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# Journal of Tourism, Sports Management & Marketing

Research Article

# The Dynamic Causal Relationship Between Tourism, Air Pollution, And Pandemic Diseases Outbreak: Evidence from Caribbean Small Island Developing States

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***Received:*** *February 12, 2021;* ***Revised:*** *March 7, 2021;* ***Accepted:*** *March 9, 2021*

## ABSTRACT

*We investigate the dynamic causal relationship between tourism, air pollution ($CO_2$ emissions) and pandemic diseases outbreak in 12 small island states in the Caribbean. We employ a bootstrap panel Granger causality test developed by Konya (2006) to analyze the causal relationship. Our test results provide support for significant negative causality running from pandemic outbreak and $CO_2$ emissions to tourism in all 12 countries. These outcomes are very sensitive to the cross-sectional dependences and heterogeneity across the countries. Our empirical findings provide important implications for policymakers as several popular tourist destinations are already planning on easing their COVID-19 lockdown measures and border restrictions and are moving toward welcoming tourists back as they seek to recover economically from the global recession brought on by the coronavirus pandemic. Specifically, the results suggest that policy measures to improve air quality, protect the environment, and mitigate the spread and severity of pandemic diseases such as COVID-19 may lead to improvements in health outcomes and boost tourism.*

***Keywords:*** *Tourism, Air pollution, COVID-19, Pandemic outbreak, Panel data causality, Caribbean Small Island Developing States.*

## INTRODUCTION

In 2011, the World Tourism Organization (WTO 2011) predicted that international tourist arrivals worldwide would increase by 3.3 percent a year, on average, until 2030. This was before a novel corona virus, also known as COVID-19, emerged at the end of 2019 in the Wuhan area of China, and eventually spread to other parts of the world through the movement of people in early 2020. As of October 11, 2020, the World Health Organization (WHO 2020) reported that the virus has infected more than 220,000 people in the Caribbean. The effects have not only been devastating in the loss of lives but also jobs, as many countries worldwide have introduced strong containment and mitigation measures to reduce the spread of the virus. Total and partial lockdowns include measures such as shutting down borders, airports, and cruise ports, prohibiting transit for non-essential reasons, self- or mandatory quarantine, cancelling events, closing schools and non-essential business, among others. These measures brought global travel and tourism to a complete standstill.

The Caribbean is the world's most tourism dependent region in terms of the industry's contribution to gross domestic product (GDP) (WTTC 2018). In 2018, the combined total contribution of the travel and tourism sector to GDP was 25.84 percent in the Caribbean relative to other regions, as presented in Figure 1. According to Mooney and Zegarra (2020), tourism accounts for a large share of GDP in many economies in the Caribbean - ranging from 8 percent of GDP in Trinidad and Tobago, 36.6 percent in The Bahamas, 79.8 percent in British Virgin Islands, and 82.9 percent in Aruba. On average, the tourism sector also directly accounts for approximately 12 percent of total employment, and indirectly for another 20 percent (WTTC, 2018). The pronounced reliance on tourism by many small states in the Caribbean makes them especially vulnerable to the sudden pause in global tourism.

