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Geopolitical Risk and Tourism Stocks of Emerging Economies

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Abstract: A bulk of literature suggests that geopolitical events such as terrorist attacks dampen tourism demand. However, there is little research on whether this effect helps predict the return of the tourism equity sector. We provide country-level evidence on whether local and global geopolitical risk (GPR) predicts the first and second moments of tourism stocks in emerging economies. This objective was achieved by employing the non-parametric causality-in-quantiles (CiQ) model and a cross-quantilogram (CQ) test, which allowed us to uncover the predictive potential of GPR for the tourism sector equities. Our findings, obtained through the CiQ model, suggest that while both local and global GPRs carry significant potential for predicting the returns and volatility of tourism stocks of most emerging economies under normal market conditions, they seem to play no such role in certain countries. These countries include South Korea, for which only a limited number of tourism stocks trade on the domestic stock market compared to other sectors, and Colombia, for which both the domestic stock market and tourism sectors are at an emerging stage. Further, it turns out that, compared to its local counterpart, global GPR has a more pronounced predictive power for the tourism stocks of emerging economies. Finally, with some exceptions, the results are qualitatively similar, and hence reasonably robust, to those when a directional predictability model is applied. Given that geopolitical shocks are largely unanticipated, our findings underscore the importance of a robust tourism sector that can help the market recover to stability as well as an open economy that allows local investors to diversify country-specific risks in their portfolios. Implications and directions for future research are discussed.

Keywords: Geopolitical risk; tourism stocks; causality-in-quantiles; cross-quantilogram

1. Introduction

Geopolitical risk (GPR) is a global phenomenon, continuing to cascade from one country to another. Much of the global GPR stems from the United States (US), primarily due to the country's dominance around the global geopolitical landscape [1]. The US, being both the superpower and the world's largest economy, exerts greater influence on counterpart countries through economic, political, military, and geographic linkages [2]. Despite this dominance of the US, many emerging economies, including Pakistan, Afghanistan, Syria, and Israel, undergo GPR shocks that are driven mainly by their local events. GPR shocks, whether from a local or a global source, entail a wide range of consequences for global business cycles, financial markets, and industries. Several real-world events, such as the 9/11 attacks in the US and the 2015 Paris terror attacks, have occurred in recent years that have shown that GPR could have severe repercussions for the tourism industry across the world [3–6]. Studies have recently started investigating the predictive potential of GPR for aggregate equity indices of emerging markets [7]. However, no study has yet explored the capacity of GPR to predict the sectoral equities in emerging markets, the tourism sectors of which have a special connection with GPR. Against this backdrop, the predictive power of local and global GPR could be particularly important for emerging markets as these markets are often subject to inflows (outflows) of "hot money" in (from) their financial system, which can be somewhat destabilizing given their exposure to GPR [1,7].

The tourism sector is one of the major sectors in emerging stock markets, and as with any other sector, one of the significant challenges faced by equity investors is the prediction of tourism stocks. The tourism sector attracts a substantial amount of investment [8], and the stocks of its constituent firms are considered highly attractive by individual as well as institutional investors. Being part of the consumer discretionary sector, tourism stocks are characterized by cyclicality, meaning that although they perform well in economic upturns (booms), their prices tend to plummet significantly during economic downturns (recessions). The cyclical behavior of tourism stocks poses predictability challenges for investors under various market conditions. Investors can make the most of their investments in tourism stocks by taking appropriate actions should they be able to precisely predict the returns and volatilities of those stocks well in advance. The prediction of tourism stocks is therefore imperative for investors in order to prevent losses and ensure gains on their investments.

The theoretical framework for GPR's predictive potential for tourism stocks can be built from the seminal works evolving from Sharpe [9] to Fama and French [10], which essentially deal with the pricing of capital markets' systemic risk, whose primary sources are macroeconomic and geopolitical events of the economy. Following this framework, some studies have already considered the impact of macroeconomic variables, such as policy uncertainty, on stock returns of the tourism sector [11]. However, research on the predictive power GPR for stock returns is scant and emerging. Over the last couple of decades, several geopolitical events, such as the 9/11 attacks in the US, the Gulf War, the 2003 Iraq invasion, the Ukraine/Russia crisis, the 2015 Paris terror attacks, the ongoing escalation of the Syrian conflict, the US-North Korea tensions over nuclear proliferation, the Qatar-Saudi Arabia proxy conflict, the US's recognition of Jerusalem as Israel's capital, the US's cancellation of Iran's nuclear deal, and, most recently, the killing of an Iranian commander by the US and the prompt Iranian revenge, have occurred that have led to escalated GPR on a global scale, posing a wide range of threats to the tourism sector around the world. Under such a heightened geopolitical landscape, the predictability of various industry stocks becomes an immediate challenge, especially for the tourism companies, which are well-known to reflect high sensitivity to systemic risks [12]. During the 2015 Paris terror attacks, for instance, a number of tourism stocks in Europe experienced huge losses due to the GPR caused by the incident [13]. Similar losses were reported by tourism stocks around the world, which would have been avoided by tracking the early warning signals of GPR's impact on tourism stocks. Hence, there is a great deal of motivation among investors to predict movements in tourism stocks using GPR, which is one of the potential proxies for the systematic risk in an economy.

In this study, we assess the predictability of emerging economies' tourism sector equities based on local and global GPRs. To this end, we employ the non-parametric causality-in-quantile (CiQ) test. The test incorporates elements of the K-th order nonlinear causality test introduced by Nishiyama et al. [14] with the CiQ analysis of Jeong et al. [15] and can, therefore, be regarded as a generalization of the former. The CiQ method has the following novel features: First, the method is robust enough to take into account the misspecifications because it can spot the underlying dependence structure between the time series under study. This feature is of critical importance since stock returns are known to exhibit nonlinearities (see Bekiros et al. [16] for a comprehensive discussion on this issue). Furthermore, through this approach, we can check the causality-in-first moment (mean) as well as the causality-in-second moment (variance). The CiQ model also enables us to capture the causality that may occur in the tails of the joint distribution of the variables. The causality in tails becomes particularly essential if the dependent variable has fat tails—something that holds for stock returns [7]. Lastly, since this model helps us analyze the causality-in-second moment, it can also capture possible volatility spillovers. Such an analysis is vital as causality in the conditional mean might not occur during certain times, while, at the same time, interdependencies in the higher-order moments may prove relevant during other times. However, one drawback of this approach lies in its inability to capture the strength or the magnitude of the underlying causal relationship. In order to account for this drawback, we employ the cross-quantilogram (CQ) model proposed by Han et al. [17], which enables modeling of the lagged correlation between two stationary time series across various quantiles of the series' distribution. A distinctive feature of this framework is that it allows us to compute the lagged correlation (or lead-lag correlation) between two time series by going beyond the conditional mean of the distribution. It, therefore, helps to examine the correlation structure between two time series at various quantiles of the distribution. The CQ accounts for extreme co-movements of the time series under consideration by relying on lower, medium, and upper quantiles of the two time series. Another benefit of this approach is that it enables us to compute the cross-correlation between the time series over a large number of lags. The methodology, therefore, offers an innovative indicator of the cross-correlation between time series subjected to varying market conditions.

Our findings suggest that while both local and global GPRs carry significant potential for predicting the returns and volatility of tourism stocks of most emerging economies under normal market conditions, they seem to play no such role in certain countries. These countries include South Korea, for which only a limited number of tourism stocks trade on the domestic stock market compared to other sectors, and Colombia, for which both the domestic stock market and tourism sectors are at an emerging stage. It further turns out that, compared to its local counterpart, global GPR has a more pronounced predictive power for the tourism stocks of emerging economies. Finally, with some exceptions, the results are qualitatively similar, and hence reasonably robust, to those when a directional predictability model is applied. Given that geopolitical shocks are largely unanticipated, our findings underscore the importance of a robust tourism sector that can help the market recover to stability as well as an open economy that allows local investors to diversify country-specific risks in their portfolios. This study contributes to the existing literature in the following ways. Most of the past literature on the nexus between GPR and the tourism industry has explored the linkage between terrorism and tourism demand [3,18–20]. In the context of emerging economies, some recent studies have considered GPR and related it with tourism demand [21,22]. However, the present study goes one step further by suggesting that GPR's predictive power is not just restricted to tourism demand but rather trickles down into the market performance of tourism stocks. The study also builds upon the recently proposed evidence of quantile-dependence between GPR and tourism stocks [23]. Supplementing the regional evidence of tourism stock-US GPR interaction [23], we provide country-level evidence by considering the predictive potential of local and global GPR for the returns of tourism sector equities of emerging economies.

The balance of the study unfolds as follows. Section 2 provides a brief review of the literature related to the topic. Section 3 introduces the methodology. Section 4 details the dataset and preliminary tests. Section 5 includes empirical findings. Section 6 concludes.

2. Literature Review

The literature on the nexus between the tourism industry and GPR was pioneered by studies that relate terrorism with tourism demand (see [3,18–20,24,25], among others). While most of these past works consider terrorism and its relationship with tourism demand, the concept of GPR is much broader in scope and encompasses terrorism; hence, these previous studies tend to provide limited insights on the GPR and tourism industry nexus. Secondly, these studies have mostly focused on developed economies such as European countries and the US, and the case of emerging economies has not received much attention. Exceptions include [21], which specifically looked at the impact of GPR on the tourism demand of emerging economies, and [22], which found that GPR exerts a more substantial influence on the tourist arrivals than economic policy uncertainty in India—another emerging economy. Furthermore, this strand of literature pays overwhelming attention to the adverse effects of geopolitical events, i.e., terror attacks, on tourism demand, while the case of tourism stocks of listed companies has been largely ignored.

