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DYNAMIC COMMON CORRELATED EFFECTS OF GEOPOLITICAL RISK ON INTERNATIONAL TOURISM ARRIVALS

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Abstract

Research background: Geopolitical risk is currently recognized as a worldwide concern that significantly affects various economic sectors. As a consequence, rising geopolitical risks can cause a decline in the number of tourist arrivals.
Purpose: The aim of this paper is to examine the applicability of a commonly used dynamic model, the autoregressive distributed lag model (ARDL), in a panel data context and the effect of geopolitical risk on explaining tourist demand in chosen countries across long and short time periods.
Research methodology: On 18 developing economies, the Cross-sectionally Augmented Distributed Lag (CS-ARDL) technique is used.
Results: The results of the test show interesting insights. Although the consequences of geopolitical threats in the short term are significant and have a negative impact on tourist arrivals, in the long term, results show there is no effect. Specifically, a rise in geopolitical risk decreases foreign visitor visits in the short term but has no lasting impact.
Novelty: Using an econometric model, this study contributes to the limited research on the link between geopolitical risk and tourist arrivals.

Keywords: geopolitical risk, international tourism, CS-ARDL testing method, Dynamic Panel

JEL classification: H56, Z3, C12

Introduction

Based on a count of newspaper articles discussing geopolitical tensions, Caldara and Iacoviello (2022) have developed a new measure of unfavourable geopolitical events and have analysed their development and economic repercussions since 1900. Eight categories make up the search: war threats (Category 1), peace threats (Category 2), military build-ups (Category 3), nuclear threats (Category 4), terror threats (Category 5), war starting (Category 6), war escalating (Category 7), and terror acts (Category 8). The risk of war conflicts, terrorist attacks, and tensions between states that interfere with the regular and peaceful development of international relations is known as geopolitical risk (GPR) (Caldara, Iacoviello, 2018, p. 2). The GPR index measures the likelihood that these occurrences will occur as well as the additional risks associated with an intensification of current geopolitical events.

Geopolitical risk is now understood to be a global issue that has a considerable impact on a number of economic sectors (finance, trade, business, tourism, etc.). A common report format for the huge transnational corporations of numerous international entities and bodies is now "geopolitical risk." For instance, all these studies (World Economic Forum, World Bank, Institute for Economics and Peace) identify geopolitical risks as the most significant and widely understood risks that could have an impact on the global business environment. In this setting, against a backdrop created by the complicated interplay between geopolitics and the economy, as well as the escalating interdependencies and reciprocal circumstances, it becomes obvious that tourism as a social and economic activity is affected by geopolitical events. Negut (2008) states in his research that if geopolitics is an expression of an act of power, tourism is an expression of freedom, which is increasingly conditioned by these power games (Neguţ, Neacşu, 2013).

Due to worries about safety and stability, travel plans are often put off or cancelled when geopolitical risks rise. This will not only result in a decline in the number of tourists but also in a reduction in tourism expenditures. But Demir, Gozgor, and Paramati (2019) say that travellers are more likely to be forced to go on trips during these times.

The tourism industry is very important to the economy because it creates jobs, opens up new export markets, and provides public services. Given how important the tourism industry is to the economy, it is important to understand the risks that could affect it. The risk from geopolitics is one of these elements (Hailemariam, Ivanovski, 2021). The estimation of long-term effects is crucial in economics. Typically, the concept of "long-run relations" is linked to the steady-state solution of a structural macroeconomic model. Frequently, the same

long-term relationships can also be derived from arbitrage conditions within and between markets. In contrast, the analysis of short-run effects is model-dependent and susceptible to identification issues (Chudik *et al*., 2016).

The aim of this study is to determine the effect that geopolitical threats have on tourism activity, which originates from the background already indicated. The novelty of this research comes from its focus on geopolitics and tourism, two fields that were previously difficult to connect. However, the reality of today attests to this contradictory existence: when war or terrorist attacks are involved, the tourist phenomenon is affected in the most unanticipated ways, from the removal of landmarks, which are wiped off the map, to quantitative and qualitative alterations in tourism flows. This research's stunning novelty – moving from geopolitics to economics – is another noteworthy aspect. From liberalism and unrestricted economic globalization to the resumption of wall and fence building, authoritarian nations, presidents for life, the emergence of nuclear conflict, and international terrorism. In this chaotic environment, the manifestations of hard power (i.e., geopolitics) and freedom constrained by power struggles (i.e., tourism) are compelled to work together.

