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GEOPOLITICAL RISKS AND TOURISM IN A DEVELOPED ECONOMY: HONG KONG

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ABSTRACT

Geopolitical risk is one of the factors that affects the decisions of consumption and investment, and it is regarded a business threat in the world. In this thesis, we test the effect of geopolitical risks on tourism in Hong Kong during 2010-2019 by applying a vector autoregressive (VAR) model between tourist arrivals in Hong Kong and a recently introduced index – the geopolitical risk (GPR) index – to measure geopolitical risks, with 3 control variables – oil prices, global economic policy uncertainty (EPU), and the US equity market volatility (VIX). Our results reveal that geopolitical risk has a long-lasting negative effect on tourist arrivals in Hong Kong, although this effect decreases over time. We also find that this negative influence is more moderate in Hong Kong in comparison with other regions such as Turkey and India. Therefore, tourism in Hong Kong has stronger resilience than tourism in emerging economies. Our findings provide potential implications by advancing our understanding of how geopolitical risk affects tourism in a developed economy. Policymakers and the government should recognize the adverse effects of geopolitical risk and monitor the GPR index to avoid possible decline of tourist arrivals caused by geopolitical risk.

Keywords: Geopolitical risks; tourism; developed economy; Hong Kong.

1. INTRODUCTION

Hong Kong is a developed region located at the south of China. It is a special administrative region that enjoys exclusive policies. For example, visitors from most countries can travel to Hong Kong without a visa. Having been one of Asia's largest manufacturing economies during 1950 to 1980, the main economy of Hong Kong is led by service sector nowadays. Tourism is one of the four pillar industries of Hong Kong, and it is one of the top destination cities for tourists in Asia. It is also one of the main sources of tax for the government. In 2017, tourism accounted for about 4% of GDP and for about 257,100 employees, comprising about 7% of total employment in Hong Kong (Facts & Statistics - Tourism Commission). Jin (2011) has proven the tourism-led-growth hypothesis in Hong Kong, affirming that growth of tourism leads to economic growth in Hong Kong. Nevertheless, in recent years, several political issues that happened in Hong Kong affected severely its economy and tourism. The latest one, also one of the heaviest protests that ever happened in the history of Hong Kong, took place from June to December 2019. Eleven countries or regions have issued tourism warnings against Hong Kong during that period, and it eventually led to a decrease of 14% in total arrivals in Hong Kong in 2019 (Facts & Statistics - Tourism Commission).

These political conflicts are considered a type of geopolitical risks. Defined by Caldara & Iacoviello (2018), geopolitical risks are “risks associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations.” According to “The Global Risks Report 2021” issued by the World Economic Forum (2021), geopolitical risks are considered one of the top global risks by impact in the world. They are deemed by professional investors and politicians as one of the most essential factors that affect consumption and investment decisions(Demiralay & Kilincarslan, 2019). Increased geopolitical risks result in postpone or even cancellation of certain activities such as investment, travelling, international trade, for the concern of insecurity and uncertainty. Hence, it is essential to determine how geopolitical risks can affect tourism to give investors and the government a better insight into the future development and a prediction of economic growth.

In the past, since there was no time-varying indicator (Demiralay & Kilincarslan, 2019), researchers only focused on one single factor of geopolitical risks such as terrorist attacks (Llorca-Vivero, 2008; Chang & Zeng, 2011; Feridun, 2011; Buigut, 2018), political instability (Clements & Georgiou, 1998; Fletcher & Morakabati, 2008; Ingram et al., 2013; Ivanov et al., 2017), or wars (Smith, 1998; Fleischer & Buccola, 2002; Lee, 2006; Butler & Suntikul, 2013). Caldara & Iacoviello (2018) have filled this gap by creating a new index – the geopolitical risk (GPR) index. This index was built up by calculating the frequency of appearance of geopolitical risks in news of 11 newspapers. These 11 newspapers are worldwide top newspapers, where cross-broader tensions, risks, and events are discussed. In contrast to other indexes that only contain information of one single factor such as terrorism, a subgroup of geopolitical risks, the GPR index incorporates more information. Therefore, by including more types of geopolitical risks, the GPR index encompasses more completed information, for which it is superior to other indexes of geopolitical risk.

Ever since its introduction, there is increasing interest in using the GPR index to measure geopolitical risks. Many papers explored the influence of geopolitical risks on economic activities. For example, Balcilar et al. (2018) examined the impact of geopolitical risks on stock market in the case of BRICS; Apergis et al. (2018) investigated if geopolitical risks helps predict volatility of stock return in defense companies. Aysan et al. (2019) studied how geopolitical risks affect returns and volatility of Bitcoin; Gupta et al. (2019) studied the effect of geopolitical risks on trade flows using a gravity model. Bilgin et al. (2020) explored how geopolitical risks affect government investment. Demiralay & Kilincarslan (2019) were the first to apply this index to the tourism sector; they analyzed the relationship between geopolitical risks and travel and leisure stock. Jiang et al. (2020) investigated a similar topic on Chinese-listed companies stock.

Demir et al. (2019) were the first to explore the relationship between tourist arrivals and geopolitical risks by employing the GPR index in panel models. Balli et al. (2019), Lee et al. (2021), and Gozgor et al. (2021) also used panel data to explore how geopolitical risks affect tourist arrivals. Other authors focused on one single country by using time series models. For example, Saint Akadiri et al. (2020) and Demir et al.

(2020) studied the effect of geopolitical risks on tourist arrivals in Turkey; Tiwari et al. (2019) and Ghosh (2021) explored how geopolitical risks influence tourism in India.

Previous studies mostly focus on emerging countries since it is more likely to have geopolitical risks in developing countries, and these regions are usually more sensitive to economic or geopolitical instabilities in comparison with developed countries because their legal system, order system, and institutional arrangements are usually incomplete (Gray, 1997). Thus, we intend to fill this gap in the literature by exploring how geopolitical risks affect tourism in a developed economy: Hong Kong. We try to investigate this impact to provide insights to policy makers not only in Hong Kong, but also in other regions with similar economic structures. Thus, this study has relevant policy implications for investors and governments. To the best of our knowledge, this is the first thesis that uses the GRP index of Caldara & Iacoviello (2018) to study the relationship between geopolitical risks and tourism in a developed region by using a vector autoregressive (VAR) model.

We find that the impacts of geopolitical risks to tourism in Hong Kong are negative and adverse, and these impacts last in the long term. Geopolitical risks have a significant adverse influence on the tourist arrivals in Hong Kong at the first, eighth, and twelfth lags; a 1% rise of GPR index results in a 0.087% drop of tourist arrivals within the following month. In addition, a 1% increase in geopolitical risks results in a 0.081% drop of tourist arrivals eight months afterwards. Finally, a 1% increase in geopolitical risks causes a decline of 0.059% of tourist arrivals in the following year. Our findings also reveal that this adverse effect is more moderate in Hong Kong than in regions like India (Tiwari et al., 2019; Ghosh, 2021) and Turkey (Saint Akadiri et al., 2020), Thus, tourism in Hong Kong has stronger resilience to geopolitical risks than emerging economies do.

