:

a) An increase in the income of neighbors allows for increasing domestic demand.
b) The infrastructure developed in neighboring countries can move tourists from other countries to neighboring countries with more developed tourism infrastructures.

According to the results, the former dominates the latter, suggesting that the movement of tourists between neighboring countries provides the bulk of tourism demand in these countries.

The increased levels of prices in countries lead to a decrease in tourist arrivals as a result of rising domestic good and service prices for tourists, whereas increased prices in neighboring countries have opposite effects on the arrival of domestic tourists because it gives rise to reduced domestic relative prices of goods and services in countries compared to neighboring countries so, on the one hand, this leads to the movement of tourists from neighboring countries and, on the other hand, tourists in other countries change their travel origin from neighboring countries to the domestic with lower relative prices.

Policy Implications

The domestic geopolitical and pandemic risks of countries in accordance with our theoretical expectations lead to a decrease in tourist arrivals to countries, although the spatial effects of such variables are different from each other. Although the increased risk of pandemics in neighboring countries does not have a significant effect on domestic tourist arrivals, the GPRs in neighboring countries with regional effects significantly increase domestic tourist arrivals. Although the increase in GPRs in neighboring countries can increase the regional risk of tourists entering a particular geographical area and impose a negative effect on the entry of domestic tourists, the test results indicate that such risks lead passengers to change their direction from neighboring countries with higher GPRs to the domestic.

The profound spatial effects of macroeconomic variables in neighboring countries on a particular country highlight the need for considering the spatial interactions on how tourism industry determinants affect countries, an issue that should be considered in future studies. The results of the study indicate that the tourism industry policies in countries must be implemented with respect to structural conditions and risks to the neighboring countries.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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