This research provides empirical insight into how geopolitical worries impact international travel demand. Geopolitical risk is a significant predictor of tourist demand, as indicated by panel causality results.

1. Literature review

Since the 9–11 attacks on New York in 2001, which affected the global economy and many industries, particularly the tourism industry, in the world, researchers have shown a consistent interest in studying the impact of geopolitical risks. The majority of studies examine the impact of geopolitics on territorial disputes, diplomatic tensions, and terrorism on a vast array of economic issues (Tavares, 2004; Saha, Yap, 2014).

In comparison to other industries, the international tourism industry is one of the first to be affected by certain geopolitical risks. Balli, Uddin, and Shahzad (2019) explain that the effect of geopolitical risk on international tourism demand in popular tourist destinations is negligible. Drakos (2004) says that terrorism has a big effect on industries like airlines and tourism.

In their study, Lanouar and Goaied (2019) showed that global tourism is impacted by political unrest, terrorism, and natural disasters. Literature on the relationship between political risk and tourism reveals that geopolitical conflicts, tensions, or political risks

generate economic and political uncertainty and have a significant impact on tourism demand (Muzindutsi, Manaliyo, 2016). On the other hand, Antonakakis *et al.* (2017) contend that as the tourism industry changes and grows, it responds to external shocks and adapts to broader political and economic environments. Fundamentally, both domestic and foreign political and economic environments have distinctive characteristics that have a significant impact on tourism, market actors, and the economy. No nation has been able to shield its tourism industry from the adverse effects of geopolitical risks. Therefore, geopolitical risk can have a significant impact on international tourist arrivals, the number of overnight stays, tourism imports, and several other significant measures of tourism development if an adequate policy is not implemented (Lanouar, Goaied, 2019). It is generally accepted that everyone places a high value on their personal safety and strives to avoid any type of threat to it. According to Bassil, Saleh, and Anwar (2019), the existence of danger in tourism-supplying locations can have a negative effect on the number of tourists received.

For instance, Saha and Yap (2014) found that terrorism and political instability negatively affect the development of tourism, with the impact of political instability on tourism being greater than the impact of terrorist attacks, using the panel dataset in 139 countries for the years 1999–2009. Ghaderi *et al*. (2017) state that there is a positive (negative) effect of security on international tourist arrivals in 29 developed economies (45 developing economies) for the period from 2006 to 2012. They do this by using the system's Generalized Method of Moments (GMM) estimations. Gozgor *et al*. (2017) discovered a negative correlation between Turkey's inbound tourism and the military's increased political influence. Saha *et al.* (2017) conclude, using fixed-effects estimations, that economic freedom and civil liberties have a positive impact on inbound tourism for 110 countries between 1995 and 2012. According to research by Hailemariam and Ivanovski (2021), geopolitical risk has a significant and negative impact on the export of tourist services. In their study, Das, Kannadhasan, and Bhattacharyya (2019) infer that the economic market's response to shocks or volatility is significantly influenced by geopolitical risk. Geopolitical risk, according to Balcilar *et al.* (2018), is the primary variable influencing business cycles, financial markets, and economic directions.

According to Agiomirgianakis, Serenis, and Tsounis (2017), short-term fluctuations in tourism demand are significantly influenced by political unrest and terrorist upheavals. A small body of research suggests that the tourism industry is resistant to the negative effects of geopolitical risks. For instance, Uriely, Maoz, and Reichel (2009) assert that when there is a chance for both sides to profit from tourism, geopolitical conflicts are frequently disregarded. Krakover (2013)

mentioned the success of the Israeli tourism industry as a shining example of success in the face of ongoing conflict.

In this paper, a tourism demand analysis is conducted. According to the theory of tourism demand, there are two primary methods for analysing tourism demand (Goh, 2012). Initially, a socio-psychological framework (widely recognized as the destination choice theory) posits that travel motivation is the most influential factor in tourism demand. Evidently, continuing political instability in tourism areas and quality of life (well-being) can influence feelings and tourism demand (see, e.g., Ram *et al.* 2014). To analyse tourism demand, tourism economists also consider an "economic framework" known as market demand theory.

