Geopolitical Risks and Tourism Stocks: New Evidence from Causality-in-Quantile Approach

Ibrahim D Raheem[a*] and Sara le Roux[b]
[a] Tubman Institute, York University, Toronto, Canada
[b] Oxford Brookes Business School, Oxford Brookes University, Headington Campus, Oxford
* Corresponding author: i_raheem@ymail.com

Abstract
This study examines the relationship between Geopolitical Risks (GPR) and Travel and Leisure (T&L) stocks. The scope of this study is based on six emerging countries. Analyses are done using a non-parametric causality-in-quantile approach, whose advantages include: (i) robustness to misspecification errors; (ii) simultaneously examine causality in mean and variance. We find that GPR is weakly related to the T&L stock for both Indonesia and South Korea. However, significant relationships ensue for India, China, Malaysia, and Israel. It is also observed that GPR can better predict the volatility of T&L stock compared to stock returns. These results are robust to alternative measures of GPR.

JEL codes: C22, G15
Keywords: Geopolitical risks, tourism, quantile causality.

Introduction

The initial focus of studies, academics, and policymakers has been on terrorism. Understandably, adequate attention has been devoted to examining the influence of terrorism on socio-macroeconomic fundamentals. In this instance, the emphasis has been on the actual occurrences of terrorist attacks and their effect on economic indicators. However, recent events have necessitated the need to re-evaluate the conceptual approach of terrorism to account for relatively newer facets of terrorism that were hitherto not apparent, but have similar effects/consequences with the actual form of terrorism (Caldara and Iacoviello, 2018; Gillen and Mostafanezhad, 2019). For instance, threats of nuclear attacks or territorial invasion hypothetically have similar effects as if the actual threat had been carried out. Also, geopolitical tension between countries is a risk that cannot be ignored due to its significant effect on such economies. Geopolitical risk is a new concept that enclaves actual occurrence, threat, and risk of occurrence. Caldara and Iacoviello (2018) define geopolitical risk as "the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations." Caldara and Iacoviello created the geopolitical risk (GPR) index that captures terrorist acts and threats, war risks, nuclear threats, and military-related tensions. Hence, GPR is considered a broader measure of global uncertainty, which incorporates terrorism.

It is generally acknowledged that one of the most prominent casualties of geopolitical risk/terrorism is the tourism and hospitality industry/sector. Succinctly, tourism is vulnerable to exogenous shocks such as wars, terrorist attacks, and nuclear threats (Kim and Marcouiller, 2015; Seraphin, 2017). In addition, Chesney et al. (2011) argued that the airline industry, an arm of the tourism sector, is more vulnerable to terrorism than any other industry/sector.[1] The aftermath of the 9/11 attack on the global tourism sector has aroused the interest of governments, policymakers, and investors about the need to understand the dynamics between terrorism and the tourism sector. More recently, studies have shown a keen interest in the linkage between terrorism and tourism, with a consensus that there is a negative correlation between these two variables (Zopiatis, 2019; Damilaray and Kilincarslan, 2019) Seabra et al., 2020). Empirical studies have followed the paradigm shift in the conceptualisation of terrorism to geopolitical risks. For instance, early studies have examined the terrorism-tourism nexus (e.g. Chen, 2007 and 2011; Chang and Zeng, 2011; Wolff and Larsen, 2014; Goldman and Neubauer-Shani, 2017), while recent studies have linked tourism to the GPR index (Damilaray and Kilincarslan, 2019; Gillen and Mostafanezhad, 2019; Hassan et al., 2020).

[1] The estimate of the direct cost of the 9/11 attack is in excess of $30 billion (Enders and Olson, 2012). Also, it was estimated that the Paris attack of 2015 led to a plunge of about €2 billion in the European travel and tourism industry (Wearden and Allen, 2015). Terrorism has reduced the European Union's GDP to the tune of €180billion (RAND, 2018).

These studies have some apparent shortcomings. The principal flaw relates to the assumption of linearity between GPR and Tourism and Leisure (T&L) stocks. The common forms of nonlinearity studied in the literature are heterogeneity, dual causation, and asymmetry (Zopiatis et al., 2019; Demiralay and Kilincarslan, 2019). Making a case for the T&L stocks and focusing on asymmetry, there tends to be an implicit assumption that there is a one-for-one relationship in the nexus. In other words, the higher the severity of this attack, the higher (roughly in the same magnitude) would the tourism sector be adversely affected. Zopiatis et al. (2019) is the first study to dispel this assumption by showing distinctive differences among the types of incidents and how they affect the regions under investigation. Hence, the results suggest that terrorism does not affect stocks equally, or that bigger terrorist acts only mildly affect the tourism sector as compared to the less severe attacks.