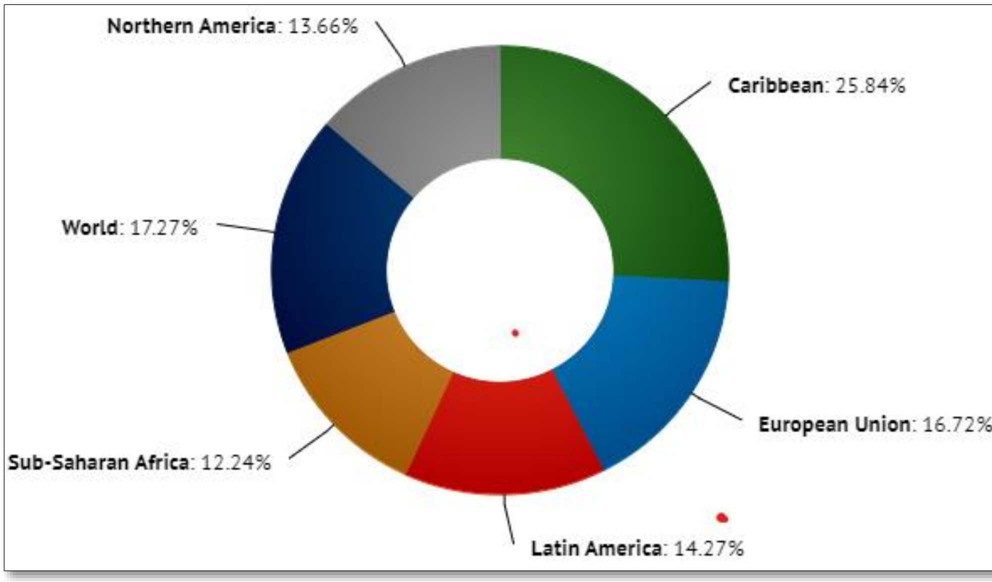


**Figure 1. Tourism total contribution to GDP - Percentage of GDP.**

***Source**: World Travel and Tourism Council Data 2018*

According to the Inter-American Development Bank (IDB, 2020), tourism arrivals to the Caribbean declined by as much as about 4 percent during the global financial crisis of 2008. The IDB (2020) also projected that the near-complete shutdown of both air travel and cruise ship activity due to the COVID-19 pandemic could lead to declines ranging from 40 to 70 percent. The WTO (2020) predicted, based on their early estimates, that COVID-19 pandemic could shrink economic activity and growth in the Caribbean by 6.2 percent in 2020.

Tourism is one of the engines of economic growth in the Caribbean and a major employer, and as a result, several governments are already planning to ease their COVID-19 lockdown measures and reopen their borders to (tourism) businesses as they seek to recover economically from the global recession brought on by the coronavirus pandemic. However, the consensus is that tourism constitutes a vector through which many diseases with epidemic and pandemic potential can be transmitted domestically and across countries worldwide because of the industry's reliance on human mobility (Richter 2003). In addition, studies have shown that the rapid expansion of international tourism and tourism infrastructure required more fossil fuel energy in order to generate economic activities, and that the energy-associated carbon emissions result in environmental degradation and climate change (Zhang & Zhang, 2020; Zaman et al., 2017; Katircioglu et al., 2014); Tiwari et al., 2013; IPCC, 2013). Experts acknowledge that climate change increases the frequency and severity of disease outbreaks (World Economic Forum, 2019) and may be putting people at risk for more pandemics like COVID-19. Given the prospect of future pandemics, research investigating the relationship between tourism, air pollution, and pandemic outbreaks is important because the results can prove useful in developing measures that improve response strategies, stimulate economic recovery, create conditions for long-term expansion of the tourism economy, and help improve environmental outcomes in the near and longer-term.

Being the most tourism dependent region and one of the world's top tourist destinations, the Caribbean presents an ideal case study for the current pandemic issue. International tourist arrivals to Caribbean destinations increased from 11.4 million in 1990 to 17.1 million in 2000, 35.4 million in 2015, and 36.6 million in 2017. According to WTO (2020), the powerful hurricanes Irma and Maria, which hit the region in the later part of 2017, led international tourist arrivals to drop to 25.68 million in 2018. The robust recovery in the most hurricanes affected tourist destinations in 2017 sparked Caribbean tourism to rebound strongly to post record stayover and cruise arrivals in 2019. According to Caribbean Tourism Organization (CTO 2020), stayover arrivals grew by 4.4 percent to reach 31.5 million and cruise visits increased by 3.4 percent to 30.2 million. In addition, 2020 looked even brighter until the COVID-19 coronavirus, which arrived in the Caribbean in early March, changed that outlook.

This impressive growth of the Caribbean tourism has been accompanied by an increase in fossil energy consumption and in greenhouse gasemissions, in particular $CO_2$, which frequently cause serious damage to the environment of the countries (Gossling, 2012) and directly affects human health[1]. Although it is hard to estimate the direct impact of air pollution on respiratory syndromes such as COVID-19, the general consensus is that some of the same factors that cause climate change are also worsening the pandemic. Specifically, scientists and scholars report that prolonged exposure to dirty air, most of which results from the extraction and burning of the same fossil fuels that are driving climate change, can leave people at greater risk of contracting the COVID-19 virus, and at greater risk of serious illness and death (Conticini et al., 2020; Coccia, 2020). Given the importance of the tourism sector in the Caribbean economy, a better understanding of how tourism, air pollution and contagious diseases outbreaks are interrelated is vital in designing tourism policies that will assure a more sustainable post-pandemic tourism sector.

The Caribbean countries share several common characteristics, which include location, limited natural resources, small domestic markets, a low degree of export diversification, and proneness to natural disasters and extreme events. In addition, they share relative remoteness, extreme openness of their economies that are highly sensitive to economic cycles in advanced economies, and a high level of dependence on tourism in terms of contribution to GDP, employment, and exports. Notwithstanding these similarities, the countries also vary greatly in their economic, social, political, cultural, and ethnic character, and in their level of international visitor arrivals, and resilience to shocks. These characteristics further suggest that the relationship between tourism, air pollution, and pandemic disease outbreak such as the COVID-19 in the Caribbean may be country specific.