In a more related stream of literature, studies typically link terror attacks to the performance of tourism stocks (see, for example, [12,26–29]). A general message from these studies is that terrorism dampens tourism demand and hence leads to the poor performance of tourism stocks. However, aside from only relying on terrorist attacks—which is a subset of the geopolitical events—these studies predominantly resort to an event-based approach for investigating the effect of terrorist incidents on the stock market. While the event-based approach works quite well in hindsight for understanding the impact of a given event, it carries limited predictive value. Second, these studies typically rely on single and major geopolitical events in a specific developed country, mostly in the US or France, and ignore the simultaneity and continuity of geopolitical events taking place in other countries, accounting for which is more desirable for prediction-based studies.

Recently, some researchers have focused on related questions in different markets. For instance, considering four regional indices of tourism stocks, namely Global, Asia-Pacific, Europe, and North America, Demiralay and Kilincarslan [23] analyzed the vulnerability of travel and leisure (tourism) stocks to GPR by employing the orthodox quantile regression approach. Their findings indicate a greater vulnerability of tourism stock returns to GPR during bearish market conditions, and this vulnerability is driven mostly by GPR threats. GPR acts, on the other hand, influence tourism stocks during all market conditions. Another study by Jiang et al. [30] investigated the relationship between Chinese tourism stocks and two news-based measures of risk, namely GPR and economic policy uncertainty (EPU), by employing the quantile-on-quantile model. The empirical findings of this study suggest that GPR exerts significant influence on tourism stock return in China, and this influence is more pronounced during bearish market conditions compared to bullish market conditions. Furthermore, the asymmetrical impact of GPR and EPU on tourism stocks becomes more obvious during extreme market conditions when there is a tourist off-season. Although these works provide greater insights on the link between GPR and tourism stocks, they did not consider how the tourism stocks of emerging economies might respond to GPR. More importantly, these studies created no distinction between local and global GPR and how tourism stocks' vulnerability to GPR might differ depending upon domestic and foreign sources of GPR. Creating this distinction is particularly important for emerging economies whose vulnerability to local and global GPR shocks is well known.

Global and local GPRs may cause the return and volatility of tourism stocks through cash flow and discount rate channels. The rising level of GPR raises security concerns that cause tourists to postpone or even cancel their travel plans [31,32], which in turn adversely affects tourism demand [33,34]. Moreover, a fragile geopolitical environment forces tourism companies to introduce additional security measures that typically come at increased costs, such as higher insurance premiums [35,36]. Both the reduced tourism demand and the increased costs translate into lower company earnings and reduced dividends, thus causing stock price movements. Furthermore, since GPR is just another form of systematic risk, it can also drive the return and volatility of tourism stocks through a discount rate channel.

While this literature provides a sound theoretical framework for further investigations involving GPR, it lacks the following contributions. First, most of this literature considers the effects of terrorism, which is just a subset of GPR and thus offers a minimal scope. While addressing this limitation, GPR provides a much broader scope as it simultaneously captures all the risks that arise from multiple sources, like wars, geopolitical tensions, terror attacks, geopolitical acts, threats, and so forth. Second, the previous literature fails to distinguish, and thus disentangle, the effects of local geopolitical events from those of global ones. Third, except Balli et al. [21] and Tiwari et al. [22], most studies focus on the terrorism-tourism demand nexus within the context of developed countries or top tourist destinations. In contrast, the case of emerging economies from this perspective has often been overlooked in the literature. In this study, we address these missing points.

3. Methodology

Our methodology consisted of two parts. In the first part, we ascertained whether there was a causality running from GPR to tourism stocks. In the second part, we explored whether this causality of GPR also had directional predictability for tourism stocks. The first task was achieved by applying a novel approach known as causality-in-quantiles while the second job was done through another unique approach called the cross-quantilogram. In the following, we provide a brief description of each approach and refer the interested reader to original papers.

3.1. Causality-in-Quantiles (CiQ) Approach

To capture the causality-in-quantiles from GPR to tourism sector equities, we employed the non-parametric causality-in-quantiles approach of Balcilar et al. [37]. Built upon the models proposed by Nishiyama et al. [14] and Jeong et al. [15], this approach not only combines the nonlinearities with extreme dependence structures but also accounts for data structures that are not normally distributed [37]. What follows is a brief description of this approach, while we refer the interested readers to [37] for more details. Following the steps in [37], we denoted the tourism indices as sp_t and the GPR indices as gpr_t. If gpr_t caused sp_t concerning the following lag-vector of $\{gpr_{t-1},\ gpr_{t-2}, \ldots, gpr_{t-p}, sp_{t-1},\ sp_{t-2}, \ldots, sp_{t-p}\}$ in the qth quantile, then according to [15] the following relationship was satisfied:

$$Q_q\big(gpr_t \big| gpr_{t-1},\ gpr_{t-1}, \ldots, gpr_{t-p}, sp_{t-1},\ sp_{t-1}, \ldots, sp_{t-p}\big) \\ = Q_q\big(gpr_t \big| gpr_{t-1},\ gpr_{t-1}, \ldots, gpr_{t-p}\big) \quad (1)$$

Conversely, if gpr_t did not cause sp_t in the qth quantile, we had the following inequality:

$$Q_q\big(gpr_t \big| gpr_{t-1},\ gpr_{t-1}, \ldots, gpr_{t-p}, sp_{t-1},\ sp_{t-1}, \ldots, sp_{t-p}\big) \\ \neq Q_q\big(gpr_t \big| gpr_{t-1},\ gpr_{t-1}, \ldots, gpr_{t-p}\big) \quad (2)$$

where $Q_q\big(gpr_t \big| gpr_{t-1},\ gpr_{t-1}, \ldots, gpr_{t-p}, sp_{t-1},\ sp_{t-1}, \ldots, sp_{t-p}\big)$ represented the qth quantile of gpr_t, which was time-dependent, while q ∈ (0,1).

Suppose $GPR_{t-1} = \big(gpr_{t-1},\ gpr_{t-1}, \ldots, gpr_{t-p}\big)$, $SP_{t-1} = \big(sp_{t-1},\ sp_{t-1}, \ldots, sp_{t-p}\big)$, and $K_t = (SP_t, GPR_t)$. Let $F_{sp_t|K_{t-1}}\big(sp_t \big| K_{t-1}\big)$ be the conditional distribution of sp_t given K_{t-1}, $F_{sp_t|SP_{t-1}}\big(sp_t \big| SP_{t-1}\big)$ be the conditional distribution of sp_t given SP_{t-1}, and $F_{sp_t|K_{t-1}}\big(sp_t \big| K_{t-1}\big)$ be a continuous in sp_t for almost all K_{t-1}. Further, the qth quantile of sp_t given K_{t-1} was defined by $Q_q(K_{t-1})$, while the qth quantile of sp_t given GPR_{t-1} was defined by $Q_q(GPR_{t-1})$. Thus,

$$Q_q(K_{t-1}) = Q_q\big(sp_t \big| K_{t-1}\big), \quad (3)$$

and

$$Q_q(GPR_{t-1}) = Q_q\big(sp_t \big| GPR_{t-1}\big). \quad (4)$$

Hence, $F_{sp_t|K_{t-1}}\left\{Q_q(K_{t-1})\middle|K_{t-1}\right\} = q$ certainly holds. Therefore, by making use of the relations given in Equations (1) and (2), the causality-in-quantiles hypothesis was given as

$$H_0 : P_r\left\{F_{sp_t|K_{t-1}}\left\{Q_q(SP_{t-1})\middle|K_{t-1}\right\} = q\right\} = 1$$
$$H_1 : P_r\left\{F_{sp_t|K_{t-1}}\left\{Q_q(SP_{t-1})\middle|K_{t-1}\right\} = q\right\} < 1$$

Next, the distance indicator of the causality-in-quantiles approach was defined by following [15], and was given as

$$J = \{\varepsilon_t E(\varepsilon_t|K_{t-1}) f_k(K_{t-1})\}, \tag{5}$$

where ε_t is the error in regression, the marginal density function of K_{t-1} is denoted by $f_k(K_{t-1})$, while the estimator of ε_t, defined as $\hat{\varepsilon}_t$, was given as follows:

$$\hat{\varepsilon}_t = 1\left\{sp_t \leq \hat{Q}_q(SP_{t-1})\right\} \tag{6}$$

where $\hat{Q}_q(SP_{t-1})$ represents the quantile-estimator of the qth quantile of sp_t given SP_{t-1}.

Next, the estimation of $\hat{Q}_q(SP_{t-1})$ was performed by employing the non-parametric kernel approach, and was given as follows:

$$\hat{Q}_q(SP_{t-1}) = \hat{F}^{-1}_{sp_t|SP_{t-1}}\left(sp_t\middle|SP_{t-1}\right) \tag{7}$$

where

$$\hat{F}^{-1}_{sp_t|SP_{t-1}}\left(sp_t\middle|SP_{t-1}\right) = \frac{\sum_{i=p+1,i\neq t}^{T} L\left(\frac{sp_{t-1}-sp_{i-1}}{h}\right) 1\{sp_i \leq sp_t\}}{\sum_{i=p+1,i\neq t}^{T} L\left(\frac{sp_{t-1}-sp_{i-1}}{h}\right)}$$

represents the Nadaraya–Watson kernel estimator. L(•) and h denote the known kernel function and the bandwidth used in the kernel estimation, respectively.