Other flaws in the literature are as follows: (i) the sole reliance on terrorism without accounting for other geopolitical uncertainties that equally have significant effects on tourism stocks; (ii) limited scope/time series analysis with a focal lens mainly pointed towards the United States. Hence, there is no basis for comparison. In addition, tourism stocks have been confirmed to be sensitive to political events, which are unique across countries (Chen, 2007); (iii) aggregation issues. Demir and Gozgor (2018), Damilaray and Kilincarslan (2019), and Seabra et al. (2020) use aggregated data based on regional groupings. A fundamental problem with this type of data is the sensitivity of results to changes in the assigned weights or the use of non-weighted data. As an extension, the weight size attributed to each component is debatable. The attending policy implications of the results, based on non-aggregated data, would be more practical compared to a scenario where there may be a considerable discrepancy in the allocation of the weights. More worrisome is the inability of these studies to justify the use of aggregate series when data is available in disaggregated form. Another shortcoming of the aggregate measure is its inability to account for heterogeneity- a fundamental feature that should not be ignored; (iv) we focus on the finance aspect of tourism. This is in contrast to the norm where tourism is focused on the number of arrivals, and receipts, among other measures (Seabra et al., 2020). The decision to focus on the financial side of terrorism is based on the fact that the industry has been growing at a geometric progression; hence, there is a need to focus on the implications for investors.

We address these shortcomings by relying on a non-parametric causality-in-quantiles test. Furthermore, the issue of aggregation is solved by using time-series data. Based on the foregoing, the objective of our study is to examine the causality between GPR and tourism-Travel & Leisure (T&L)- stocks for selected emerging countries. The choice of emerging countries is attributed mainly to the fact that they are increasingly becoming popular holiday destinations. In addition, there has also been a spike in tension, risks, and threats in these countries. Essentially, we seek answers to the following research questions: (i) are the T&L stocks vulnerable to GPR? (ii) which of the indices of GPR (threat, risks, and act) significantly affect tourism stocks? (iii) are T&L stocks sensitive to the state of the market conditions (i.e., does quantile distribution has effect on the nexus)?

We make three novel contributions to the literature. First, we join the few studies that link GPR indices to the leisure and tourism stocks. Second, we use the recently developed non-parametric causality-in-quantiles test of Balcilar et al. (2017), which is a hybrid framework of Nishiyama et al. (2011) and Jeong et al. (2012).[2] The choice of the method is due to the nonlinearity explained earlier. The method is suited for scenarios where the predictor and predicting variables are nonlinearity causal. An additional advantage of this methodology is its robustness to misspecification errors. Also, the methodology is not limited to causality in mean, as there might be the existence of causality in the tails of the distribution; hence this helps capture the effect of GPR during different market states such as the bear-bull phases. In addition, the methodology also helps to study causality in variance and spillover volatility. Finally, our analysis is country-level specific. As such, we avoid the use of aggregated/weighted series. As a follow-up to the point above, the scope of this study ensures that there is sync in the variables of interest, thus avoiding approximation. In simple terms, the selected countries have data for both GPR and tourism.

Our results show that GPR effects are more prominently felt on volatility rather than the returns of T&L stocks and at quantiles below the median. The impact of GPR is heterogeneous among the selected countries. GPR influences the stock volatility in Israel, Malaysia, India, and China. However, the same cannot be said about Indonesia and South Korea. The rest of the paper is structured as follows. A brief literature review is presented in Section 2. Section 3 houses data and methodology, while Section 4 presents the empirical results. Finally, Section 5 offers the conclusion and attendant policy implications.

2. Brief Literature Review

This study is related to two strands of the literature. The first strand analyses the relationship between terrorism and the tourism sector. Neumayer (2004) is one of the most influential studies in this context. The study shows that one of the effects of terrorism is the drop in the number of tourist arrivals. This has served as the benchmark for succeeding studies, which have replicated the hypothesis using various methodologies and scopes. Some studies have described how tourists avoid visiting places renowned for being targets of violent attacks (de Sausmarez, 2013; Wolff and Larsen, 2014; Solarin, 2015).

A few studies have focused on how a particular terrorist event affects tourism. Much of these studies are related to the September 11, 2001 (9/11, henceforth) terrorist attack in the United States. For instance, Ito and Lee (2005) examined the effect of 9/11 on air travel, an important component of the tourism industry. Arana and Leon (2008) examined the short-

[2] Other related methods include cross-correlation function, and Granger causality test. These tests are not able to account for nonlinearity and misspecification error.

run impact of 9/11 on demand for tourists' preferences for competing destinations in the Mediterranean and the Canary Islands. Using a stated preference model, the authors show that the attack had changed the utility preference and profiling of destinations. Tarrant (2010) estimated that the aftermath effect of the political unrest, on April 10, 2010, in Thailand cost the country's tourism sector about $300 million. Korstanje and Clayton (2012) reveal that the aftermath effect of the 9/11 terrorist act saw a decline in about 13.5% of U.S. tourists to the Caribbean and a loss of about 365,000 jobs. Other non-US events have also been studied, for example, Baker and Coulter (2007) for Bali; Lee (2010) for Singapore; Steiner (2010) for some developing countries.