2. Data and method

This paper analyses tourism demand measures, and international arrivals (Kazakova Kim 2021; Demir *et al.* 2020; Demir, Gozgor, Paramati, 2019). The annual data spans the years 2000 through 2020 (T = 17). The most important variable of interest is the Global Political Risk Index (GPRC), which is calculated for 18 developing economies (N = 18): Argentina, Belgium, Switzerland, Denmark, Finland, France, Italy, Hungary, Norway, the Netherlands, Germany, Poland, Portugal, the Russian Federation, Ukraine, the United Kingdom, Spain, and Sweden. The information gathered by Caldara and Iacoviello (2019) is utilized to assess global political risk. The geopolitical risk index made by Caldara and Iacoviello is based on monthly data, so in this paper, monthly data are calculated to become yearly data, or more precisely, the average for each year. As a form of robustness check, a control variable such as the global GDP per capita is used, which is defined by real US dollar (USD) prices in logarithmic form. International tourist arrivals, total population, and geopolitical risk are also in logarithmic form, with data from the World Travel and Tourism Council (WTTC) (2021), the World Bank, and Matteo and Iacoviello's Country Specific Geopolitical Risk Index.

Estimating long-term relationships is a key part of applying economic models in the real world, especially macroeconomic models. The relationships between macroeconomic variables such as tourism and the geopolitical risk index are one example. With pure time series data, the autoregressive distributed lag (ARDL) model is frequently employed to estimate long-run relationships. ARDL models estimate the short-run coefficients and derive the long-run coefficients in reverse. In comparison to time series models, panel data models add a further dimension. The models of time series cover one-panel units, and slope heterogeneity between units is not a concern. The first step of this empirical method is to determine the integration

order of the data. This is significant because, in order to estimate an ARDL model, the variables in the regression must be either integrated of order zero I(0) or at most integrated of order one I(1). In the presence of two-order I(2) integrated variables, the ARDL bounds testing method cannot produce reliable results. Fisher-type panel unit root tests are utilized to test for unit root in a group of panel series. This test's foundational framework is an enhanced Dickey-Fuller (ADF) regression for panel data (Attard, 2019).

Dynamic, common-correlated effects are the ones that will be implemented. MG estimates are obtained by dynamic common-correlation effects in two steps (Ditzen, 2018): In order to accommodate heterogeneous slopes, the coefficients of interest for each cross-sectional unit are first estimated. The estimates for each unit are averaged over all groups. According to Pesaran (2006) and Chudik and Pesaran (2015), dynamic common-correlated effects add cross-sectional averages and lags to account for cross-sectional dependence. Furthermore, it allows for instrumental-variable (IV) estimation and tests for weak cross-sectional dependence in the error terms. Additionally, Chudik and Pesaran's (2015) recursive mean adjustment or the "half-panel" jackknife correction method allows dynamically common-correlated effects to correct for small-sample time-series bias. By including lags of the cross-sectional means, it enables the consistent estimation of a dynamic panel when compared to estimating panel time series models with heterogeneous slopes (xtmg command in STATA) (Eberhardt, 2012). In addition, it can impose the restriction that coefficients be homogeneous across all units. It also accommodates unbalanced panels. Blackburne and Frank (2007) compare xtdcce2 to the pooled mean-group, mean-group, and dynamic fixed effects models (xtpmg command in STATA), which avoid maximum likelihood estimations and allow for the fitting of models with endogenous independent variables.

The Westerlund test ultimately leads to the implementation of a P-ARDL error correction model.

The cointegrating relationship is specified as:

$$\ln TA_{it} = y_i + \beta_{1i}\ln GPRC + \beta_{2i}\ln GDPpc + \beta_{3i}\ln POP + e_{it} \quad (1)$$

where y_i is the panel-specific mean and the cointegrating parameters, β_{1i}, β_{2i}, β_{3i} are panel-specific cointegration parameters.

The primary independent variables of interest and other explanatory variables that complete the regression model are geopolitical risk (lnGPRC), gross domestic product per capita (lnGDPpc), and total population (lnPOP). In addition, the research introduces lagged

variables of dependent variables as explanatory factors, taking dynamism into consideration. This work produces a unique model in logarithmic form, as shown below:

$$\ln TA_{it} = \alpha_1 + \alpha_2 \ln TA_{\text{it}-1} + \alpha_3 \ln GPRC_{it} + \alpha_4 \ln GDPpc_{it} + \alpha_5 \ln POP_{it} + \varepsilon_{it} \quad (2)$$

where, i represents the country (i =1, …, N) while t is for the time period (t = 1, …, T), α_1 is constant term and α_{t} to α_5 are coefficients of the variable, ε_{it} is error term.