The rest of the study advances as follows. Section 2 presents a literature review on the relationship between the GPR index and tourism. Section 3 specifies the methodology employed in our thesis. Section 4 illustrates the data and discusses the empirical results. In section 5, we conclude the thesis and present policy implications.

2. LITERATURE REVIEW

There is very few literature on the effects of geopolitical risks on tourism by using GPR index since it is a recently introduced index. The existing literature on this topic can be divided into literature that focuses on the impact of GPR on economic activities in tourism sector and analysis of the effects of GPR changes on tourist arrivals.

Demiralay & Kilincarslan (2019) investigated the sensitivity of travel and leisure industry stock indices in 4 regions (Global, Asia-Pacific, Europe, and North America) to geopolitical risks. They found that geopolitical risks negatively affect the stock return of travel and leisure industry in these regions. Moreover, the negative impacts are more serious when the travel and leisure sector performs poorly. Hasan et al. (2020) examined whether geopolitical risks can forecast return of tourism equity; the authors concluded that in many developing economies, local and global GPR can potentially forecast the returns and volatility of tourism stocks when the market is in a normal condition. However, they do not find the same effect in certain economies like South Korea and Colombia. Jiang et al. (2020) focused only on the effects of GPR on the Chinese market of tourism; they investigated how geopolitical risk and economic policy uncertainty impact the Chinese tourism-listed company stock return, and they showed that the adverse effect of GPR on Chinese tourism stock return lasts in the long run. Antonakakis et al. (2017) examined the relationship between geopolitical risks and oil market. Their results show that geopolitical risks yield adverse impacts on oil returns and volatility.

Many studies demonstrated that geopolitical risks hold an adverse effect on tourist arrivals by using GPR index as a proxy of geopolitical risk. Demir et al. (2019) used panel data of 18 countries during 1995-2016, and their findings reported that geopolitical risks negatively influence inbound tourism. Similarly, Lee et al. (2021) showed that geopolitical risk has negative impacts on tourism by employing panel data of 16 countries. Gozgor et al. (2021) also found that geopolitical risks have a negative effect on capital investment in tourist sector on a panel of 18 developing economies. However, the results of Balli et al. (2019) revealed that not all countries have the same reaction to geopolitical risks. Certain countries are almost immune to geopolitical risks, while others are heavily affected by geopolitical risks.

Saint Akadiri et al. (2020) examined the direction of causality among GPR, tourism, and economic growth in Turkey; their results indicated that Granger-causality runs from GPR to economy and to tourism. Besides, a one-standard-deviation shock to geopolitical risk negatively influences tourism and economy both in the short and long term. Using the data of Turkey as well, Demir et al. (2020) studied the asymmetric effects of geopolitical risks on Turkey's tourist arrivals, and the authors found that these effects are asymmetric in the short term. In addition, both Ghosh (2021) and Tiwari et al. (2019) demonstrated that geopolitical risks hold an adverse effect on tourism in India in the long run.

As far as we know, this is the first thesis that explores the connection between tourist arrivals and geopolitical risks by employing GPR index in a developed region using a VAR model. Current literature only focuses on this topic on emerging countries. Nonetheless, a same incident can have different impacts on developing and developed economies. For instance, Zeman & Urban(2019) reported that terrorism also cause damages to tourism in developed countries but only the most serious ones, and the effects only last in the short term; Thompson (2011) found that terrorism triggers bigger impacts on developing regions than in developed regions, as developed countries recover faster from a terrorist attack. Hence, since a terrorist attack is a type of geopolitical risks, the objective of this thesis is to investigate whether geopolitical risks as a whole affect developed economies differently than developing countries.

3. METHODOLOGY

This section outlines the methodology that we use in the thesis. We first explain the vector autoregressive (VAR) model, a multivariate time series model that is suitable for measuring lagged effects between GPR index and tourist arrivals. Next, we describe the Augmented Dickey–Fuller (ADF) unit root test of Dickey & Fuller (1979), a test that we use in this study for examining whether the variables are stationary or not. Further, we describe the Johansen (1988, 1991)'s cointegration tests, which determine whether the variables are cointegrated or not. We also define the Granger-causality tests for testing the causality between tourist arrivals and GPR index, once the VAR model is established.

3.1. VAR models

A VAR model is a multivariate time series model containing a system of *n* equations of *n* distinct, stationary response variables as linear functions of lagged responses and other terms. Geopolitical risks are estimated to have lagged impact on tourist arrivals since trips are normally planned in advance. VAR models are widely used in economics. Certain studies used VAR models to examine the impacts of specific variables on tourism or impacts of tourism on economic growth. For example, Liu et al. (2020) examined the impact of economic policy uncertainty on the relationship between tourism and economic growth with a mixed-frequency vector autoregression model; Ali et al. (2018) studied how the Malaysian economy responds to macroeconomic shocks by using a VAR model; Jin (2011) used a five-variable VAR model to analyze the effect of tourism on economy in Hong Kong.

Let $\log(arrivals_t)$ and $\log(GPR_t)$ be the monthly logarithm of tourist arrivals and the logarithm of the GPR index of Caldara & Iacoviello (2018), respectively. We also use the logarithm of monthly US volatility index $\left(\log(VIX_t)\right)$, the logarithm of global economic policy uncertainty index $\left(\log(EPU_t)\right)$, and the first difference of the logarithm of West Texas Intermediate (WTI) oil prices (ΔOIL_t) as controls. While we show that the logarithm of oil prices is not stationary, for which we need to use its first difference that is stationary, $\log(EPU_t)$ and $\log(VIX_t)$ are both stationary that can be employed directly in the VAR model. As for $\log(arrivals_t)$and $\log(GPR_t)$, although we show that they are not stationary, we find that they are cointegrated, for which they could also be applied in the VAR model. Hence, the general form of our VAR(*p*) model can be written as follows:

$$\log(arrivals_t) = C_0 + \sum_{i=1}^{p} A_i \log(arrivals_{t-i}) + \sum_{i=1}^{p} B_i \log(GPR_{t-i}) + \beta_1 \log(VIX_t) + \beta_2 \log(EPU_t) + \beta_3 \Delta OIL_t + \varepsilon_t, \quad (1)$$

$$\log(GPR_t) = C_0^* + \sum_{i=1}^{p} A_i^* \log(arrivals_{t-i}) + \sum_{i=1}^{p} B_i^* \log(GPR_{t-i}) + \beta_1^* \log(VIX_t) + \beta_2^* \log(EPU_t) + \beta_3^* \Delta OIL_t + \varepsilon_t^*, \quad (2)$$

where Δ denotes a first-difference operator, C_0 and C_0^* are constants, $A_{\mathrm{i}}, A_{\mathrm{i}}^*, B_i, B_i^*, \beta_1, \beta_1^*, \beta_2, \beta_2^*, \beta_3$, and β_3^* are coefficients, *p* is the number of lags, and ε_t and ε_t^* are white noise residuals (serially uncorrelated with zero mean and constant variance).