Another interesting study is by Goldman and Neubauer-Shani (2017), who examined the nexus from four different perspectives: perpetration by foreign attackers against local victims, perpetration by local attackers against foreign victims, perpetration by foreign attackers against foreign victims, and perpetration of terror attacks against foreign private parties. Among the numerous interesting results, the authors found an inverse-U relationship between tourism arrival and the number of terrorist attacks perpetrated by foreigners. Samitas et al., (2018) focused on the Greek tourism industry. Furthermore, deploying causality test models, the study confirms there is a negative relationship between tourism and terrorism, and the causality runs from terrorism to tourism.

The second strand of the literature expanded the conception of terrorism to capture war risk, nuclear threats, and military-related tensions— this strand of the literature focuses on the effect of GPR on the tourism stock performance. Demiralay and Kilincarslan (2019) used a regional dataset (namely Global, Asia-Pacific, Europe, and North America) to show the negative effect of GPR on the tourism stock for regions except Asia-Pacific. They further showed that of the GPR indices, threat has the domineering impact. Balli et al. (2019) concluded that the negative consequence of terrorism is negligible for popular tourist destinations. Using Granger causality analysis, Akadiri et al. (2020) reveal that GPR leads to tourism depression. Hasan et al. (2020) focus on the linkage between GPR and tourism stocks of emerging countries and prove that GPR is an efficient predictor of stock returns, especially when the market is in a calm condition. Kumar (2021) seeks to analyse the extreme risk spillover from the changes in uncertainty variables to the European T&L sector stocks using a copula-based CoVaR approach. His findings indicate the significant downside (resp. upside) risk spillover effect from the extreme upside (resp. downside) movements in the uncertainty variables, respectively. Jiang et al. (2022) examine the comparative effect of GPR and economic policy uncertainty on Chinese tourism-listed stocks. Results from the linear regression show that GPR has more lasting negative effects. The results of the quantile regression are more prominent at the lower quantiles.

On the demand side of tourism, most studies have reported adverse effects of GPR on inbound terrorism (Demir et al., 2019), the number of tourism arrivals (Tiwari et al., 2019), and tourism receipts (Alola et al., 2019). Using the SVAR model, Hailemariam and Ivanovski (2021) show that GPR negatively and significantly impacts U.S. tourism export services.

3. Method and Data

3.1 Method

The earlier studies have examined the uncertainty-tourism nexus using a classical linear regression model. The advantage of this model is attributed to its simplicity. Conversely, the main criticism is that it only estimates models along the central tendency, as there might be some causality along the tail distributions. Hence, the method is not capable of estimating models along quantile distributions. The quantile regression (Q.R.) technique has helped solve this problem. Despite the impressive innovation Q.R. made, latter studies have outlined its demerits/failures: (i) it is unable to capture endogeneity caused by nonlinearity between dependent and independent variables, (ii) it only estimates the mean model and is unable to capture the causality in variance spillover, (iii) it is not robust to misspecification errors. The non-parametric causality-in-quantile model has helped to address these concerns (Balcilar et al., 2017).

Balcilar et al. (2017) proposed a nonlinear quantile-based causality model based on the works of Nishiyama et al. (2011) and Jeong et al. (2012). Since the model is bivariate in nature, T&L stock returns is depicted by y_t, while the various indices of GPR is represented by x_t. The null hypothesis of the model is that at Qth quantile, x_t does not cause y_t. Mathematically, Jeong et al. (2012) show that x_t does not cause y_t in the Qth quantile with respect to the lag of vector of $\{y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\}$ if:

$$Q_\theta\left(y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\right) = Q_\theta\left(y_t | y_{t-1}, \dots, y_{t-p}\right) \qquad (1)$$

Where, x_t causes y_t in the Qth quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\}$ if:

$$Q_\theta\left(y_t | y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\right) \neq \quad Q_\theta\left(y_t | y_{t-1}, \dots, y_{t-p}\right) \quad . \qquad (2)$$

Note: $Q_\theta(y_t|.)$ is the Qth quantile of y_t condition on t and 1>θ>0.

Let $Y_{t-1} \equiv \left(y_{t-1}, \dots, y_{t-p}\right), X_{t-1} \equiv \left(x_{t-1}, \dots, x_{t-p}\right), Z_t \equiv (X_t, Y_t)$ and $F_{yi|y_{t-1}}(y_t|Y_{t-1})$ represent the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, in that order. It is assumed that the conditional distribution $F_{y_t|Z_{t-1}}(y_t|Y_{t-1})$ is continuous in y_t for almost Z_{t-1}. If $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, then $F_{y_t|z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, with a possibility of unity. Based on equations 1 and 2 above, the null and alternate hypothesis can be expressed as:

$$H_0: P\{F_{y_t|z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad (3a)$$

$$H_1: P\{F_{y_t|z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad (3b)$$

Jeong et al. (2012) used the distance measure J defined as $J = \varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})$, where, ε_t is the residual, while $f_Z(Z_{t-1})$ is the marginal density of Z_{t-1}. Note that ε_t is observed based on eq (3a), which is only true if $E[1\{y_t \leq Q_\theta(y_{t-1})|Z_{t-1}\}] = \theta$. The distance measured can also be specified as

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(y_{t-1}|Z_{t-1})\} - \theta\right\}^2 f_Z(Z_{t-1})\right] \quad (4)$$