Next, we explicitly estimated the causality in the second moment because the rejection of causality in the first moment does not imply non-causality in the second moment. To examine the causality in higher moments, we assumed the following model:

$$sp_t = g(SP_{t-1}, GPR_{t-1}) + \varepsilon_t \tag{8}$$

Under this model, the following hypotheses were devised to test the causality (-in-quantiles) in higher moments:

$$H_0 : P_r\left\{F_{sp_t^p|K_{t-1}}\left\{Q_q(SP_{t-1})\middle|K_{t-1}\right\} = q\right\} = 1 \text{ for } p = 1, 2, 3, \ldots, P$$
$$H_1 : P_r\left\{F_{sp_t^p|K_{t-1}}\left\{Q_q(SP_{t-1})\middle|K_{t-1}\right\} = q\right\} < 1 \text{ for } p = 1, 2, 3, \ldots, P$$

Once again, by following [15], the kernel-based feasible test statistic was formulated to test whether gpr_t caused sp_t from the qth quantile of the moment up to the pth quantile by employing Equation (8). A sequential approach proposed by [14] helped conduct the weighted non-parametric test with joint density. A two-variable vector autoregressive (VAR) model of order one was used as part of this test. The bandwidth selection was made via the least square cross-validation techniques. Finally, we employed the Gaussian-type kernels for L(•) and P(•).

3.2. Cross-Quantilogram (CQ) Approach

Once we confirmed through the application of the CiQ model that GPR carries predictive potential for tourism stocks, we proceeded to measure the directional predictability of GPR for tourism stocks. This was achieved through another unique, quantile-based approach known as the CQ. Introduced by Linton and Whang [38], the quantilogram captures the association across various parts of the distribution of a given stationary time series. In other words, the quantilogram is the correlogram across quantile [17] that tests the null hypothesis of no directional cross-correlation in each time series [38]. The test for the correlation was conducted through quantilogram comparison to a point-wise confidence interval. In order to evaluate the cross-correlation of quantiles between two stationary time series, Han et al. [17] advanced the univariate quantilogram model to a multivariate framework, in which the information regarding the underlying relationship is taken into account. Moreover, the asymptotic properties of the underlying distribution are validated uniformly over a range of quantiles. Some advantages of directional correlation for quantilogram compared to other tests are that the approach is based on the quantile hits that, like ordinary correlogram techniques, do not entail moment conditions, and it is applicable for series with strong tails [17].

According to Han et al. [17], the CQ can capture the serial correlation between the two time series at various conditional quantiles, say $\left\{x_{1t} < q_{1,t}\ (\tau_1)\right\}$ and $\left\{x_{2,t-k} < q_{w,\ t-k}\ (\tau_2)\right\}$ for any pair of τ. The quantile range to evaluate the directional correlation is denoted by τ. Furthermore, the quantile of $x_{i,t}$ is $q_i(\alpha_i) = \inf(\upsilon : F_i(\upsilon) \geq \alpha_i)$ for $\alpha_i \in (0, 1)$, and the indicator function expressed by $1\,[\cdot]$ and $\left\{1[y_{it} \leq q_{i,t}(.)]\right\}$ called "quantile hit" process for $i = 1,\ 2$. Thus, [17] defined CQ to be cross-correlation for the quantile-hit processes for $k = 0,\ +1,\ +2,\ \ldots,\ \infty$ where $\psi_a(u) \equiv 1[u < 0] - a$ can be written as

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau 1}\left(x_{1,t} - q_{q,t}(T_1)\right)\psi_{\alpha 2}\left(x_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau 1}^2\left(x_{1,t} - q_{q,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau 2}^2\left(x_{2,t} - q_{2,t-k}(\tau_2)\right)\right]}} \tag{9}$$

In Equation (9), the CQ measures serial dependency between the two series at different quantiles. Considering $\alpha = (\alpha_1,\ \alpha_2) = (\alpha_{T-STOCK}, \alpha_{GPR})$ as an example, the CQ measures the cross-correlation between the tourism sector returns being above or below quantile $q_{T-STOCK}(\alpha_{T-STOCK})$ at time t and the GPR change-rate being above or below quantile $q_{GPR}(\alpha_{GPR})$ at time $t-1$. Therefore, $\rho_\alpha(1) \neq 0$ implies that no correlation or time-lag effect between movement in GPR and tourism sector returns at $\alpha = (\alpha_{T-STOCK}, \alpha_{GPR})$.

Building on a linear quantile regression framework by Koenker and Bassett [39], Han et al. [17] define $q_{i,t}(\tau_i) = y_{it}^T\,\gamma_i(\tau_i)$ with a $d_i * 1$ vector of the unknown parameters $\gamma_i(\tau_i)$ for $i = 1,\ 2$. The CQ sample analogue in the inverse direction proposed by [17] as given in Equation (10) expresses a minimization problem which estimates the unknown parameters where $\rho(u) \equiv u(a - 1[u < 0]), \hat{\gamma}(\tau) \equiv \left[\hat{\gamma}_1(\tau_1)^T, \hat{\gamma}_2(\tau_2)^T\right]$ and $\hat{q}_{i,t}(\tau_i) = y_{it}^T\,\hat{\gamma}_i(\tau_i)$ for $i = 1,\ 2$. For observations $\left\{(x_t, y_t)\right\}_t^T = 1$, the sample counterpart of CQ is

$$\hat{\gamma}_i(\tau_i) = \mathrm{arg}min_{\gamma_i \epsilon \mathbb{R}^{d_i}} \sum_{t=1}^{T} \daleth_{T_i(x_{it} - y_{it}^T \gamma_i)} \tag{10}$$

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=1}^{T-k} \psi_\alpha(y_t - \hat{\mu}_\alpha)\psi_{\alpha 2}(y_{t-k} - \hat{\mu}_\alpha)}{\sqrt{\sum_{t=1}^{T-k} \psi_\alpha^2(y_t - \hat{\mu}_\alpha)}\sqrt{\sum_{t=1}^{T-k} \psi_\alpha^2(y_{t-k} - \hat{\mu}_\alpha)}},\ k = 1, 2, \ldots, T-1 \tag{11}$$

Based on ρα (k), the quantile-based Ljung–Box–Pierce statistic is obtained for H0: ρα (k) = 0 for all k ϵ 1, . . . , p as

$$\hat{Q}_\alpha^{(p)} = \frac{T(T+2)\sum_{k=1}^{p} \hat{\rho}_\alpha^2(k)}{T-k} \tag{12}$$

where p refers to the number of lags of the time series $\alpha = (\alpha_{T-STOCK},\ \alpha_{GPR})$, and $\hat{Q}_\alpha^{(p)}$ represents the portmanteau test of directional correlation from one time series to another in Equation (12).

In this study, the results were specified with a lag length of one. Additionally, we utilized 1000 bootstrap iterations and a significance level of 0.05. A lag length of one indicated that we measured the correlations between two months. The bootstrap was selected with iterations between 100 and 1000, and hypotheses were tested at a 5 percent level of significance. Heat maps were used to provide the cross-quantile unconditional bivariate correlation between the two distributions and to present the CQ analysis visually.

4. Data and Preliminary Tests

As mentioned above, the purpose of this paper is to ascertain whether GPR carries any predictive potential for tourism stocks. To this end, we collected monthly tourism indices of 13 emerging economies from Thomson Reuters Datastream. The Datastream Global Equity Indices were utilized in this study. Both the selection of countries and the sample period were based on the availability of tourism stock indices, whereas the sample period varied for each country. Our sample countries included Brazil, China, Colombia, India, Israel, Malaysia, Mexico, Philippines, Russia, South Africa, South Korea, Thailand, and Turkey. Caldara and Iacoviello [1] developed GPR indices for 18 emerging economies, of which only those included in our sample have their tourism sector indices available, thus constituting our sample. We followed the emerging economies categorization suggested by [1]. The GPR indices for these emerging economies were sourced from the economic policy uncertainty website (https://www.policyuncertainty.com/gpr.html). GPR can bring about severe consequences for emerging economies' capital flows, as higher GPR forces investors to pull capital out of emerging economies and move towards safe havens [1]. As previously stated, a key benefit of these news-based GPR indices is that they are much broader in scope as they cover not only terror attacks, but also other aspects of geopolitical conflicts such as war risks, military challenges, and conflicts in the Middle East, and thus capture a wider spectrum of exogenous geopolitical uncertainty events happening all across the globe. Given the country's dominant role across the global geopolitical landscape, we used the GPR index of the US as a proxy for global GPR.

Before we formally moved to analyze the predictive potential of GPR for tourism indices, it was essential to determine the kind of predictability test that would be suitable for this analysis. We began by examining the descriptive statistics of tourism and GPR indices. Tables 1 and 2 report the descriptive statistics of the tourism and GPR indices, respectively. In both the tables, the skewness and kurtosis values indicate that most of the tourism indices (all the GPR indices) are negatively (positively) skewed and fat-tailed. Moreover, the results of the Augmented Dicky–Fuller unit roots test suggested that all the stock returns and GPR series were stationary. Finally, the Jarque–Bera test statistics indicated that all the tourism and GPR index series were not normally distributed, providing some preliminary justification for using a quantile-based model. In other words, there was sufficient support for examining the causal effect of GPR over the entire conditional distribution of tourism stock returns, rather than just at the conditional mean.