We select the lag order *p* of the dependent variable that minimizes the Akaike Information Criteria (AIC) in a VAR between $\log(arrivals_t)$ and $\log(GPR_t)$ as follows:

$$AIC = -2l(\widehat{\boldsymbol{\theta}}) + 2k, \tag{3}$$

where $l(\widehat{\boldsymbol{\theta}})$ is the log-likelihood function of the vector of parameter estimates of the VAR model of Equations (1)-(2), and *k* denotes the number of parameters in the VAR model.

Once we estimate the VAR model, we test whether the residuals of the VAR model are not serially correlated to validate our results. We use the Lagrange multiplier test in this study, which tests for residual autocorrelation in a VAR model assuming a VAR model for the error vector, $\varepsilon_t = D_1\varepsilon_{t-1} + \cdots + D_h\varepsilon_{t-h} + \cdots + v_t$, where $v_t$is a white noise error (Lütkepohl, 2005). We test the null hypothesis $H_0: D_1 = \cdots = D_h = 0$ for both VAR residuals ε_t and ε_t^* of Equations (1)-(2) against the alternative hypothesis that at least one lagged residual is significant ($H_A: D_i \neq 0,$ for at least one i). The test statistic is referred to a Rao *F* distribution (Rao, 1967).

3.2. Unit root tests

We apply the Augmented Dickey–Fuller (ADF) unit root test of Dickey & Fuller (1979) on all series. Testing for stationarity is crucial because the estimation results of time series regression may be wrong if all variables are not stationary. In the framework of the ADF test, testing for non-stationarity is equivalent to testing for the existence of unit root. The ADF test consists of testing the null hypothesis that $\gamma = 0$ (Y_t has a unit root) against the alternative hypothesis that $\gamma < 0$ (Y_t does not have a unit root) on the following regression under the null hypothesis:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \varepsilon_t, \tag{4}$$

where α is constant, t represents a deterministic time trend, *p* is the number of lags of the first differences of the dependent variable, and ε_t is a white noise error term. We run this specification with a constant and a deterministic trend because it increases the power of the ADF test. Besides, the lags of the first differences of the dependent variable avoids autocorrelation of ε_t in Eq. (4). We select the number of lags *p* in Eq. (4) that minimizes the AIC up to a maximum of 12 lags. Hence, we apply the ADF test of Equation (4) to each monthly series. If we fail to reject the null hypothesis for a series, then we take the first differences of this series, and we check whether it is stationary or not.

3.3. Cointegration tests

We use Johansen's (1988, 1991) procedure to check the cointegration relationship between $\log(arrivals_t)$ and $\log(GPR_t)$ since we find that both variables are not stationary. If both variables are nonstationary and cointegrated, then we can run a VAR on these series without taking first differences of them. Then, we do not lose information by differentiating these series. The test of cointegration checks whether two or more series display a long-term relationship given that they are nonstationary. Thus, if the non-stationary variables are cointegrated, they move together and converge to an equilibrium over time in the long run (Satrovic & Muslija, 2017). This method tests the cointegration based on the VAR of order *p* given by:

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \boldsymbol{A}_1\boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{Y}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{5}$$

where $\boldsymbol{Y}_t = (\log(arrivals_t), \log(GPR_t))'$ is a length 2×1 vector of variables that are integrated of order one (nonstationary) and $\boldsymbol{\varepsilon}_t$ is a 2×1 vector of innovations. We can rewrite Equation (5) as

$$\Delta\boldsymbol{Y}_t = \boldsymbol{\mu} + \boldsymbol{\Pi}\boldsymbol{Y}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i\,\Delta\boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{6}$$

where $\boldsymbol{\Pi} = \sum_{i=1}^{p} \boldsymbol{A}_i - \boldsymbol{I}$ and $\boldsymbol{\Gamma}_i = -\sum_{j=i+1}^{p} \boldsymbol{A}_j$. If the rank of $\boldsymbol{\Pi}$ is one, then there are 2×1 matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ with rank one such that $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ and $\boldsymbol{\beta}'\boldsymbol{Y}_t$ is stationary with one cointegrating relationship, where the column of $\boldsymbol{\beta}$ is a vector of cointegration relationships between $\log(arrivals_t)$ and $\log(GPR_t)$.

3.4. Granger-causality tests

The concept of Granger-causality (Granger, 1969) tests the restriction that all lags of a given variable do not help predict current values of a response variables. Thus, it consists of a F-test that none of the lags of a predictor are significant in the VAR(*p*) model of Equations (1)-(2). Granger-causality is a measurable concept of causality or directed influence for time series data, defined using predictability and temporal precedence (Roebroeck, 2015). This method is widely used in research for identifying a long-run relationship and the direction of this relationship. If the $\log(arrivals_t)$ is regressed on lagged values of $\log(arrivals_t)$ and $\log(GPR_t)$, and at least one coefficient of the lags of $\log(GPR_t)$ is statistically significantly, then it can be argued that $\log(GPR_t)$ Granger-causes $\log(arrivals_t)$, this is, lagged values of $\log(GPR_t)$ can help predict $\log(arrivals_t)$.

We apply a Granger-causality test to verify whether lagged values of the GPR affect current tourist arrivals in Hong Kong. Then, we perform the following *F* test on the VAR(*p*) model of Equations (1)-(2):

H_0: $\log(GPR_t)$ does not Granger-cause $\log(arrivals_t)$ ($B_i = 0$, for all $i = 1, \ldots, p$)

H_A: $\log(GPR_t)$ Granger-causes $\log(arrivals_t)$ ($B_i \neq 0$, for at least one $i \in \{1, \ldots, p\}$).