It should be noted that $J \geq 0$ in Eq. (3a) on the condition that H_0 in Eq. (4) is true. The feasibility kernel-based sample analog of J is expressed as:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{t=p+1,s\neq t}^{T} K\left(\frac{Z_{t-1}Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \quad , \quad (5)$$

where, K(.) is the kernel function with bandwidth h and the sample size is represented by T, while p is the lag operator and $\hat{\varepsilon}_t$ is the estimate of the unknown residual, which is computed as follows:

$$\hat{\varepsilon}_t = 1\{y_t \leq \hat{Q}_\theta(\theta|Y_{t-1})\} - \theta \quad , \quad (6)$$

where, $\hat{Q}_\theta(Y_{t-1})$ is the estimate of the Qth conditional quantile of y_t given Y_{t-1}. $\hat{Q}_\theta(Y_{t-1})$ can be estimated with the aid of non-parametric kernel method defined as:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|y_{t-1}}(\theta|Y_{t-1}) \quad , \quad (7)$$

where $\hat{F}^{-1}_{y_t|y_{t-1}}(y_t|Y_{t-1})$ represents the Nadarya-Watson kernel estimator given by:

$$\hat{F}^{-1}_{y_t|y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) 1(y_s \leq y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \quad , \quad (8)$$

where, L(.) is the kernel function with h bandwidth.

3.2 Data

The variables of interest in this study are GPR and T&L stock returns. The source of the GPR data is Caldara and Iacoviello (2019). GPR is a monthly index that counts the number of times words related to geopolitical tension are used in some leading national and international newspapers. The index is constructed by searching articles, including references to six groups of words. Caldara and Iacoviello further explained that their technique is based on the approach below: "*Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a U.S. involvement. Group 2 includes words directly related to nuclear tensions. Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively. Finally, Groups 5 and 6 aim at capturing press coverage of actual adverse geopolitical events (as opposed to just risks), which can be reasonably expected to lead to increases in geopolitical uncertainty, such as terrorist acts or the beginning of a war. The authors further disentangle the direct effect of adverse geopolitical events from the effect of pure geopolitical risks by constructing two indexes. The Geopolitical Threats (GPT) index only includes words belonging to Search Groups 1 to 4 above. The Geopolitical Acts (GPA) index only includes words belonging to Search Groups 5 and 6*."

The T&L stock is collected from the Bloomberg terminal. We then log-linearise the data and find that they are stationary. In line with the extant literature, we calculated the return of the natural log of the series as its first difference.[3]

Based on data availability, the scope of this study is limited to six emerging countries: India, Malaysia, Indonesia, Israel, South Korea, and China.[4] Analyses are conducted based on monthly data from January 2000 – October 2019. The data summary is presented in Table 1. An overview of the table shows no evidence of normality in the series based on Jarque-Bera test. This is the first pointer that validates the use of causality-in-quantiles test. Statistics for India and China are negatively skewed while others are positively skewed with excess kurtosis. The GPR index is also positively skewed accompanied by excess kurtosis.

Table 1: Summary Statistics

	Indonesia	S.Korea	Malaysia	India	China	Israel	GPR
Mean	0.042	0.125	0.119	0.041	2.145	0.002	4.965
Std Dev	0.025	0.014	0.143	0.012	1.042	0.019	0.458
Min	0.006	0.125	0.034	0.006	0.524	-0.145	3.521
Max	0.108	0.254	1.318	0.109	6.052	0.046	5.619
Jarque-Bera	550.05	534.015	10663	1024.36	329.5	15516	16.525
Skewness	0.906	11.658	4.542	-0.965	-0.706	2.164	0.448
Kurtosis	9.254	153.164	26.876	19.254	12.364	85.216	5.116

Source: Author's computation

[3] The essence of this transformation is to ensure that the series in the model are stationary, as this is a requirement for the non-parametric causality in quantiles test.

[4] The small sample size in this study is based on the intuition that we are using a high frequency (monthly) and disaggregated (country level) data.

4.0 Results Discussion

Although the objective of this paper is to examine the non-parametric causality running from GPR to T&L stock returns and volatility, for reasons attributed to completeness, we first examine the conventional Granger causality test, using VAR(1), whose result is reported in Table 2. The choice of the lag length is determined by the Schwarz Information Criterion (SIC) and Alkaike Information Criterion (AIC). Nishiyama et al. (2011) also support using the first lag.

Summarising the results, there is no evidence of causality between the series. However, the extent of the validity of this result is weak. This is not unconnected to the fact that the test is based on the mean causality and is not robust to misspecification error. To confirm another source of nonlinearity, we use the Brock et al. (1996) BDS tests on the residuals of an AR(1) model. The results of this test are shown in Table 3. A close examination of the table summarises that the null hypothesis of the residuals at different embedded dimensions is rejected at 1% significance level.

Table 2: Granger Causality Test

Country	F-Statistic
Indonesia	1.025
South Korea	0.366
China	0.168
Malaysia	1.049
India	0.863
Israel	1.315

Source: Author's computation

Null hypothesis: GPR does not Granger cause T&L stock.