The cross-sectionally Augmented Distributed Lag (CS-ARDL) approach leverages the lagged dependent factor and permits weak exogenous explanatory factors inside the error correction term to maintain the dynamic behaviour (Ditzen, 2021). According to Chudik and Pesaran (2015), the CS-ARDL is a novel kind of ARDL that handles CD in the presence of an I(0) or I(1) order of integration and reveals the long-run pooled values. This method allows for an omitted factor bias, requires co-integration of variables, and necessitates the dynamic specification of the model so that weak exogeneity in the explanatory variables is taken into account and residual correlations disappear. The CS-ARDL method assesses unit-specific ARDL descriptions to diagnose the effects of unidentified comparable variables that are used to investigate implicit long-term effects. The CS-ARDL technique tackles both short-term and long-term cross-sectional dependency. Extending details to Eq. (2), the CS-ARDL model specification(s) are as follows:

$$\begin{aligned} \Delta \ln TA_{it} &= \alpha_{it} + \delta_i \left(\ln TA_{it-1} - \mu_i X_{it-1} - \varphi_i \overline{\ln TA_{t-1}} - \varphi_{2i} \overline{X_{t-1}} \right) + \\ &+ \sum_{j=1}^{p-1} \gamma_{ij} \Delta L \ln TA_{it-j} + \sum_{j=0}^{q-1} \theta_{ij} \Delta X_{it-j} + \eta_{1i} \overline{\Delta L \ln TA_t} + \eta_{2i} \overline{\Delta X_t} + \varepsilon_{it} \end{aligned} \quad (3)$$

where, based on Eq. (2), $\Delta \ln TA_{it}$ present the dependent factors for cross sectional dimension j (where j = 1, 2, 3, …, J) and time t (where t = 1, 2, 3, …, T). μ_i signifies the explanatory variable coefficients. γ_{ij} and θ_{ij} are the coefficients of the dependent and independent factors, respectively independent terms in the short run. η_{1i} and η_{2i} presents the mean of the dependent and independent variables, in short run. $\overline{\ln TA_{t-1}}$ present the means of the dependent factors in the long run. $\overline{X_{t-1}}$ signifies all explanatory variables during the long run. $\ln TA_{it-1}$ indicates the dependent variable in the short run. ΔX_{it-j} signifies the explanatory factors in the short run. $\overline{\Delta L \ln TA_t}$ signifies the mean of the dependent terms within the short run. $\overline{\Delta X_t}$ signifies the mean of the explanatory terms in the short run. ε_{it} signifies the error term.

3. Results and discussion

Table 1 provides descriptive statistics for the selected model variables with 378 observations.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
lnTA (International tourist arrivals)	367	16.711	1.165	13.705	19.199
lnGPRC (Global political risk)	378	–2.605	1.323	–5.171	0.826
lnGDPpc (Gross domestic product per capita)	378	10.126	0.951	6.489	11.541
lnPOP (population)	378	16.920	1.053	15.317	18.803

lnTA natural logarithm of international tourist arrivals, lnGPRC natural logarithm of the Geopolitical Risk Index, lnGDPpc natural logarithm of gross domestic product per capita, lnPOP natural logarithm of total population.

Source: author's calculation.

Analyses start with a test for stationarity. In addition, tests for cross-sectional dependency and lag selection criteria are performed. Before beginning the P-ARDL regression, a test is also run to check the model selection's validity. The data were examined for the existence of unit roots (stationarity) using a robust variant of the Fisher-type unit-root test based on enhanced Dickey-Fuller tests. All variables are integrated, or of order I(1), which meets the Pesaran *et al.* (2001) requirement for running an ARDL model (shown in Table 2 and Appendix 1). The null hypothesis of the unit root test asserts that all panels contain a unit root. The results of the conducted test show that the p-value is lower than 0.01 and the null hypothesis can be rejected at the level of statistical significance of 1%, which confirms that there are no unit roots in the panel and that all variables are stationary in their levels.