Table 1. Descriptive statistics of stock returns.

Country	Abbr.	Mean	Std. Dev.	Skew.	Kurt.	J.B.	ADF	Obs.
Malaysia	MAL	0.661	8.060	−0.334	5.854	143.937 ***	−18.691 ***	402
Turkey	TUR	2.312	19.437	0.524	6.428	183.665 ***	−20.668 ***	343
Mexico	MXC	0.441	8.085	−0.106	5.677	98.551 ***	−17.693 ***	328
South Korea	KOR	−0.018	9.181	0.035	4.673	28.267 ***	−15.484 ***	242
Russia	RUS	1.711	13.109	0.621	10.751	626.504 ***	−13.065 ***	244
India	IND	0.779	11.058	0.714	8.067	408.729 ***	−16.661 ***	354
Brazil	BRZ	2.464	9.750	−0.462	3.713	3.805	−5.868 ***	67
China	CHN	0.248	12.227	2.182	24.412	6227.464 ***	−11.844 ***	313
South Africa	SAF	−0.152	10.585	−0.892	9.946	700.645 ***	−17.808 ***	327
Columbia	COL	−1.220	9.904	−0.020	4.182	5.713 *	−10.214 ***	98
Thailand	THL	0.283	11.264	0.118	5.954	135.062 ***	−20.619 ***	369
Israel	ISR	−0.156	12.416	−0.387	10.614	776.046 ***	−17.713 ***	318
Philippines	PHL	0.803	9.279	−0.098	10.439	535.338 ***	−17.654 ***	232

Note: * and *** indicates significance at 10%, 5%, and 1%, respectively.

Table 2. Descriptive statistics of geopolitical risk series.

Country	Mean	Std. Dev.	Skew.	Kurt.	J.B.	ADF	Obs.
US	83.464	61.295	3.185	18.636	4929.199 ***	−5.554 ***	415
Malaysia	91.652	35.319	1.682	8.260	652.879 ***	−7.268 ***	402
Turkey	115.223	41.679	1.052	4.303	87.470 ***	−6.833 ***	343
Mexico	101.846	25.872	1.075	4.527	95.066 ***	−4.889 ***	328
South Korea	110.507	43.906	1.505	5.824	171.716 ***	−8.157 ***	242
Russia	107.774	30.169	0.940	3.759	41.771 ***	−5.967 ***	244
India	91.897	28.871	2.368	10.390	1136.604 ***	−4.995 ***	354
Brazil	112.472	32.714	0.858	4.045	11.259 ***	−4.930 ***	67
China	104.014	26.842	1.426	4.892	152.763 ***	−11.844 ***	313
South Africa	96.526	32.208	1.093	5.381	142.355 ***	−7.088 ***	327
Columbia	65.845	26.742	0.816	4.184	16.611 ***	−6.527 ***	98
Thailand	95.072	39.484	1.810	7.756	549.341 ***	−11.255 ***	369
Israel	86.886	21.954	0.981	4.079	66.426 ***	−2.809 ***	318
Philippines	107.391	34.175	0.671	3.157	17.630 ***	−3.699 ***	232

Note: *** indicates significance at 10%, 5%, and 1%, respectively.

We further motivated the use of the quantile-based approach by statistically investigating the possibility of nonlinearity in the tourism stock returns and the GPR series. To this end, we applied the Brock et al. (BDS) [40] test on the residual of an autoregressive AR (1) model for the stock returns and GPR series. Table 3 provides the results of the BDS test for the stock returns.

Table 3. BDS test for nonlinearity.

m	MAL	TUR	MXC	KOR	RUS	IND	BRZ	CHN	SAF	COL	THL	ISR	PHL
2	4.22 ***	11.02 ***	4.336 ***	5.757 ***	0.73	6.386 ***	−5.87 ***	5.19 ***	1.45	−11.58 ***	5.28 ***	5.69 ***	0.59
3	7.04 ***	39.19 ***	5.142 ***	7.356 ***	5.18 ***	6.423 ***	−4.92 ***	0.08	4.86 ***	0.85	4.51 ***	9.02 ***	1.42
4	19.77 ***	76.91 ***	1.320	72.339 ***	−7.35 ***	25.417 ***	−2.83 ***	−7.39 ***	6.73 ***	−7.17 ***	19.26 ***	5.81 ***	−1.29
5	51.25 ***	−6.54 ***	−5.343 ***	204.085 ***	−4.86 ***	−8.017 ***	−1.85 *	−4.87 ***	−6.46 ***	−4.80 ***	94.98 ***	−3.87 ***	46.95 ***
6	158.64 ***	−4.68 ***	−3.806 ***	−5.146 ***	−3.47 ***	−5.773 ***	−1.31	−3.46 ***	−4.63 ***	−3.47 ***	−4.27 ***	−2.72 ***	446.49 ***

Note: The entries indicate the z-statistics BDS test based on the residuals of AR (1) model of stock return series. m denotes the embedding dimension of the BDS test. * and *** indicate significance at 10%, 5%, and 1% levels, respectively.

For all the stock returns (and GPR) series, the BDS test provided plenty of support for the rejection of the null of i.i.d. residuals at various embedding dimensions (m). Thus, the results offer strong evidence of nonlinearity in the tourism stock return and GPR series of all sample countries. The presence of nonlinearity would mean that the standard linear Granger causality test cannot be deemed robust and reliable for the tourism stock-GPR relationship. Therefore, the causality or predictability in this relationship needs to be investigated in a nonlinear or quantile-based framework.

5. Empirical Findings

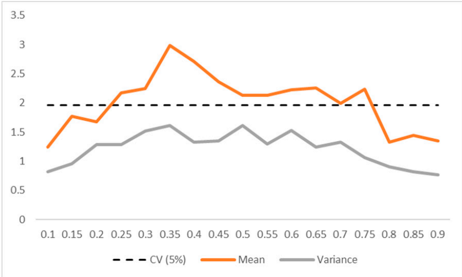
The results for the non-parametric causality-in-mean and causality-in-variance running from GPR to tourism stocks are presented in Figure 1. For each country, the effects of local and global GPR, shown in parallel, are presented in panels (a) and (b), respectively. For all countries, the first-moment causality (causality-in-mean) and the second-moment causality (causality-in-variance) are shown for their local GPRs as well as for global GPR. In each causality figure, the horizontal axis represents quantiles (ranged between 0.10 and 0.90) and the vertical axis denotes test statistics. The quantile range 0.10–0.25 represents extreme negative returns or bearish market conditions while the quantile range 0.75–0.90 corresponds to extreme positive returns or bullish market conditions. Similarly, the quantiles 0.25–0.75 indicate average returns or normal market conditions. The orange and grey lines indicate causality-in-mean and causality-in-variance, respectively, whereas the dashed line signifies 5% critical value.

Notable differences can be drawn across our sample countries. The first observation drawn from the results is that GPR predicts tourism indices for most of the countries. Except for South Korea, Thailand, Russia, Israel, Brazil, and Colombia for which local GPR shows limited predictive potential, at least one type of GPR (local or global) predicts the returns or variance of the tourism sector. The tourism stocks of these countries are mostly vulnerable to global GPR shocks. Since we used US GPR as a proxy for global GPR, this finding might be driven by the overwhelming exposure of those countries to global (US) geopolitical tensions which seem to matter more for equity market participants in the tourism sector of those countries. This could be particularly true for South Korea, Russia, and Israel, whose geopolitical synchronicity or close linkages with the US are well known. As the key allies of the US in the Korean Peninsula and Middle East, respectively, South Korea and Israel are potentially more vulnerable to GPR from the US. Similarly, as an archrival of the US throughout history, Russia has been involved in many geopolitical conflicts globally which often tend to include the US as well. Notably, Thailand is one of the top tourism destinations whose tourism demand is strongly linked to global GPR as compared to the local counterpart [21]. Furthermore, the tourism equity sector of this bunch of countries are at an emerging stage, e.g., South Korea and Thailand. The vulnerability of the tourism equity sector for countries experiencing more predictability from global GPR could be underpinned by similar country characteristics. The findings related to these countries are in contrast with [21], which found local and global GPR to have significant influence on these emerging economies' tourism demand.

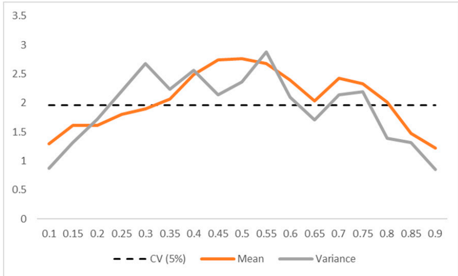
The countries seemed to form groups with regard to their tourism stocks' predictability from local and global GPR. Tourism stocks of the first and biggest group of countries, which includes India, Israel, Malaysia, Mexico, Philippines, South Africa, Thailand, and Turkey, experienced significant causality-in-mean from local GPR. Interestingly, South Africa was the only country for which local GPR also led to significant causality-in-variance. With the inclusion (exclusion) of China and Russia (Philippines), the same group of countries also experienced causality-in-mean from global GPR to their tourism stocks. Notably, export revenues make up a big bulk of these counties' GDP; accordingly, it is not surprising that local GPR would affect the tourism sector equities.