Table 3: BDS Test

m	z-statistic of residuals of the AR(1) model of T&L stock returns	P-value	z-statistic of residuals of the VAR(1) model of T&L stock returns	P-value
2	23.165	0.000	23.014	0.000
3	29.046	0.000	29.001	0.000
4	35.154	0.000	34.896	0.000
5	39.466	0.000	39.234	0.000
6	42.024	0.000	41.915	0.000

Note: m stands for the number of (embedded) dimension which embed the time series into m-dimensional vectors, by taking each m successive points in the series. Value in cell represents BDS z-statistic corresponding to the null of residuals.

Empirical results for the non-parametric causality-in-quantiles test for stock returns and volatility are presented in Table 4. The estimation for the quantile ranges between 0.10 and 0.90. The statistics depicted in the table are the test statistics for the alternative quantiles of the conditional distribution of return and volatility measures. The null hypothesis of non-causality at that concerned quantile is rejected at a 5% level when the test statistic is above the critical value of 1.96.

To recall, we use the three indices of the GPR coined by Caldara and Iacoviello (RISK, THREAT, and ACT). We start with the risk element of the index. An overview of Table 4 Panel A shows that GPR affects the T&L stock returns of Malaysia, India, and Israel, across the entire conditional distribution. This implies that the state of the market conditions (bear, normal, or bull) does not affect the GPR's predictive power on stock returns. However, the significance of the model is limited to the mid-quantile range (0.40-0.60) for Indonesia and South Korea. This implies that GPR is only effective when the market condition of the T&L stock is in moderate and stable states (i.e., neither in bear nor bull states). This finding implies that investors require compensation for their investment due to their exposure to the measures of risks. Following the asset pricing principle, GPR is a systematic risk factor that drives T&L stock returns. Thus, to accurately price the stock, the valuation models should account for the influence of GPR. These findings raise questions about the general belief that these assets exhibit hedging behaviour during tranquil and turbulent periods. Across the entire distribution, insignificant coefficients were reported for China. Results presented thus far are, in part, similar to some earlier studies. For instance, Demiralay and Kilincarslan (2019) show that GPR does not influence the Asian and Pacific tourism industry; Hassan et al. (2020) reveal that geopolitical tensions and uncertainty are good predictors of tourism stocks for Indonesia, South Korea, and Israel.

Almost similar results play out for THREAT and ACT components of the index. In essence, the relationship between GPR and tourism stocks is not sensitive to the measures of the GPR index. A potential explanation could be linked to the fact that theoretical expositions have shown that financial assets (tourism stocks inclusive) respond to uncertainty and negative news. It can be hypothesized that such reactions do not account for the severity or types of such uncertainties. Saying it differently, financial assets will respond to uncertainties irrespective of the latter being mild or major.

Table 4: Empirical Results

	Indonesia			South Korea			China		
Panel A: Mean									
	Risk	Threat	Act	Risk	Threat	Act	Risk	Threat	Act
0.10	0.734	0.464	0.447	0.472	0.325	0.237	0.1214	2.034*	0.143
0.20	0.637	0.565	0.413	0.696	0.456	0.258	0.495	1.995*	0.266
0.30	0.673	0.729	0.303	6.031*	5.978*	0.973	0.326	2.035*	0.216
0.40	4.995*	3.020*	3.166*	5.358*	5.319*	3.134*	0.369	1.032	0.314
0.50	6.195*	3.510*	4.132*	2.332*	2.255*	2.892*	1.147	1.569	0.365
0.60.	3.984*	2.989*	3.999*	0.979	0.812	2.789*	0.126	1.036	0.411
0.70	2.142*	2.102*	1.879	1.223	0.827	0.522	0.448	0.668	0.956
0.80	0.698	0.701	0.498	0.764	0.494	0.360	1.587	0.466	1.035
0.90	0.179	0.247	0.093	0.480	0.537	0.239	1.859	0.194	0.265
Panel B: Variance									
0.10	5.150*	5.465*	4.325*	3.326*	4.564*	4.021*	2.033*	3.097*	2.326*
0.20	4.123*	4.123*	4.452*	3.818*	4.217*	3.436*	1.996*	3.331*	3.021*
0.30	2.515*	2.376*	2.618*	2.241*	2.004*	1.378	2.065*	2.826*	4.021*
0.40	0.852	0.778	0.807	0.761	0.565	3.682*	2.214*	2.962*	4.421*
0.50	0.339	0.323	0.126	0.819	0.779	0.644	2.369*	3.069*	3.032*
0.60.	0.711	0.839	0.244	1.055	0.792	0.299	2.562*	2.826*	2.811*
0.70	0.709	0.763	0.394	0.542	0.461	0.342	3.401*	2.963*	2.758*
0.80	0.631	0.371	0.792	0.484	0422	0.230	3.048*	3.027*	2.135*
0.90	0.383	0.208	0.527	0.387	0.285	0.216	3.031*	2.825*	1.2265

Source: Authors' computation

Note: * implies the rejection of non-causality at a 5% level.