The cross-sectional dependency (CD) test done by Pesaran (2015) on the regression does not demonstrate the existence of common variables influencing the cross-sectional units (no cross-sectional dependence). Since the p-value = 0.02 which is less than 5%, therefore it rejects the null hypothesis of weak CD (the null hypothesis of the test is, that the error term (or variable) is weakly cross-sectional dependent). The correlation between model variables may be positive, suggesting that when one score grows, so does the other, or negative, showing that a decrease in one variable results in a decrease in another. The degree and direction of the linear link between two variables are measured by correlations. The correlation coefficient may vary from –1 to +1, where -1 represents a perfect negative correlation, +1 represents a perfect

positive correlation, and 0 represents no connection at all. The results of the correlation matrix are provided in Appendix 2 and show that there is no strong correlation between variables in the model. For the Panel ARDL model, regressions were estimated independently to determine the best lag duration for each variable. First, it obtained an optimal lag structure for each country separately, and then it used the most common lag across the countries for each variable. While the addition of more lags enhances the regression fit, this comes at the expense of a greater variation in the estimated coefficients. To balance this trade-off, a data-driven method for optimum lag selection might be based on either the Akaike information criterion (AIC) or the Schwarz/Bayesian information criterion (BIC); for this study, BIC was utilized. For that purpose, it uses the Ardl command by Kripfganz and Schneider (2017) (using loop) for each country. The findings reveal the following selection of lags: lnTA (1), lnGPRC (0), lnGDPpc (0), and lnPOP (0). Next, the homogeneity or heterogeneity of each slope coefficient was determined (for more details, see Pesaran and Yamagata, 2008). Results indicate that the delta test statistic is low enough to reject the null hypothesis of slope uniformity (shown in Appendix 3).

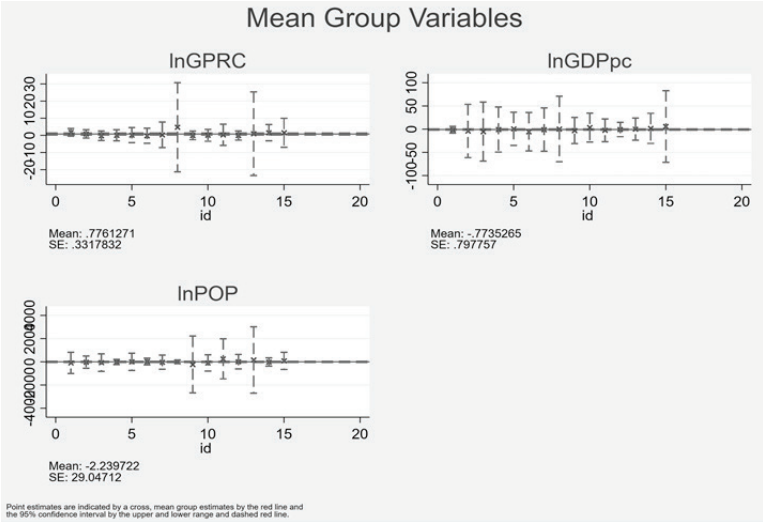


Figure 1. Range plot for MG estimates of the variables lnGPRC, lnGPDpc and lnPOP

Source: authors calculations.

Figure 1 is a range plot of the MG estimations for the coefficients of lnGPRC, lnGDPpc, and lnPOP. The highest point of the range plot is the highest point of the 95% confidence interval, and the lowest point is the lowest point of the confidence interval. The cross represents

the approximate location. In addition, the point estimate of the MG and the confidence interval of 95% are provided. Additionally, a Westerlund test of cointegration between tourism arrivals, geopolitical risk, gross domestic product, and the total population is conducted. Under the alternative hypothesis that all panels are cointegrated, the panels option is used to test the null hypothesis of no cointegration. The variance ratio statistic contradicts the null hypothesis that there is no cointegration. The result of the variance of the ratio (statistic) is –1.7864 with a p-value of 0.03, which indicates that each panel is cointegrated (shown in Appendix 4). The first Hausman test suggests that the MG model is more advantageous than the pooled model, with a p-value of 0.00 (chi = 18.86). In the second Hausman test, the pooled MG and the pooled model are compared. The preferred model is concluded to be the pooled MG model with a p-value of 0.00 (chi = 15.10). The xtdcce2 command contains all coefficients in the Hausman test. Following

Table 2. Results of the (dynamic) Common Correlated Effects Estimator – Pooled Mean Group