From global GPR, causality-in-variance was found significant for all countries in the first group, excluding India. In addition, note that wherever found present in our results, both causality-in-mean and causality–in-variance are generally found to prevail under normal market conditions (i.e., between 0.30-0.70 quantiles). This finding implies that, mostly, it would be possible to predict the returns and volatility of emerging economies' tourism stocks during normal market conditions. However, the predictive potential of GPR may not be useful when the tourism sectors of emerging economies are going through bullish or bearish market conditions. Our finding that GPR contains predictive power under normal market conditions of the tourism stocks is in contrast with the recently proposed evidence by Demiralay and Kilincarslan [23] and Jiang et al. [30] that travel and leisure stocks show more sensitivity to GPR when they perform poorly, i.e., under bearish market conditions. Their studies, however, considered travel and stocks of four regions and GPR of the US only, whereas we focused on the tourism sector equities of individual countries. Perhaps investors are more concerned about GPR movements when the equity market is going through normal conditions as a fragile geopolitical environment not only hurts tourism demand but also forces tourism companies to introduce additional security measures that typically come at increased costs [35,36]. Under extreme market conditions, there are many other factors that cause anxiety among investors and hence, GPR may not have much incremental effect during extreme movements of stock prices. Supporting this view, some recent studies have documented GPR's potential to exert average effects on the tourism demand of emerging economies [21,22].

Malaysia

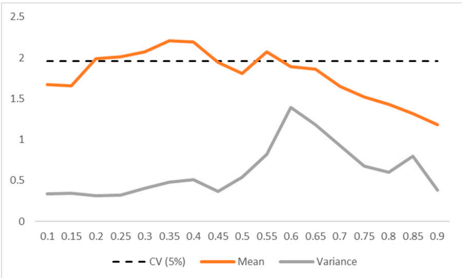


(a)



(b)

Turkey



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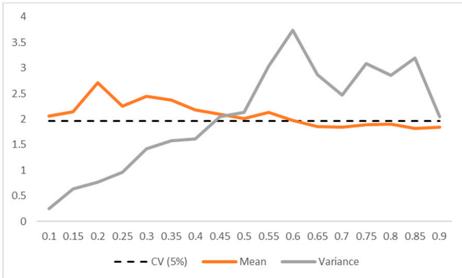
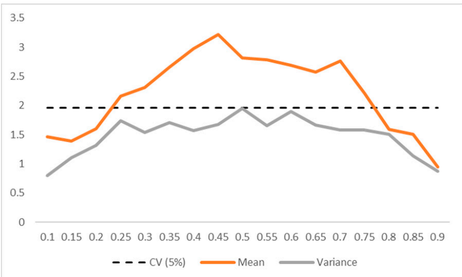


(b)

Mexico



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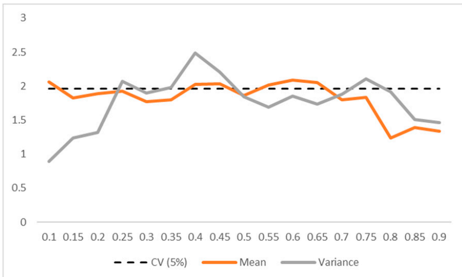

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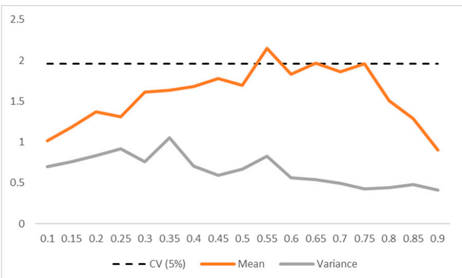
South Korea



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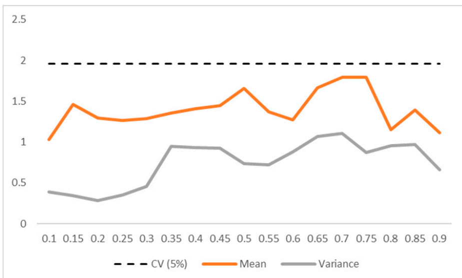
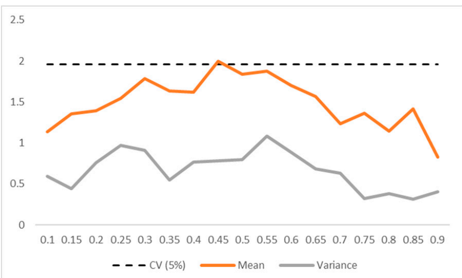


(b)

Russia



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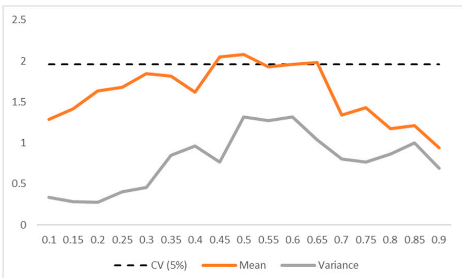
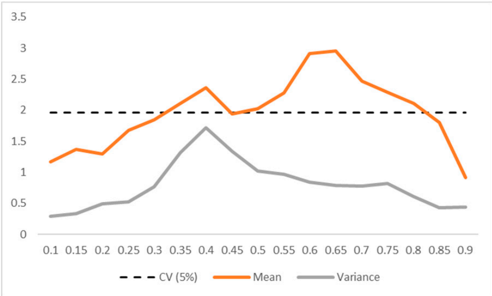


(b)

Figure 1. *Cont.*

India



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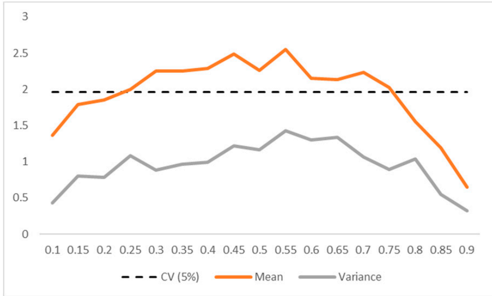

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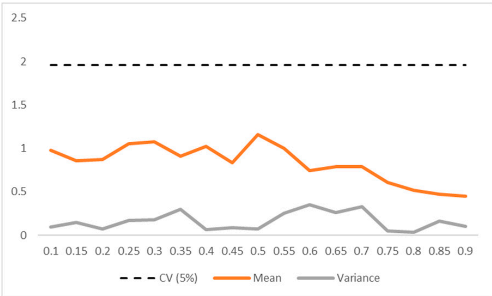
Brazil



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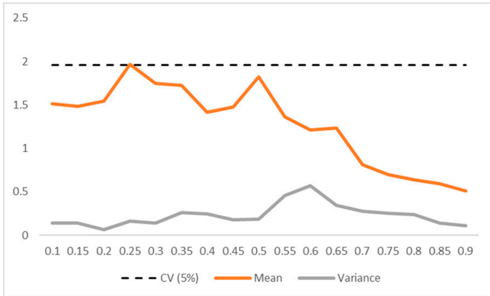

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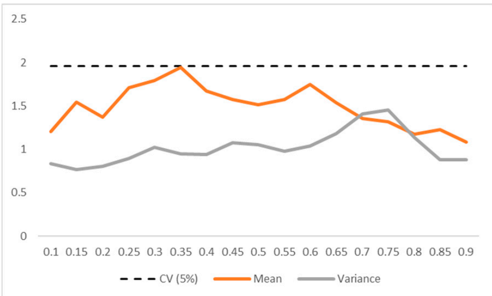
China



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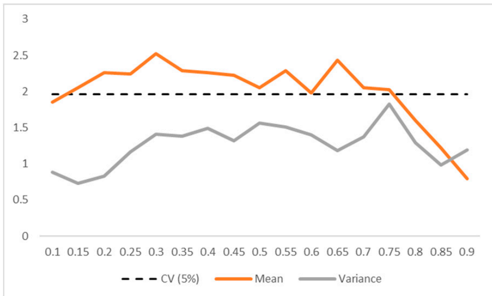
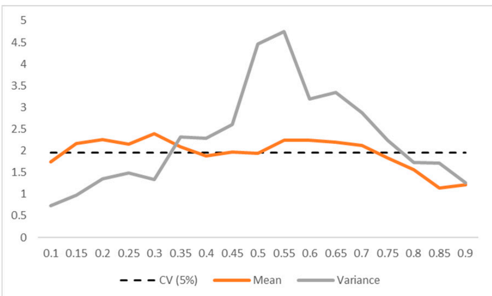


(b)

South Africa



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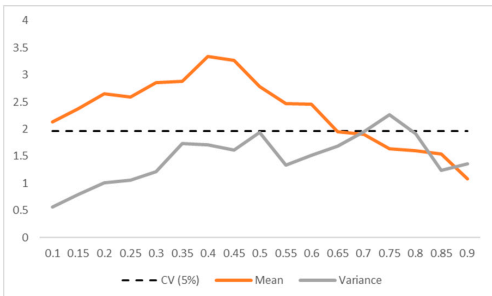


(b)