A different scenario is obtained when the volatility of stock is considered. For instance, significant results are obtained for the lower quantile of the conditional distribution, ranging between 0.10 to 0.30 for both Indonesia and South Korea. The significant effect at lower quantiles of the conditional distribution of T&L stocks follows rational intuition, as terrorism is expected to affect uncertainty more in this region than at the upper quantiles. However, GPR "non-parametrically causes" stock price volatility over the entire conditional distribution for the remaining countries under investigation. A comparison of the results from both the return and volatility models (Table 4 Panels A and B) shows that GPR has a more pronounced effect on the volatility of stock prices. These results are akin to earlier studies (see Bouri et al., 2019; Aspergis et al., 2017; and Balcilar et al., 2016 and 2017). The results imply that the dynamic between GPR and T&L stocks is enhanced through the volatility channel. Finally, it should be mentioned that the volatility of stock prices has negative economic consequences. Thus, this negative vibe could be avoided if policy measures take cognizance of incidences related to GPR.

Table 4: Empirical Results Cont'd

	Malaysia			India			Israel		
	Risk	Threat	Act	Risk	Threat	Act	Risk	Threat	Act
Panel A: Mean									
0.10	2.000*	2.016*	3.216*	1.956*	0.949	1.998*	2.229*	2.323*	3.321*
0.20	2.022*	2.021*	3.559*	1.996*	2.001*	2.102*	2.328*	2.512*	3.336*
0.30	2.036*	2.128*	3.418*	2.016*	0.897	2.210*	2.441*	2.325*	3.458*
0.40	2.259*	2.416*	3.361*	2.325*	3.202*	2.333*	2.255*	2.465*	3.519*
0.50	2.326*	2.321*	3.021*	2.411*	3.520*	2.217*	2.742*	2.624*	3.554*
0.60.	2.696*	2.144*	2.925*	2.515*	2.818*	2.114*	2.958*	2.748*	3.472*
0.70	2.748*	2.746*	2.988*	2.684*	2.015*	1.879	2.856*	3.031*	3.663*
0.80	2.305*	3.025*	3.014*	2.554*	1.856	1.658	2.759*	3.332*	3.847*
0.90	2.029*	2.497*	3.376*	2.026*	1.237	1.745	2.594*	3.410*	3.954*
Panel B: Variance									
0.10	3.017*	4.165*	3.024*	4.016*	3.255*	2.415*	2.447*	2.985*	3.752*
0.20	3.165*	4.398*	2.997*	4.032*	3.754*	2.521*	2.745*	2.987*	2.621*
0.30	3.265*	4.598*	2.996*	3.954*	3.478*	2.014*	2.321*	3.014*	2.441*
0.40	3.486*	4.448*	3.254*	3.995*	2.590*	1.878	2.411*	3.321*	1.952
0.50	3.592*	4.559*	3.329*	3.845*	1.568	1.558*	2.236*	3.225*	1.851
0.60.	2.925*	5.089*	3.016*	4.225*	2.180*	2.654*	2.102*	3.144*	1.523
0.70	2.748*	5.149*	3.445*	4.025*	1.379	2.771*	2.210*	2.854*	1.428
0.80	2.519*	5.578*	3.647*	3.563*	0.808	2.844*	2.114*	2.799*	1.033
0.90	2.613*	4.915*	3.016*	2.025*	0.447	2.697*	1.999*	2.966*	0.325

Source: Authors' computation

Note: * implies the rejection of non-causality at 5% level.

As a robustness check for our results, we use an alternative measure of volatility. Rather than using the squared returns, we rely on the univariate GARCH model. There is no noticeable difference between these new sets of results and those presented earlier.[5]

5. Conclusion

It has been observed that there has been a surge in the wave of geopolitical uncertainty (GPR) across the globe, which thus has negative consequences on both financial and macroeconomic fundamentals. On the financial fundamentals, GPR has been linked to aggregated stock returns. However, a similar linkage using disaggregated stock is missing. To fill this perceived gap, the current study examines the relationship between GPR and Travel and Leisure (T&L) stocks for six emerging tourist attraction countries (Indonesia, South Korea, Malaysia, India, China, and Israel).

Analyses are based on the non-parametric causality-in-quantile method due to its ability to misspecification errors and examine causality along tail distributions rather than mean distribution. Some interesting results were obtained. We show that Indonesia and South

[5] In the interest of brevity, we refrain from presenting these results. They can, however, be made available upon request.

Korea present weak results, while the reverse is the case for the remaining countries under investigation. It is also demonstrated that the volatility model results are more enhanced than the return model. The above results are robust to the variant measures of GPR.