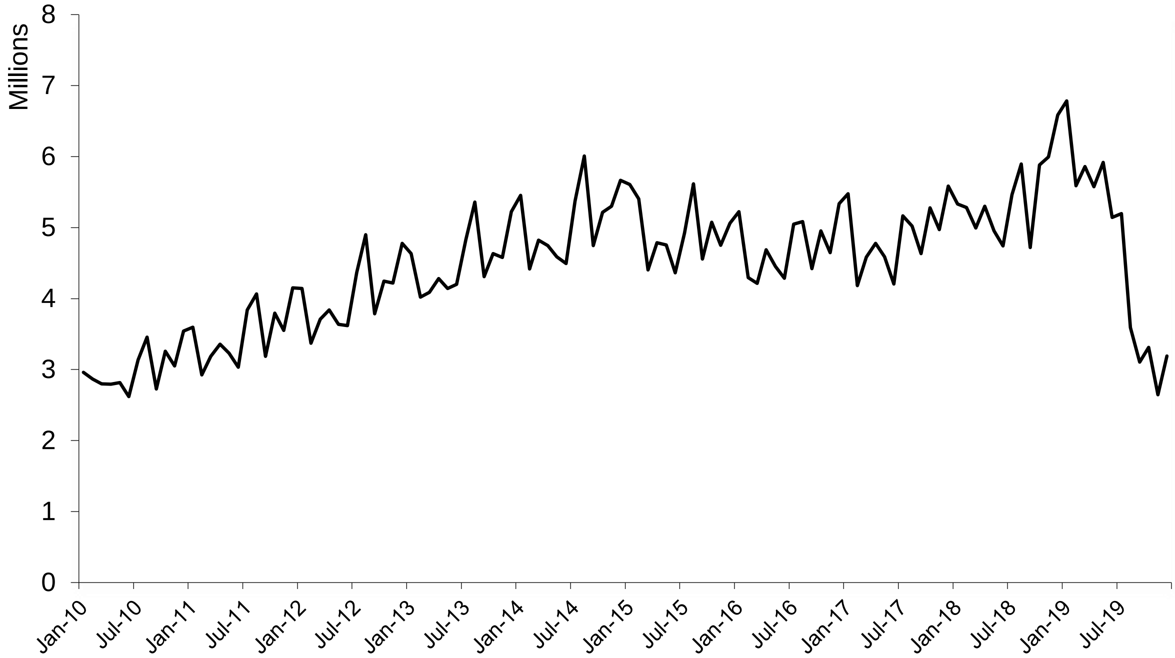
We reject the null hypothesis that $\log(GPR_t)$ does not Granger-cause $\log(arrivals_t)$ if at least one lag of $\log(GPR_t)$ is statistically significant on the VAR(*p*) of Equation (1).

4. RESULTS

In this section, we describe the data that we use in this study and the empirical results. First, we explain the data, and we present some summary statistics. Next, we discuss the results of VAR model of Equations (1)-(2) together with the Granger-causality, cointegration, and autocorrelation tests.

Our monthly data span from January 2010 to December 2019, yielding 120 monthly observations for each variable. Even though the data of 2020 are available, to avoid the influence of pandemic of Covid-19, we do not use these series for 2020. We use monthly tourist arrivals in Hong Kong, which is downloaded from the official website of Hong Kong Tourism Board (HKTB) (https://partnernet.hktb.com/en/research_statistics/index.html). Figure 1 below shows the evolution of monthly tourist arrivals in Hong Kong from January 2010 to December 2019. The number of tourist arrivals increased constantly between 2010 and 2014; it fluctuated around a constant trend of 5 million monthly arrivals between 2015 and 2018. Finally, it significantly decreased in 2019 because of the protests in Hong Kong.

Figure 1. *Monthly tourist arrivals in Hong Kong*



Source: Hong Kong Tourism Board (https://partnernet.hktb.com/en/research_statistics/index.html).

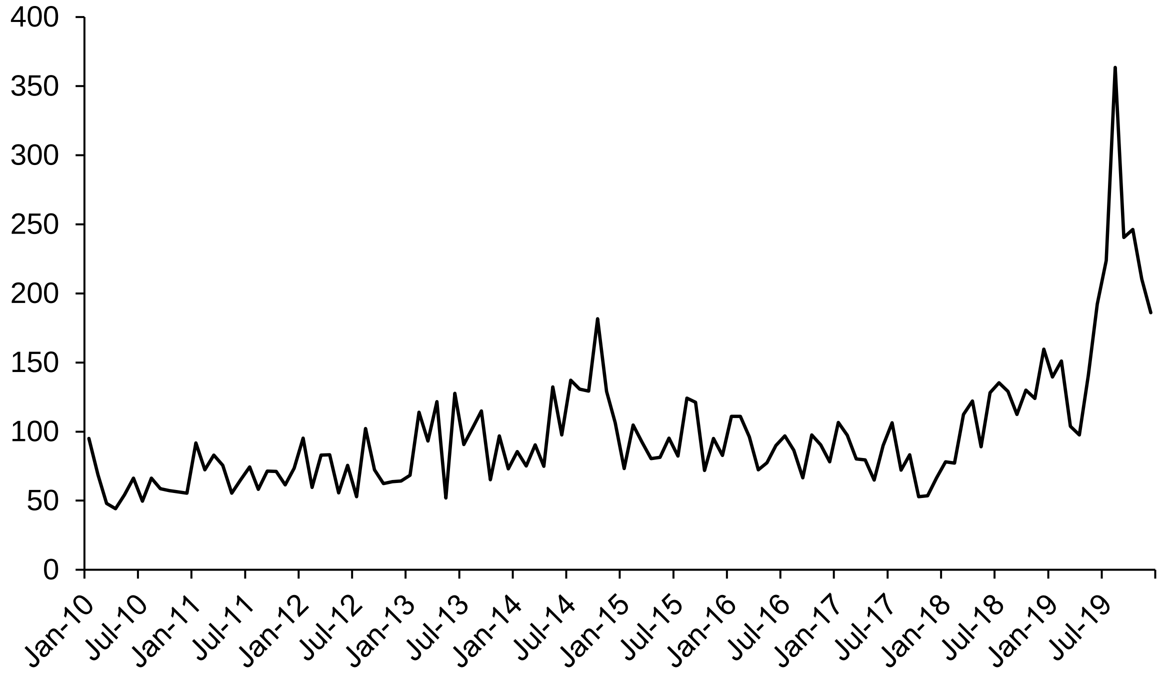
We obtained the monthly geopolitical risk (GPR) index from the website Geopolitical Risk (GPR) Index (www.matteoiacoviello.com). There are two types of indexes: benchmark index and historical index. We use the benchmark index in this study. This index is built up by calculating the number of news that mentioned geopolitical risk of Hong Kong in 11 influential newspapers around the world: The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post. The GPR index is calculated according to the equation below:

$$GPR \approx \frac{G}{U}, \tag{7}$$

where *G* is the number of articles mentioning geopolitical tensions, and *U* is the total number of articles. Each month, the ratio *G*/*U* (normalized to equal 100 during the period of 2000-2009) is the geopolitical risks index. As a result, if the GPR index is higher than 100, it is a high GPR index, indicating a high degree of geopolitical risks.