Figure 1. *Cont.*

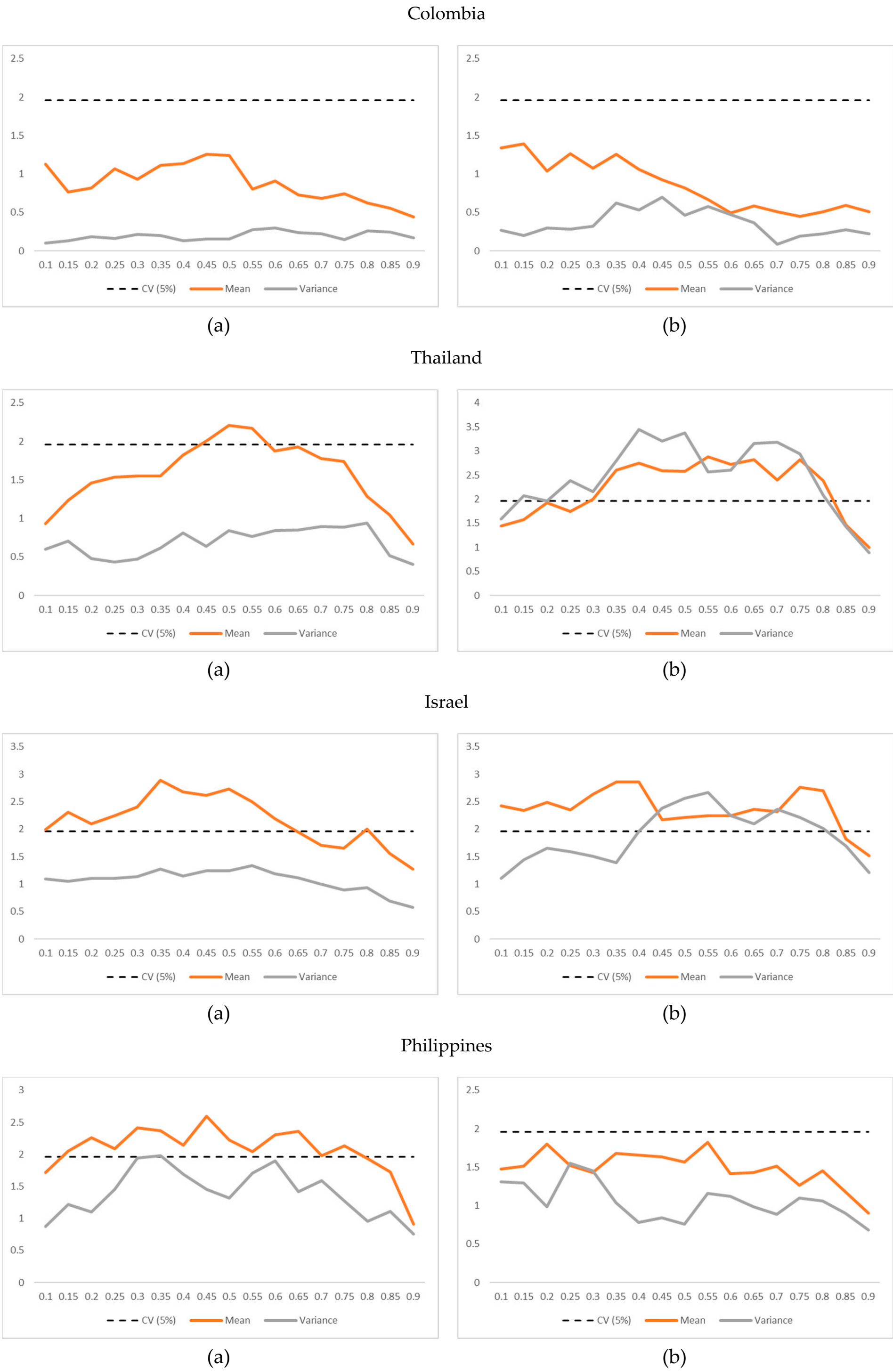


Figure 1. The figure presents the results for non-parametric CiQ(causality-in-quantiles)-in-mean and in-variance from local and global geopolitical risk (GPR) to tourism stocks at various quantiles. (**a**) Impact of local GPR; (**b**) Impact of global GPR. The orange and grey lines represent the causality-in-mean and the causality-in-variance, respectively, whereas the dashed line signifies the 5% critical value. The vertical axis reports the test statistic corresponding to the null, and the horizontal axis indicates the nine quantiles (from q = 0.1 to q = 0.9). Malaysia (1986M02), Turkey (1991M01), Mexico (1992M04), South Korea (1999M06), Russia (1999M04), India (1990M02), Brazil (2014M01), China (1993M07), South Africa (1992M05), Colombia (2011M06), Thailand (1988M11), Israel (1993M02), and Philippines (2000M04). () includes the starting month for the sample period of each country. All sample periods end on 2019M07.

Figure 2 includes the heat maps showing the directional predictability results from local and global GPR to the tourism stock returns of a country in panels (a) and (b), respectively. On the x- and y-axes, the quantiles hits indicate the distribution of the variable's quantile (q = (0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95)). Note that the heat map shows the 121 cells of the quantile combinations of variables and the color scale indicates the correlation between −1.0 and 1.0. In each cross-quantilogram figure, the x-axis represents quantiles of local and global GPR, and the y-axis denotes the returns quantiles of tourism indices. Although the quantiles range from 0.05–0.95, the key points are marked at 0.05, 0.25, 0.50, 0.75, and 0.95 in order to distinguish between various market conditions. The return quantiles 0.05–0.25 represent extreme negative returns or bearish market conditions while the quantiles 0.75–0.95 correspond to extreme positive returns or bullish market conditions. Similarly, the quantiles 0.25–0.75 indicate average returns or normal market conditions. The red, blue, and green colors represent a positive, negative, or no association (predictability) between (from) the previous month's values of local or global GPR index and current month returns of tourism indices of a country, respectively.

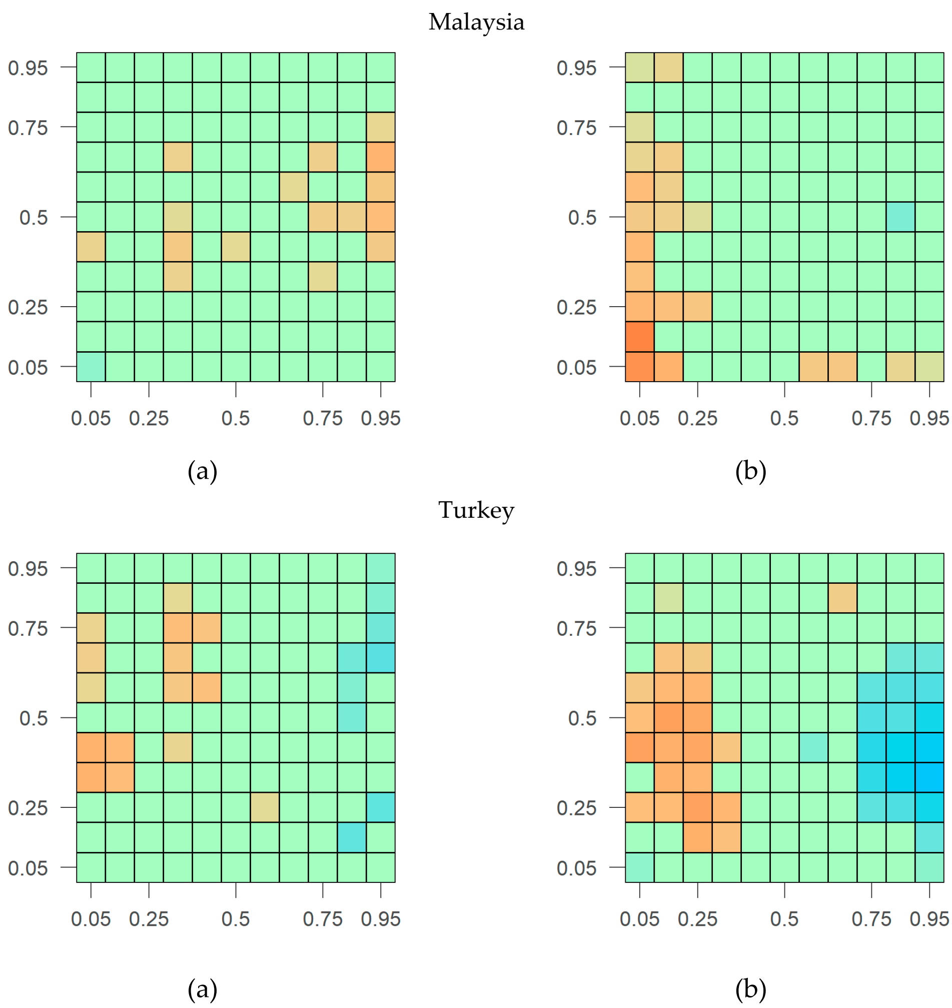
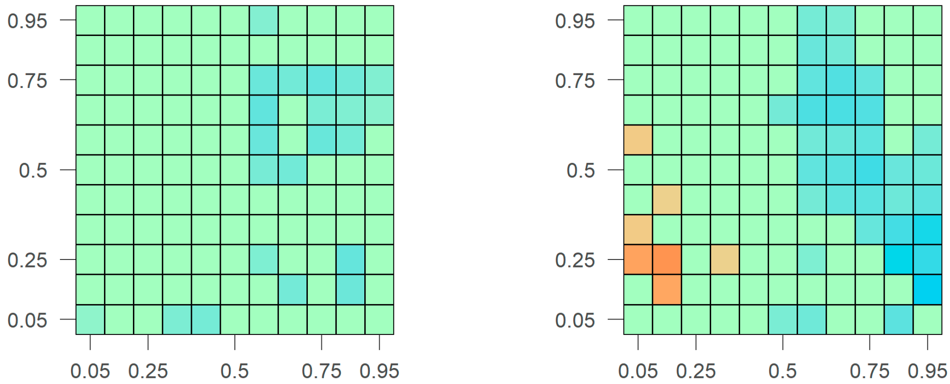