There are four important policy implications of our results. First, there is the need to set up policies seeking to reduce stock returns volatility. Such policies should include those that aim to reduce risk exposure and vulnerability to external shocks. Examples include policies related to crisis management response and contingency plans. Also, policies toward enhancing the sustainability of the industry should be patronised. Such policies include financial assistance to the industry's participants and post-crisis strategies that will ensure the continuous inflow of both tourists and, by extension, investors. Second, the effect of terrorism on tourism is dissimilar across countries and quantiles. Hence, investors need to consider country-specific cases when making portfolio allocation designs. This seems to suggest that the relationship between GPR and T&L is heterogeneous, as confirmed by previous studies (Zopiatis et al., 2019; Demiralay and Kilincarslan, 2019). For example, Indonesia and South Korea promise to be avenues for portfolio diversification when the market condition is non-normal (i.e., bearish or bullish). As such, these countries act to provide a safe haven against shocks attributed to terrorism. Third, there is the need to stem the attendant effect of market uncertainty in the form of high market volatility. Studies have shown that volatility reduces the benefit of portfolio diversification. Interestingly, our results support the stance that GPR impacts on stock more prominently via the volatility channel. Finally, it is important to account for nonlinearity in modelling T&L stocks-GPR nexus across the entire conditional distribution. The inability to account for this could result in wrong policy formulation, which could have serious negative consequences for both investors and the economy.

The methodology this study relied on is limited in the sense that it only captures relationships in a pairwise manner. Future studies could explore other nonlinear models that account for nonlinearity and control variables. This will shed light on whether the inclusion of some control variables could alter the relationship in the nexus. Also, a comparison analysis between developed/emerging and developing countries promises to be an interesting research future studies could consider. This will help provide information on the degree of susceptibility of the tourism sector to shocks.

Reference

Akadiri, S. S., Eluwole, K. K., Akadiri, A. C., and Avci, T. (2020) “Does Causality between Geopolitical Risk, Tourism and Economic Growth Matter? Evidence From Turkey”. Journal of Hospitality and Tourism Management,43, 273–277

Alola U. V., Cop S., Adewale A. A. 2019. “The Spillover Effects of Tourism Receipts, Political Risk, Real Exchange Rate, and Trade Indicators in Turkey.” International Journal of Tourism Research 21 (6): 813–23.

Apergis, N., M. Bonato, R. Gupta, and C. Kyei. (2017). “Does Geopolitical Risks Predict Stock Returns and Volatility of Leading Defense Companies? Evidence from a Nonparametric Approach.” Defence and Peace Economics, 29:6, 684-696

Araña, J.E. and León, C.J. (2008) "The impact of terrorism on tourism demand." Annals of Tourism Research 35(2), 299-315

Baker, K., & Coulter, A. (2007). “Terrorism and tourism: The vulnerability of beach vendors’ livelihoods in Bali”, Journal of Sustainable Tourism, 15(3), 249–266

Balcilar, M., R. Gupta, C. Pierdzioch, and M. E. Wohar. 2017. “Do Terror Attacks Affect the Dollar-Pound Exchange Rate? A Nonparametric Causality-in-Quantiles Analysis.” The North American Journal of Economics and Finance 41 (1): 44–56.

Balcilar, M., S. Bekiros, and R. Gupta. 2016. “The Role of News-based Uncertainty Indices in Predicting Oil Markets: A Hybrid Nonparametric Quantile Causality Method.” Empirical Economics. 53(3): 879–889.

Balli F., Uddin G. S., Shahzad S. J. H. (2019). “Geopolitical Risk and Tourism Demand in Developing Economies.” Tourism Economics 25 (6): 997–1005.

Bouri, E.; Demirer, R.; Gupta, R.; and Marfatia, H. A. (2019) “Geopolitical Risks and Movements in Islamic Bond and Equity Markets: A Note”, Defence and Peace Economics, 30:3, 367-379

Caldara, D., & Iacoviello, M. (2018). Measuring geopolitical risk. Working Paper. Board of Governors of the Federal Reserve Board.

Chang, C., & Zeng, Y. Y. (2011). Impact of terrorism on hospitality stocks and the role of investor sentiment. Cornell Hospitality Quarterly, 52(2), 165–175

Chen, M. H. (2007). “Macro and Non-macro Explanatory Factors of Chinese Hotel Stock Returns.” International Journal of Hospitality Management 26 (4): 991–1004

Chen, M. H. (2011). The response of hotel performance to international tourism development and crisis events. International Journal of Hospitality Management, 30(1), 200–212.

Chesney, M., G. Reshetarb, and M. Karaman. (2011). “The Impact of Terrorism on Financial Markets: An Empirical Study.” Journal of Banking and Finance 35 (2): 253–67

de Sausmarez, N. (2013). Challenges to Kenyan tourism since 2008: Crisis management from the Kenyan tour operator perspective. Current Issues in Tourism, 16(7–8), 792–809

Demier, E., Maria, J., Conrado, D-E abnd Garcia-Gomez, D. (2019) “The impact of geopolitical risks on cash holdings of hospitality companies: Evidence from emerging countries”, Journal of Hospitality and Tourism Management, 39, 166-174

Demir E., Gozgor G., Paramati S. R. 2019. “Do Geopolitical Risks Matter for Inbound Tourism?” Eurasian Business Review 9 (2): 183–91.