If an article contains information of elevated geopolitical risks, it is coded as 1. Otherwise, it is coded as -1 if it includes information of low geopolitical risks. If it has no information of geopolitical risks or it does not indicate if the risks are getting higher or lower, it is coded as 0. Hence, a high value of GPR index means high degree of geopolitical risks. Figure 2 displays the evolution of the monthly GPR index for Hong Kong. The GPR value of Hong Kong oscillated around a constant trend from 2010-2019. Nevertheless, the GPR index increased more than 200% in 2019 due to the protest that started since June 2019 (https://edition.cnn.com/specials/asia/hong-kong-protests-intl-hnk).

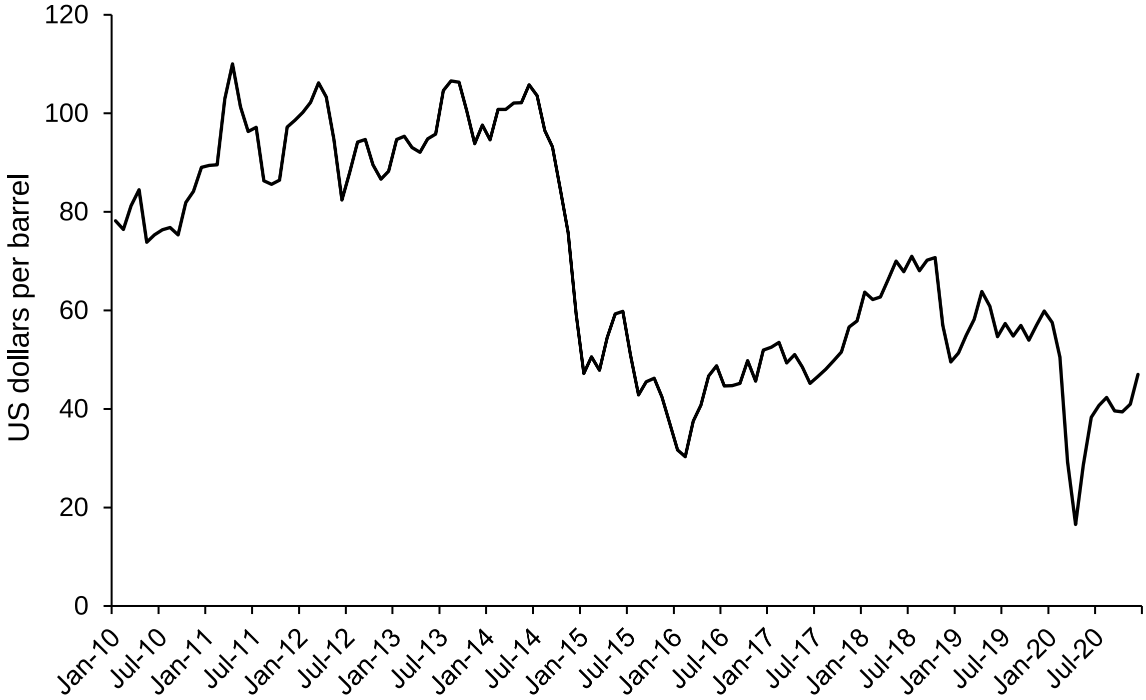
Figure 2. *Monthly GPR index of Hong Kong*



Source: Geopolitical Risk (GPR) Index (www.matteoiacoviello.com).

We employ three control variables that impact on tourist arrivals: oil prices (OIL), the global economic policy uncertainty (EPU) index, and the US equity market volatility (VIX). We obtain the monthly West Texas Intermediate (WTI) spot crude oil prices series from the Federal Reserve of St. Louis database (https://fred.stlouisfed.org/series/WTISPLC). Several papers demonstrated the importance of oil prices for tourism in different regions (see e.g., Becken & Lennox, 2012; Chatziantoniou et al., 2013; Huang et al., 2018). Figure 3 depicts the monthly fluctuation of WTI spot crude oil prices. It experiences a dramatic drop in 2014-2015 and another one in 2019-2020, when the prices dropped to the lowest level in 2010-2019. Overall, the WTI oil prices have been following a declining trend over the last ten years.

Figure 3. *Monthly WTI oil prices*

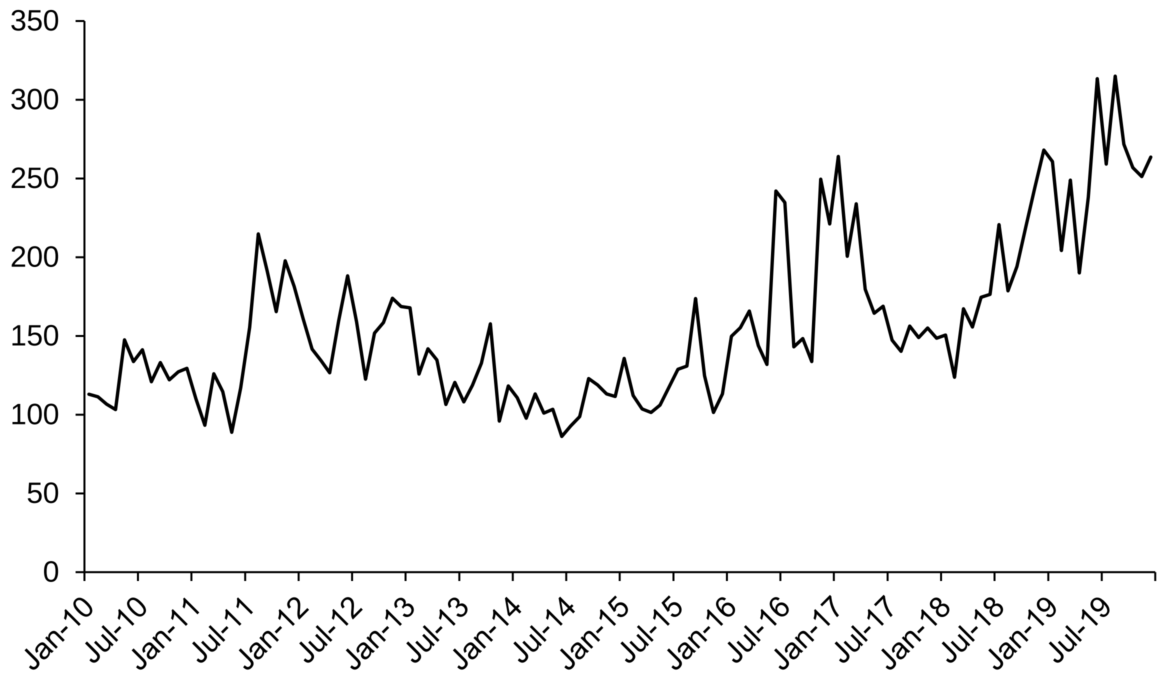


Source: FRED economic data (https://fred.stlouisfed.org/).