D.lnTA	Coefficient		p-value
Short Run Est. Mean Group			
D. lnGPRC	–0.071		0.045
D.lnGDPpc	0.454		0.000
D.lnPOP	18.826		0.096
Long Run Est. Polled			
L.lnTA	–0.295		0.834
LnGPRC	–0.144		0.864
lnGDPpc	–0.147		0.864
lnPOP	–0.152		0.993
Diagnostics test	Statist	p-value	Conclusion
Wooldridge test for autocorrelation in panel data	49.782	0.000	Present of autocorrelation
Modified Wald test for groupwise heteroskedasticity in the cross-sectional time-series FGLS regression model	19,511.30	0.000	Present of heteroscedasticity
Cross-sectional time-series FGLS regression	Coefficients Panels: Correlation:		Generalized last squares Homoscedastic No autocorrelation

Pooled Variables: L.lnTA lnGPRC lnGDPpc lnPOP.
Mean Group Variables: D.lnGPRC D.lnGDPpc D.lnPOP.
Long Run Variables: L.lnTA lnGPRC lnGDPpc lnPOP.
Cointegration variable(s): L.lnTA.
Heterogeneous constant partialled out.
Note: The method of generalized last squares (FGLS-eng. Feasible generalized least square) is applicated and the reason for that is that FGLS allows the presence of autocorrelation within the panel data, heteroskedasticity, and also correlation of the spatial section (Nguyen, Nguyen, 2021).

Source: author's calculation.

the example of Nowak-Lehmann *et al.* (2006), the paper uses feasible generalized least squares (FGLS). The ARDL analysis may be paired with the FGLS method, allowing it to address a number of estimation issues arising from autocorrelation, heteroscedasticity, and cross-section correlation among the disturbances. By weighting the regressor matrix with a weight matrix that can account for the autocorrelation of the disturbances, the heteroscedasticity of the variance of the residuals, and the cross-sectional correlation of the disturbances when applied to a system of equations, this technique transforms the variables in the regression equation.

The findings of the estimated model are shown in Table 2, and the results provide an evaluation of the long and short terms. It is possible to conclude that geopolitical risk has a negative and statistically significant relationship with short-term tourist arrivals of up to 5%, implying that a 1% increase in geopolitical risk will result in a 0.71 percent decrease in foreign tourist arrivals. The studies done by Balli *et al.* (2019); Bayraktaroğlu *et al.* (2021); Kazakova and Kim (2021); and Lee *et al.* (2021) also confirm the unfavourable and statistically significant association between geopolitical risk and tourist arrivals. The findings confirm previous research demonstrating that global and country-specific threats affect tourism demand. Also, empirical evidence indicates that geopolitical risk has a detrimental effect on international tourist arrivals in the short term and corroborates the initial idea that there is a connection between economic growth measures, tourism, and the GPR index. This provides support for the claim that minimizing risk will boost the appeal of tourist destinations, thereby generating new chances for economic growth and social development.

4. Discussion and conclusions

This paper argues that, from an economic point of view, the tourism industry is more vulnerable to geopolitical risks than many other industries. This is because the cancellation of trips and suspension of flights are almost immediate and directly effects the geopolitical risk in the tourism industry. Because they depend so much on foreign tourists, the tourist industries in less-developed countries are very vulnerable to global geopolitical issues. The findings indicate that the dynamic aspects of both local and global political environments have a significant impact on the economic performance of tourism destinations. As geopolitical threats grow, this means that the number of tourists will go down in the short term. The results show that domestic geopolitical risk causes a short-term drop in the number of tourists, but that it does not have much of an effect in the long run. This study gives real-world examples of how geopolitical worries affect the demand for international travel in the short term. Results show

that, in the long run, the tourism industry is resilient to the short-term effects of geopolitical shocks. Geopolitical risk and other outside factors have a negative effect on tourism, but the effect does not stay the same over time. The results give a more complete picture of how crisis events, such as changes in political instability, might affect tourism in countries that are geographically and historically linked. Forecasters need to look at possible external risks in order to keep the negative effects on tourist demand to a minimum. Tourist sectors in underdeveloped nations are extremely susceptible to global geopolitical concerns due to their excessive dependence on foreign tourism. Thus, tourist demand will decrease in the near term as geopolitical threats grow. In the short term, governments should take aggressive measures to prevent any potential harmful consequences of geopolitical risks. Yet, governments may not have control over the rise of GPRs (for example, political instability, war, or a conflict in an adjacent country). In this instance, governments should concentrate on other inbound tourist drivers, such as diversifying its tourism markets, as one of the methods.