Demir, E. and Gozgor, G. (2018) “Does economic policy uncertainty affect Tourism?” Annals of Tourism Research, 69(1), 15-17

Demilaray, S. & Kilincarslan E. (2019) “The impact of geopolitical risks on travel and leisure stocks” Tourism Management 75, 460–476

Enders, W and Olson, E (2012) “Measuring the Economic Costs of Terrorism. The Oxford Handbook of the Economics of Peace and Conflict. *Edited by* Michelle R. Garfinkel and Stergios Skaperdas

Gillena, J. and Mostafanezhad, M. (2019) “Geopolitical encounters of tourism: A conceptual approach” Annals of Tourism Research, 75, 70-78.

Goldman, O. and Neubauer-Shani, M. (2017) “Does International Tourism Affect Transnational Terrorism?” Journal of Tourism Research, 54(6), 451-467

Hailemariam, A. and Ivanovski, K. (2021) “The Impact of Geopolitical Risk on Tourism”, Current Issues in Tourism, 24(22), 3134-3140.

Hasan, M.; Naeem, M.A.; Arif, M.; Shahzad, S.J.H.; Nor, S.M. (2020) “Geopolitical Risk and Tourism Stocks of Emerging Economies”. Sustainability 2020, 12, 9261. https://doi.org/10.3390/su12219261

Ito, H., & Lee, D. (2005). “Assessing the impact of the September 11 terrorist attacks on U.S. Airline demand”, Journal of Economics and Business, 57(1), 75–95

Jeong, K., W. K. Härdle, and S. Song. (2012). “A Consistent Non-parametric Test for Causality in Quantile.” Econometric Theory, 28: 861–887.

Jiang, Y, Tian, G. and Wu, Y. and Mo,B. (2022) “Impacts of Geopolitical Risks and Economic Uncertainty on Chinese Tourism Listed Stocks”, Journal of International Finance and Economics, 27, 320 -333

Kim, H., & Marcouiller, D. W. (2015). Considering disaster vulnerability and resiliency: The case of hurricane effects on tourism-based economies. The Annals of Regional Science, 54(3), 945–971.

Korstanje, M. and Clayton, A. (2012) “Tourism and terrorism: conflicts and commonalities” Worldwide Hospitality and Tourism Themes, 4(1), 8-25

Kumar, D. (2021) “European travel and leisure sector and uncertainties: A risk spillover analysis”, Tourism Economics. https://doi.org/10.1177/13548166211035954

Lee, C. G. (2010). “Whether a shock has a temporary or permanent effect on visitor arrivals in Singapore”, Tourism Review International, 14(1), 43–46

Neumayer, E. (2004). The impact of political violence on tourism: Dynamic cross-national estimation. The Journal of Conflict Resolution, 48(2), 259–281.

RAND (2018) “The Fight Against Terrorism: Cost of Non-Europe Report — June 6, 2018” available on https://www.rand.org/randeurope/research/projects/the-cost-of-terrorism-in-europe.html

Samitas, A., Asteriou, D., Polizos, S., and Kenourgios, D. (2018) “Terrorist incidents and tourism demand: Evidence from Greece” Tourism Management Perspectives, 25, 23-28

Seabra, C., Reis, P., and Abrantes, J.L (2020). “The influence of terrorism in tourism arrivals: A longitudinal approach in a Mediterranean country” Annals of Tourism Research, https://doi.org/10.1016/j.annals.2019.102811

Seraphin, H. (2017). Terrorism and tourism in France: The limitations of dark tourism. Worldwide Hospitality and Tourism Themes, 9(2), 187–195.

Solarin, S. A. (2015). September 11 attacks, H1N1 influenza, global financial crisis and tourist arrivals in Sarawak. Anatolia, 26(2), 298–300

Steiner, C. (2010) "An overestimated relationship? Violent political unrest and tourism foreign direct investment in the Middle East" International Journal of Tourism Research, 12(6), 726–738

Tarrant, Bill. (2010) "Is Thailand's Political Crisis Hurting Its Economy?" Bangkok: Reuters. http://www.reuters.com/article/2010/04/25/thailand-politics-economy-idUSSGE63604Y20100425

Tiwari A. K., Das D., Dutta A. (2019) "Geopolitical Risk, Economic Policy Uncertainty and Tourist Arrivals: Evidence from a Developing Country." Tourism Management 75:323–27.

Wearden, G., & Allen, K. (November 16, 2015). Billions wiped off European travel shares after Paris attacks. The Guardian. Retrieved from http://www.theguardian.com/business/2015/nov/16/billions-wiped-off-european-travel-sharesafter-paris-attacks

William, A.M. and Hall, M. (2002) "Tourism and migration: New relationships between production and consumption" Tourism Geographies, 2:1, 5-27,

Wolff, K., & Larsen, S. (2014). Can terrorism make us feel safer? Risk perceptions and worries before and after the July 22nd attacks. Annals of Tourism Research, 44, 200–209

Zopiatis, A., Savva, C. S., Lambertides, N., & McAleer, M. (2019). Tourism stocks in times of crisis: An econometric investigation of unexpected non-macroeconomic factors. Journal of Travel Research 58(3), 459-479