We extract the EPU index from the website https://policyuncertainty.com/. It is an index built up with three types of components to measure policy-related economic uncertainty. The first component quantifies newspaper coverage of policy-related economic uncertainty. These newspapers are the USA Today, the Miami Herald, the

Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal. The second component reflects annual dollar-weighted numbers of tax code provisions set to expire in future 10 years, measuring the level of uncertainty regarding to the way that the federal tax code will take in the future. The final component is the dispersion between professional economic forecasters, by using a survey, as a proxy for uncertainty. Many papers tested the causality relationship between EPU and tourist arrivals, and there is evidence that EPU affects tourist arrivals (Demir & Gözgör, 2018; Ongan & Gozgor, 2018; Tiwari et al., 2019). Figure 4 plots the monthly global EPU index from January 2010 to December 2019. Even though the index fluctuates constantly, the graph shows a trend of increasing economic policy uncertainty over 2010-2019.

Figure 4. *Monthly global economic policy uncertainty (EPU) index*

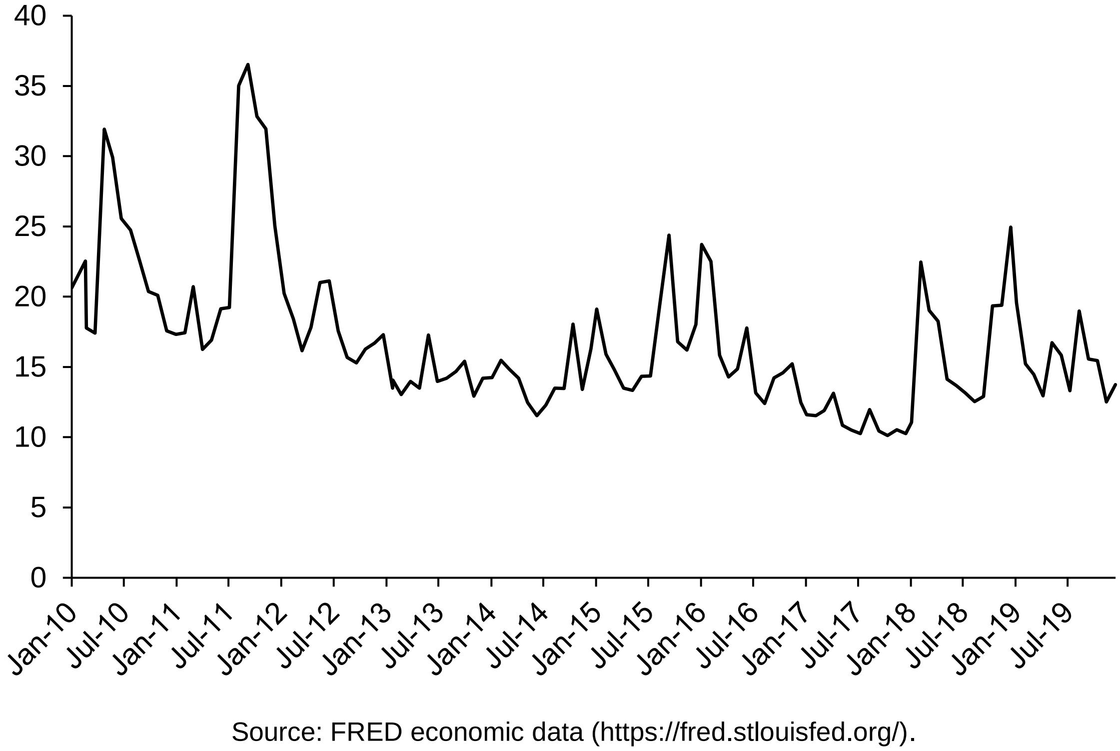


Source: FRED economic data (https://fred.stlouisfed.org/).

We obtain the US equity market volatility (VIX) index from the St. Louis Federal Reserve database (https://fred.stlouisfed.org/series/VIXCLS). It is a real-time daily index that illustrates the prediction of short-run fluctuation transmitted by stock index option prices of the Chicago Board Options Exchange (CBOE). This index has been widely used to estimate the fluctuation of stock market according to S&P 500 index options. Therefore, it is usually considered as “fear index” or “fear gauge.” Higher volatility (or higher level of the VIX) suggests that it is more likely to have a decreasing market. On the contrary, low fluctuation demonstrates a higher possibility of an increasing market. People will spend more when their expected income in the future is stable or higher, while they will spend less when their income is likely to be unstable or depreciated. Several studies have reported that equity market volatility affects tourism (Kim et al., 2012; Gokmenoglu & Hadood, 2019; Akdağ et al., 2019).

Since this is a daily index, we transformed the data into a monthly index by calculating the mean of each month. Figure 5 displays the monthly VIX index where it shows great fluctuations during 2010-2019. The index reached its highest peak in 2011, and it dropped back to the average level one year afterwards.

***Figure* 5.** *Monthly US volatility index (VIX)*



Source: FRED economic data (https://fred.stlouisfed.org/).

Table 1 reports the descriptive statistics of the five variables. The data range over different orders of magnitude because of the high volume of tourist arrivals. All series have a large standard deviation so that we take natural logarithm of each variable to stabilize their volatilities.

Table 1. Descriptive statistics

Variables	Mean	St. Dev.	Minimum	Maximum
$Arrivals_t$	4,476,658.17	920323.99	2,619,722	6,784,406
GPR_t	98.19	46.32	44.19	366.72
OIL_t	72.45	21.94	30.32	110.04
EPU_t	154.85	50.49	85.10	308.06
VIX_t	16.86	5.17	10.13	36.53

Note: This table reports descriptive statistics of the monthly tourist arrivals to Hong Kong ($Arrivals_t$), geopolitical risk index (GPR_t) of Hong Kong of Iacovello & Caldara (2018), monthly WTI oil prices (OIL_t), monthly global economic policy uncertainty index (EPU_t), and monthly US volatility index (VIX_t) from January 2010 to December 2019. The total number of observations for each series is 120. St. Dev. stands for the standard deviation of the series.

It is important to ensure that all variables are stationary before applying the VAR(*p*) model of Equations (1)-(2). Thus, we employ the ADF unit root tests of Equation (3) on each variable. Table 2 displays the result of unit root tests of the variables. Both $\log(arrivals_t)$ and $\log(GPR_t)$ are not stationary at the 1% significance level. As a consequence, we test whether both variables are cointegrated. The control variable $\log(OIL_t)$ is nonstationary at the 1% significance level. Therefore, we test the stationarity of its first difference; we find that $\Delta\log(OIL_t)$ is stationary at the 1% level (since we reject the null hypothesis of a unit root at the 1% level). Finally, we reject the null hypothesis of a unit root for $\log(EPU_t)$ and $\log(VIX_t)$; hence, they are stationary at the 1% significance level.