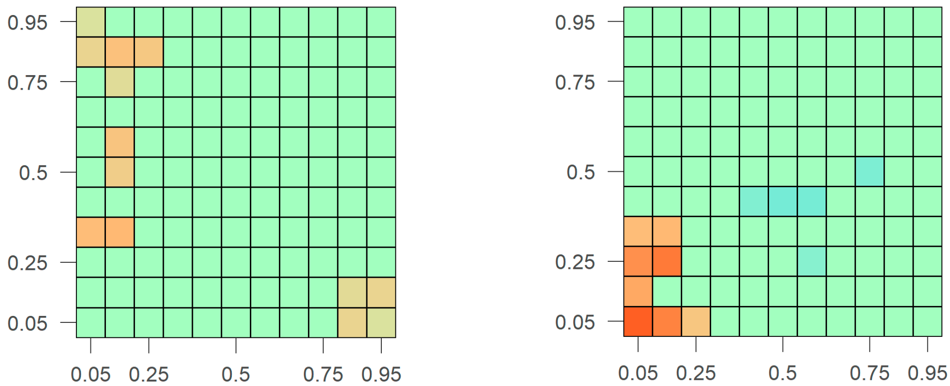
Figure 2. *Cont.*

Mexico



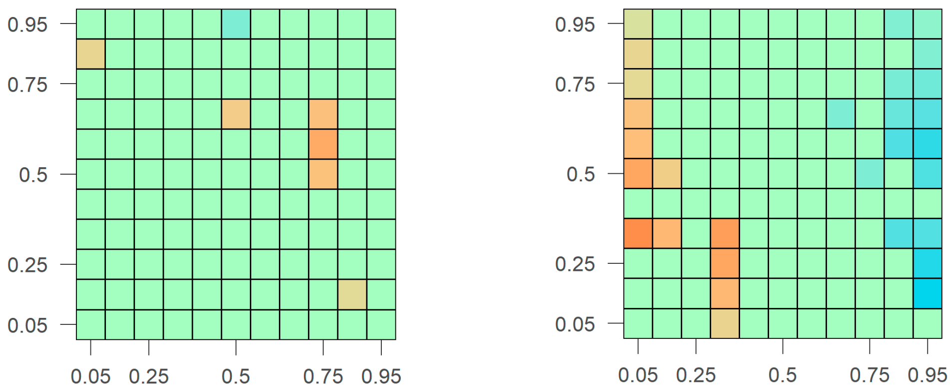
(a) (b)

South Korea



(a) (b)

Russia



(a) (b)

Figure 2. *Cont.*

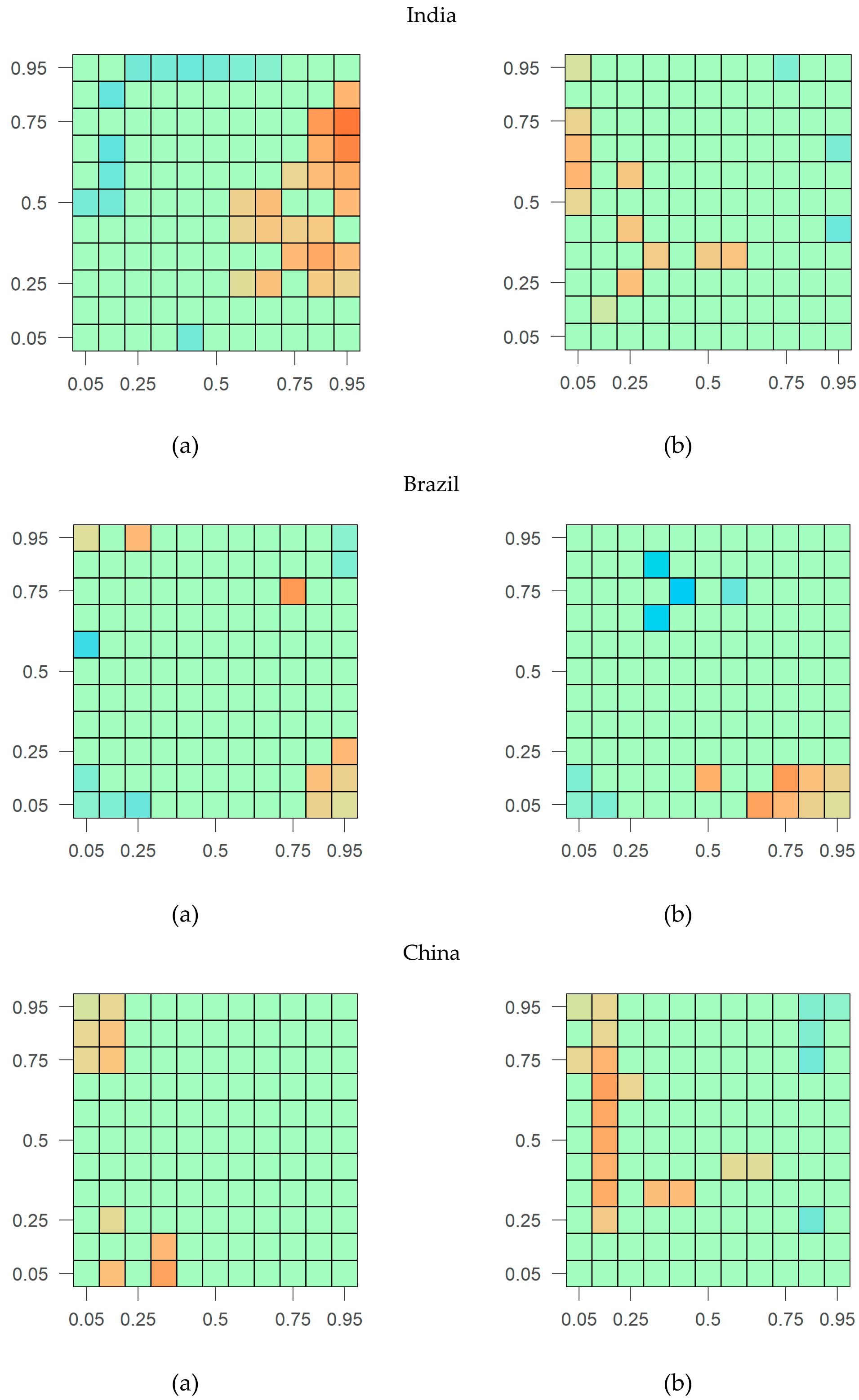
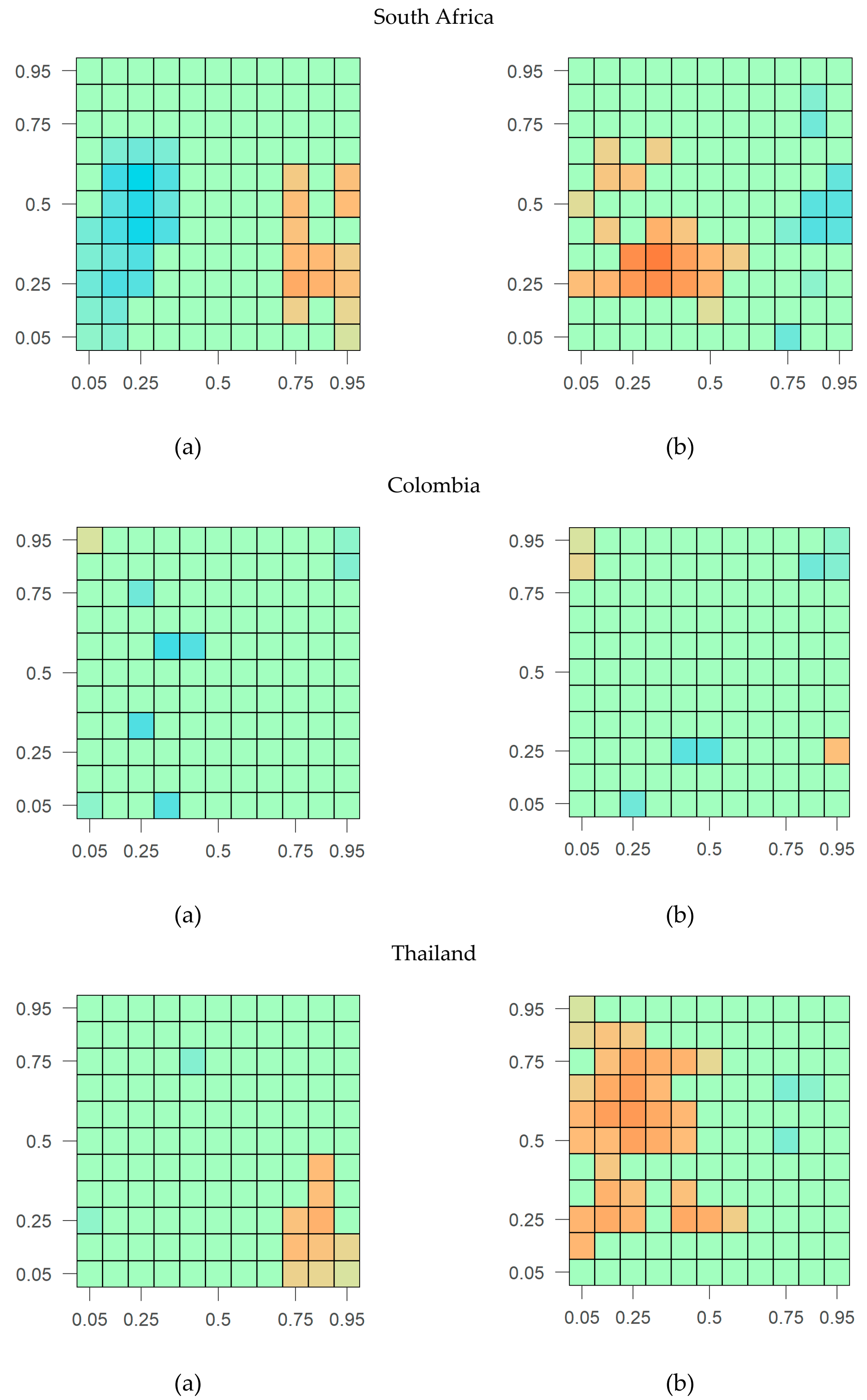