Appendix 1. Results of the Unit root test

Xtunitroot fisher lnTA, dfuller drift lags (1) (11 missing values generated)			
Fisher-type unit-root test for lnTA Based on augmented Dickey-Fuller tests			
Ho: All panels contain unit roots		Number of panels = 18	
Ha: At least one panel is stationary		Avg. number of periods = 20.39	
AR parameter: Panel-specific		Asymptotics: T → Infinity	
Panel means: Included			
Time trend: Not included			
Drift term: Included		ADF regressions: ***1 lag***	
		Statistic	p-value
Inverse chi-squared(36)	P	100.512	0.000
Inverse normal	Z	–6.063	0.000
Inverse logit t(94)	L*	–6.163	0.000
Modified inv. Chi-squared	Pm	7.602	0.000
The P statistic requires a number of panels to be finite			
Other statistics are suitable for finite or infinite number of panels			

Xtunitroot fisher lnGPRC, dfuller drift lags (1)	
Fisher-type unit-root test for lnGPRC Based on augmented Dickey-Fuller tests	
Ho: All panels contain unit roots	Number of panels = 18
Ha: At least one panel is stationary	Avg. number of periods = 21
AR parameter: Panel-specific	Asymptotics: T → Infinity
Panel means: Included	
Time trend: Not included	

Drift term: Included		ADF regressions: ***1 lag***	
		Statistic	p-value
Inverse chi-squared(36)	P	156.766	0.000
Inverse normal	Z	–9.150	0.000
Inverse logit t(94)	L*	–10.175	0.000
Modified inv. Chi-squared	Pm	14.232	0.000
The P statistic requires a number of panels to be finite			
Other statistics are suitable for a finite or infinite number of panels			

Xtunitroot fisher lnGDPpc, dfuller drift lags (1)			
Fisher-type unit-root test for lnGDPpc Based on augmented Dickey-Fuller tests			
Ho: All panels contain unit roots		Number of panels = 18	
Ha: At least one panel is stationary		Avg. number of periods = 21	
AR parameter: Panel-specific		Asymptotics: T → Infinity	
Panel means: Included			
Time trend: Not included			
Drift term: Included		ADF regressions: ***1 lag***	
		Statistic	p-value
Inverse chi-squared(36)	P	200.414	0.000
Inverse normal	Z	–11.165	0.000
Inverse logit t(94)	L*	–13.064	0.000
Modified inv. Chi-squared	Pm	19.376	0.000
The P statistic requires a number of panels to be finite			
Other statistics are suitable for finite or infinite number of panels			

Xtunitroot fisher lnPOP, dfuller drift lags (1)			
Fisher-type unit-root test for lnPOP Based on augmented Dickey-Fuller tests			
Ho: All panels contain unit roots		Number of panels = 18	
Ha: At least one panel is stationary		Avg. number of periods = 21	
AR parameter: Panel-specific		Asymptotics: T → Infinity	
Panel means: Included			
Time trend: Not included			
Drift term: Included		ADF regressions: ***1 lag***	
		Statistic	p-value
Inverse chi-squared(36)	P	138.078	0.000
Inverse normal	Z	–6.775	0.000
Inverse logit t(94)	L*	–8.120	0.000
Modified inv. Chi-squared	Pm	12.030	0.000
The P statistic requires a number of panels to be finite			
Other statistics are suitable for a finite or infinite number of panels			

Source: author's calculation.

Appendix 2. Correlation Analysis

MODEL 1 – observation 363 (Dependent variable international tourist arrivals)				
Variable	lnTA	lnGPRC	lnGDPpc	lnPOP
ln*TA*	1			
lnGPRC	0.4467	1		
lnGDPpc	–0.1207	0.0169	1	
lnPOP	0.5850	0.7239	–0.4415	1

Source: author's calculation.

Appendix 3. Testing for slope heterogeneity

H0: slope coefficients are homogenous		
	Delta	p-value
	0.196	0.845
adj.	0.228	0.820
Variable partialled out: constant		

Source: author's calculation.

Appendix 4. Westerlund test for cointegration

H0: No cointegration Ha: All panels are cointegrated		
Cointegrating vector: Panel specific	Number of panels = 18	
Panel means: Included	Avg. number of periods = 20.389	
Time trend: Not included		
AR parameter: Same		
	Statistic	p-value
Variance ratio	–1.786	0.037

Source: author's calculation.

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