Table 2. Unit root test results

Variables	ADF test *p*-value
$\log(arrivals_t)$	0.988
$\log(GPR_t)$	0.023
$\log(OIL_t)$	0.408
$\Delta\log(OIL_t)$	**0.001**
$\log(EPU_t)$	**0.005**
$\log(VIX_t)$	**0.003**

Note: The notation Δ indicates the first difference of the variable. This table shows the *p*-values of the ADF unit root test of Dickey & Fuller (Dickey & Fuller, 1979). The null hypothesis of the ADF test is that the variable has a unit root against the alternative hypothesis that the variable does not have a unit root. We use the specification of the ADF test of Equation (4) with a deterministic trend and a drift under the null hypothesis, and with a lag order of the dependent variable up to a maximum of 12 lags. We select the lag order that minimizes the AIC. Boldface values of the *p*-value of the ADF denotes rejection of the null hypothesis at the 1% significance level.

Since both $\log(arrivals_t)$ and $\log(GPR_t)$ are nonstationary, we examine whether they are cointegrated using Johansen (1988,1991)'s trace test, which is based on Granger (1981)'s error-correction model (ECM) representation. Table 3 shows the Johansen (1988, 1991)'s trace test results. The null hypothesis is that the two variables are not cointegrated. Hence, we reject the null hypothesis at the 5% significance level. Therefore,$\log(arrivals_t)$ and $\log(GPR_t)$ are cointegrated so that we can specify a VAR model with the log-levels of these variables.

Table 3. Cointegration test between tourist arrivals and GPR of Hong Kong

Rank	Trace test	*P*-value
0	29.139	0.019**
1	5.300	0.565

Note: This table presents the Johansen (1988, 1991)'s trace test of the null hypothesis that the cointegration rank between $\log(arrivals_t)$ and $\log(GPR_t)$ is of order *k* against the alternative hypothesis of *k+1*, for *k* = 0, 1. We use the specification of Equation (6) with 14 lags of the dependent variable, a restricted trend, and an unrestricted constant. We select the lag order of the dependent variable that minimized the AIC in a VAR between $\log(arrivals_t)$ and $\log(GPR_t)$, and we also tested for serial correlation of the VAR residuals. The notation ** denotes rejection of the null hypothesis at the 5% significance level.

Table 4 shows the VAR estimation results of Equations (1)-(2). To save space, we omit the estimation results of Equation (2). Table 4 illustrates that the GPR index has a significant negative effect on the tourist arrivals at the first, eighth, and twelfth lags. The coefficient of the first lag is -0.087, significant at the 5% level, indicating that when GPR increases 1%, there is a drop of 0.087% in tourist arrivals in the following month. In addition, the coefficient of the eighth lag is -0.081, significant also at the 5% level, demonstrating that when the index rises at 1%, there will be a 0.081% drop of tourist arrivals eight months afterwards. Moreover, the coefficient of the twelfth lag of GPR is significant at the 10% significance level, and its effect is smaller than the previous two other significant coefficients of the effect of GPR on tourism: a 1% increase in geopolitical risks results in a decline of 0.059% of tourist arrivals in the following year. Finally, neither of the three control variables affect the log of tourist arrivals in Hong Kong.

We also perform a Granger-causality test from $\log(GPR_t)$ to $\log(arrivals_t)$ as described in Subsection 3.4. The *p*-value of the Granger-causality test is 0.006 so that we reject the null hypothesis that $\log(GPR_t)$ does not Granger-cause $\log(arrivals_t)$ at the 1% significance level. Hence, past values of GPR_t help predict current values of tourist arrivals in Hong Kong.

We test whether the residuals of the VAR model of Equations (1)-(2) are uncorrelated to validate our results. Table 5 displays the result of the Lagrange multiplier test of autocorrelation of the VAR residuals of Equations (1)-(2); we cannot reject the null hypothesis that the VAR residuals are uncorrelated at 1% significance level. Thus, the VAR residuals are uncorrelated, indicating that the VAR is well specified.

Our findings are in line with Ghosh (2021), who reported that geopolitical risks adversely affect tourism in the long term in India, and with Demir et al. (2020), who corroborated the same effect in Turkey. Hence, our findings demonstrate that increased geopolitical risks increase the uncertainty for tourists, and thus they decrease tourist arrivals.

Table 4. VAR estimation results

Variable	Coefficient	*P*-value	Variable	Coefficient	*P*-value
constant	-2.784	0.030**	$\log(GPR_{t-2})$	-0.036	0.381
$\log(arrivals_{t-1})$	0.407	0.000***	$\log(GPR_{t-3})$	-0.027	0.520
$\log(arrivals_{t-2})$	0.325	0.004***	$\log(GPR_{t-4})$	0.057	0.211
$\log(arrivals_{t-3})$	0.241	0.007***	$\log(GPR_{t-5})$	-0.023	0.617
$\log(arrivals_{t-4})$	-0.011	0.921	$\log(GPR_{t-6})$	-0.029	0.481
$\log(arrivals_{t-5})$	0.030	0.752	$\log(GPR_{t-7})$	0.011	0.761
$\log(arrivals_{t-6})$	-0.097	0.352	$\log(GPR_{t-8})$	-0.081	0.022**
$\log(arrivals_{t-7})$	0.009	0.938	$\log(GPR_{t-9})$	-0.046	0.248
$\log(arrivals_{t-8})$	0.006	0.952	$\log(GPR_{t-10})$	-0.010	0.840
$\log(arrivals_{t-9})$	0.148	0.125	$\log(GPR_{t-11})$	0.038	0.287
$\log(arrivals_{t-10})$	-0.140	0.102	$\log(GPR_{t-12})$	-0.059	0.080*
$\log(arrivals_{t-11})$	0.157	0.196	$\log(GPR_{t-13})$	-0.059	0.118
$\log(arrivals_{t-12})$	0.682	0.000***	$\log(GPR_{t-14})$	-0.049	0.187
$\log(arrivals_{t-13})$	-0.234	0.050*	$\log(VIX_t)$	0.038	0.296
$\log(arrivals_{t-14})$	-0.220	0.187	$\log(EPU_t)$	-0.037	0.296
$\log(GPR_{t-1})$	-0.087	0.014**	$\Delta\log(OIL_t)$	-0.056	0.584

Note: This table shows the VAR estimation results of Equation (1). The resulting AIC is -2.0241. The number of observations is 106. The notation ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. The *F* test of the Granger-causality test from $\log(GPR_t)$ to $\log(arrivals_t)$ tests the null hypothesis that all lagged coefficients of $\log(GPR_t)$ are not significant against the alternative hypothesis that at least one lagged coefficient of $\log(GPR_t)$ is different from zero. The resulting *F* statistic of this test is $F(14, 74) = 2.469$, whose *p*-value is 0.006.