Figure 2. *Cont.*



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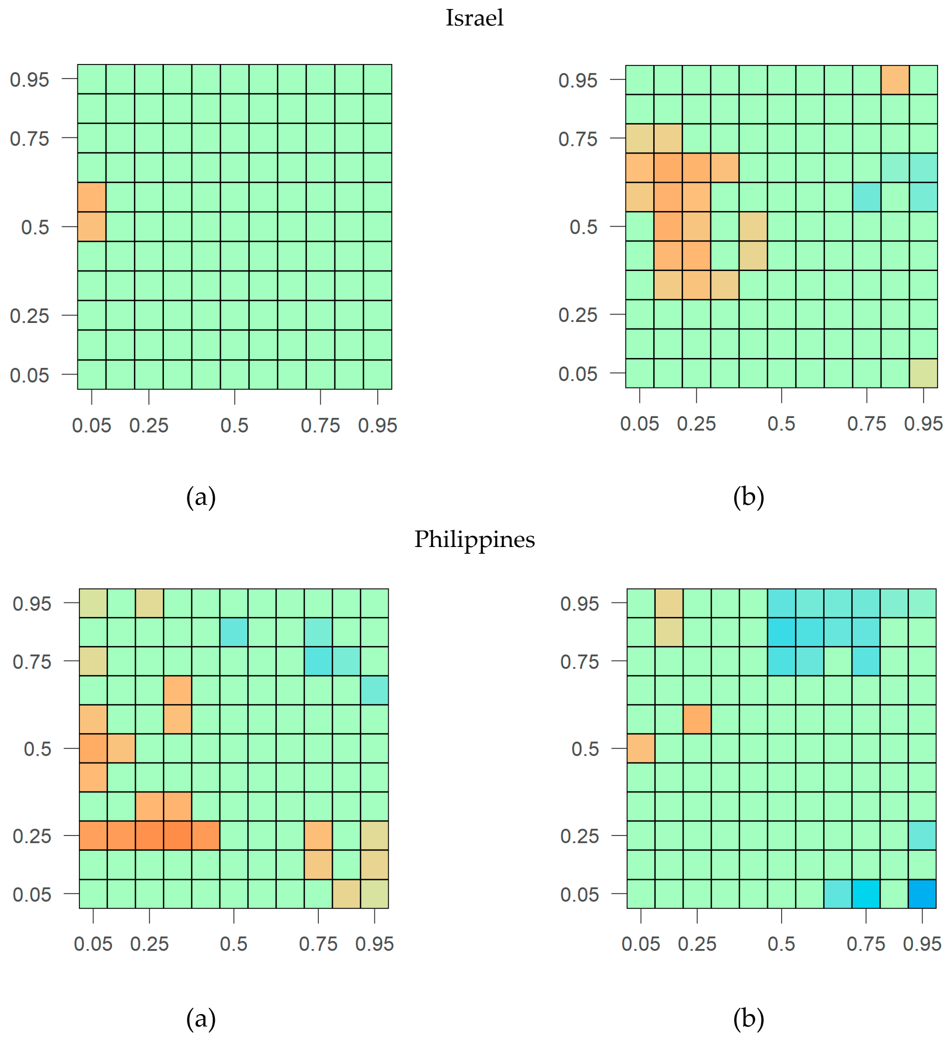

Figure 2. Heatmaps of cross-correlation between monthly local and global GPR and tourism stock returns. These figures show the cross-quantilogram (CQ) in the form of heat maps. (**a**) Impact of local GPR; (**b**) Impact of global GPR. The quantile levels with no significant directional predictability are set to zero. The colored rectangles are the predictable regions where the Box–Ljung test statistic is statistically significant. In each heatmap, the horizontal axis represents local and global GPR quantiles, while the vertical axis represents tourism stock return quantiles (from q = 0.05 to q = 0.95). Malaysia (1986M02), Turkey (1991M01), Mexico (1992M04), South Korea (1999M06), Russia (1999M04), India (1990M02), Brazil (2014M01), China (1993M07), South Africa (1992M05), Colombia (2011M06), Thailand (1988M11), Israel (1993M02), and Philippines (2000M04). () includes the starting month for the sample period of each country. All sample periods end on 2019M07.

Additionally, the presence of green, blue, and red color suggests that the association between local (global) GPR and tourism stocks exhibits quantile-based patterns that are qualitatively similar to the results obtained through the CiQ model. However, some exceptions also exist. For instance, local GPR for India and Turkey (Malaysia) shows no (negative) association with tourism stocks under lower quantiles which turn into positive as we move to the higher quantiles. An almost opposite trend is witnessed for China and Philippines. In addition, in some cases, the CQ model leads us to cautiously conclude that under normal market conditions GPRs have limited predictive potential for tourism stocks of emerging economies. It would therefore be concluded that, with some exceptions, the results obtained through the CQ model, the second layer of analysis, are qualitatively similar to those produced via the CiQ model, and hence our findings are reasonably robust when a directional predictability model is applied.

6. Conclusions

In this study, we examined the predictive potential of local and global GPR for the return of tourism stocks in selected emerging economies. The results suggest that while both local and global GPRs carry significant potential for predicting the returns and volatility of tourism stocks of most emerging economies under normal market conditions, they seem to play no such role in certain countries. These countries include South Korea, for which only a limited number of tourism stocks trade on the domestic stock market compared to other sectors, and Colombia, for which both the domestic stock market and tourism sectors are at an emerging stage. Further, it turns out that, compared to its local counterpart, global GPR has a more pronounced predictive power for the tourism stocks of emerging economies. Finally, with some exceptions, the results are qualitatively similar, and hence reasonably robust, to those when a directional predictability model is applied.

In conjunction with the traditional studies exploring the linkage between terrorism and tourism demand, as well as those emerging studies that relate GPR with tourism demand [21,22], the present study goes one step further by suggesting that GPR's predictive power is not just restricted to tourism demand but rather translates into the market performance of tourism stocks. The study also builds upon the recently proposed evidence of quantile-dependence between GPR and tourism stocks [23]. Supplementing the regional evidence of tourism stock-US GPR interaction [23] and single country analysis of [30], we provide country-level evidence by considering the predictive potential of local and global GPR for the returns of tourism sector equities of emerging economies.

The study has important implications for sustainable tourism. In the recent decades, we have seen that the tourism sector worldwide suffered huge losses due to many geopolitical events happening around the world, and the management of risks emanating from such events has become a key concern for the sustainability of the tourism industry. In the geopolitical context, risk management for tourism industry involves planning and implementation steps aimed at managing the adverse effects of GPR on tourism, and this cannot be assured without reasonable prediction of GPR and its consequences on the tourism industry. Given that the sustainability of a country's tourism industry is significantly determined by its potential to cope with changing market conditions, efficiently use resources, and offer innovative solutions and planning for risk management, our finding that GPR carries predictive potential for the tourism industry's stocks under various market conditions is particularly critical to sustainable tourism.

An obvious limitation of this paper is that it relies on GPR data of 13 emerging economies and that of the US only. Although Caldara and Iacoviello [1] have developed the GPR indices for a total of 19 countries, the tourism sector equity data were available for those 13 countries only, thus restricting our choice of sample countries. Future research may be conducted to broaden the scale of this study by including a global sample of countries which should allow us to compare the predictive power of local and global GPR for tourism stocks of various regions, namely emerging and developed markets. However, such a study would only be possible once the GPR indices for a wide range of countries are available.

Future studies can also extend the investigation by distinguishing between short-run and long-run predictability of tourism stocks using GPR. Such a distinction might give different implications for equity investors operating at different time horizons. This question could be built from the studies saying that investors operate at different investment horizons, which are expressed in different trading frequencies and are associated with various types of investors, trading tools, and strategies [41–43]. Future investigations could also extend this work by exploring whether and to what the extent the firm-specific and/or country-specific characteristics explain the results presented by this work.

Author Contributions: Conceptualization, M.H.; methodology, M.H. and M.A.N.; software, M.H. and M.A.N.; validation, M.H., M.A.N., and M.A.; formal analysis, M.H. and M.A.N.; investigation, M.H. and M.A.N.; resources, S.M.N. and S.J.H.S.; data curation, M.H., M.A.N., and M.A.; writing—original draft preparation, M.H.; writing—review and editing, S.M.N., M.A., and S.J.H.S.; visualization, M.A.N. and S.J.H.S.; supervision, S.J.H.S.; funding acquisition, S.M.N. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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