Table 5. Autocorrelation tests of the VAR residuals

	Rao *F*	*P*-value
Lag 1	0.407	0.392
Lag 2	0.325	0.526
Lag 3	0.241	0.762
Lag 4	-0.011	0.744
Lag 5	0.030	0.759
Lag 6	-0.097	0.884
Lag 7	0.009	0.779
Lag 8	0.006	0.676
Lag 9	0.148	0.804
Lag 10	-0.140	0.851
Lag 11	0.157	0.761
Lag 12	0.682	0.339
Lag 13	-0.234	0.441
Lag 14	-0.220	0.527

Note: This table reports the results of the Lagrange multiplier test of autocorrelation of the VAR residuals of Equations (1)-(2), assuming a VAR model for the error vector, $\varepsilon_t = D_1\varepsilon_{t-1} + \cdots + D_h\varepsilon_{t-h} + \cdots + v_t$, where $v_t$is a white noise error (Lütkepohl, 2005). It tests the null hypothesis $H_0: D_1 = \cdots = D_h = 0$ for both VAR residuals ε_t and ε_t^* of Equations (1)-(2) against the alternative hypothesis that at least one lagged residual is significant ($H_A: D_i \neq 0,$ for at least one i). The autocorrelation test statistic is referred to a Rao F distribution (Rao, 1967).

Nevertheless, although the negative effect of geopolitical risks to tourist arrivals in Hong Kong remains significant in the long term, its influence is declining over time. Besides, our results show that a 1% increase in the index reduces tourist arrivals by -0.087%. The negative impact of geopolitical risks on tourism in Hong Kong is much smaller in comparison with other economies such as Turkey (Demir et al., 2020), India (Tiwari et al., 2019; Ghosh, 2021). Thus, tourism in Hong Kong has stronger resilience to geopolitical risks than in Turkey and India, in line with Gray (1997) who stated that developing regions are usually more sensitive to geopolitical policy-related instabilities compared with developed countries.

Liu & Pratt (2017) also argued that destinations with higher gross national income per capita and those that are more politically open are more resilient to terrorism than those with low per capita income or with more authoritarian governments. Developed economies have more resources to develop security systems, and they recover more quickly from the damages of terrorist attacks or other geopolitical risks, while developing countries may require international help to prevent and recover from the damages of terrorist attacks or other geopolitical risks. From another perspective, Demir et al. (2019) state that it is more likely that the public make mandatory trips when geopolitical risks are high. Being one of the top financial centers in Asia, Hong Kong receives numerous business travelers every year. For these travelers, the elasticity of travelling is smaller than for leisure tourists. Hence, the possibilities of them going to Hong Kong under high geopolitical risks are higher than that of leisure tourists. Moreover, being one of the safest regions in the world, the main geopolitical risks in Hong Kong consist of political uncertainty, which is more moderate than wars or terrorist attacks that can directly harm the personal safety of travelers. Therefore, the influence of geopolitical risks on tourism in Hong Kong is more moderate than other destinations that have been investigated on this topic.

5. CONCLUSIONS

Due to the rise of globalization, the relationship among the countries is closer than ever. As a result, geopolitical risks have become one of the most concerning issues. Therefore, analyzing the impact of geopolitical risks is essential, especially in tourism since it is a highly sensitive sector to geopolitical risks. If tourists sense insecure of a destination, they may either cancel their trip or choose another destination to avoid possible harm caused by geopolitical risks. This decreases tourist arrivals and tourist income. Since the tourism-led-growth hypothesis, by which tourism can promote economic growth, has been proven by Jin (2011) in Hong Kong, the negative influence of GPR may indirectly affect the economic growth. Besides, given that there were various protests affecting the safety of Hong Kong in recent years, it is crucial to know to what degree geopolitical risks affect tourism in Hong Kong.

For this purpose, we apply a VAR model to investigate how geopolitical risks affect tourism in Hong Kong by using a newly introduced index, the GPR index, and monthly tourist arrivals in Hong Kong. We estimate a VAR model between tourist arrivals, GPR index, and three other control variables: oil prices, global economic policy uncertainty, and US equity market volatility. We find that the GPR index significantly affects tourist arrivals at the first, eighth, and twelfth lags; a 1% rise of GPR results in a 0.087% drop of tourist arrivals within the following month. In addition, a 1% increase in geopolitical risks results in a 0.081% drop of tourist arrivals eight months afterwards. Finally, a 1%

increase in geopolitical risks provokes a decline of 0.059% of tourist arrivals in the following year.

We further confirm that GPR helps predict future tourist arrivals in Hong Kong by applying a Granger-causality test. We conclude that geopolitical risks have an adverse influence on tourist arrivals in Hong Kong, and this effect remains in the long run; increases in geopolitical risks lead to both short- and long-term declines in tourist arrivals in Hong Kong.

Our findings confirm the results of Hailemariam & Ivanovski (2021), Ghosh (2021), and Tiwari et al. (2019) that geopolitical risks hold a long lasting negative impact on tourism . We further compared our results with other authors' results, and we found that the influence of geopolitical risks in Hong Kong is more moderate than in other regions like Turkey (Demir et al., 2020) and India (Tiwari et al., 2019; Ghosh, 2021). A possible reason for that may be that Hong Kong is a developed economy that has sufficient resources to prevent and recover from possible geopolitical risks. It is a safe region whose geopolitical risks are more moderate than in other regions located in complicated parts of the world; there are numerous business travelers who are more likely to travel regardless of the Hong Kong's GPR index is high.

Our findings help predict future tourist arrivals when there are changes in geopolitical risks. The government should monitor the GPR index, and when the GPR index exceeds certain range, they should adjust their policies to attract more tourists, such as launching promotions or bonuses. Besides, the result of this thesis also reveals that the influence of GPR on tourism is lagged. Policy makers should use wisely the period between the moment they detect the changes of GPR index and the moment that the adverse effect starts, intending to decrease or even eliminate this influence. Furthermore, to avoid geopolitical risks, it is essential to identify their cause. Unlike other destinations such as Turkey, whose major geopolitical risks are terrorist attacks that are difficult to predict or control, most geopolitical risks in Hong Kong stem from political uncertainty. Therefore, the government should be aware of the possible reaction of the public before they publish a new regulation or law to avoid certain violent protests again.

A possible limitation of this study is the lack of data. The GPR index is only available for 19 regions, among which there is only one developed economy: Hong Kong. Hence, we could not make further comparisons between developing economies and developed economies. Future research may analyze this topic using panel models when there are more data available. Future studies could also analyze how geopolitical risks affect each type of tourism, for example, business travel, leisure, or family, because the impact of geopolitical risks may be different on each type as different types of travelers have different elasticities of tourism demand.

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