The strong interdependencies between the Caribbean countries is inevitable due to globalization and financial integration even though each country controls its own dynamics. This makes it vital to control for cross-country dependence when deciding on an empirical modeling strategy. For the Caribbean countries, ignoring cross-sectional dependence may yield misleading causal inferences about the relationship between tourism, air pollution, and pandemic outbreaks in these countries (Pesaran, 2006). The conventional panel estimators such as the fixed effects, instrumental variables, and generalized method-of-moments estimators proposed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998) typically assume cross-sectional independence among panel units, which may lead to erroneous causal inferences when used in analysis of macroeconomics panel data that have strong inter-economy linkages. Given the potential for erroneous causal inferences using these techniques, this paper employs recent panel causality methodology that accommodates both cross-sectional dependence and cross-country heterogeneity simultaneously, rather than ignoring both or addressing only one of these issues at a time.

Our study contributes to the literature in several aspects. First, this paper focuses exclusively on Caribbean small states to analyze the relationship between tourism, air pollution ($CO_2$ emissions), and pandemic outbreak because studies have not examined them from this perspective. Second, we consider pandemic disease outbreak to be interrelated with tourism and air pollution emission through its close and well-documented association with tourism and global environmental changes (World Economic Forum 2019). The hypothesis, therefore, is that there is a causal association between tourism, $CO_2$ emission, and pandemic diseases outbreaks. To examine the hypothesized causality, we employed a tri-variate finite-order vector autoregressive framework that allows us to analyze all sets of causality relations among these variables in a simultaneous manner; therefore, our study adds an important value to the empirical literature on the tourism-air pollution-pandemic disease outbreak nexus.

[1] Exposure to ambient air pollution has been associated with premature deaths from stroke, ischemic heart disease, chronic obstructive pulmonary disease, lung cancer, dementia, lower respiratory infections, diabetes, dizziness, and psychological problems (WHO 2018).

Third, much of the literature ignored cross-sectional dependence and heterogeneity dynamics in their analysis; therefore, this paper employs Konya's (2006) bootstrap panel causality approach that enables the explicit control for parameters heterogeneity, cross-sectional dependence, and nonstationary. Using this methodology, we contribute to the existing literature by jointly addressing these concerns. Finally, to the best of our knowledge, this is the first study in the tourism-related literature to employ the bootstrap panel causality approach to investigate the relationship between tourism, $CO_2$ emissions, and pandemic outbreak in small island states. This is important because the findings from this study may be helpful to policymakers in formulating better tourism management policies for recuperating the tourism growth in tourism dependent small island states in the Caribbean and elsewhere.

The rest of the paper is organized as follows. Section 2 presents a review of the relevant literature on the nexus of tourism, $CO_2$ emissions, and pandemic diseases outbreaks. In Section 3, we discuss the methodology and data used in the research. Section 4 discusses the empirical results and policy implications from the empirical findings. Section 5 concludes.

## REVIEW OF THE LITERATURE

There is a voluminous theoretical and empirical literature on the tourism-$CO_2$ emissions nexus. Results of theoretical studies collectively suggest that the consumption of fossil energy in tourism-related activities such as catering, accommodation, transportation, and recreation lead to higher level of greenhouse gases, in particular $CO_2$, emitted into the atmosphere, and thus cause environmental and climatic degradation (Gossling, 2002; Peeters, 2005; Kelly & Williams, 2007; Lin, 2010). The studies have provided valuable insights into the relationship between tourism development and carbon emissions. However, a basic problem of these studies is that they ignore the causal link between these variables and causality direction is assumed given from tourism to $CO_2$ emissions, with no feedback.

Considerable studies have been devoted to understanding the impacts of tourism developments on $CO_2$ emissions. In contrast, relatively few studies have been conducted on the impacts of $CO_2$ emissions on tourism, especially for the case of small island economies that are heavily dependent on tourism. For instance, Durbarry and Seetanah (2015) examined the dynamic relationship between tourism and $CO_2$ emissions in the case of Mauritius and found that an increase in the number of tourists has a considerable and positive impact on $CO_2$ emissions. Al-Mulali et al. (2015) assessed the impact of tourism on $CO_2$ emissions from the transportation sector in 48 top international tourism destinations and found that tourism has a significantly positive impact on $CO_2$ emissions released from transportation in all regions except Europe. In a comparative study of 28 European Union (EU) countries, Paramati et al. (2017) found that tourism growth had an adverse impact on the environment in Eastern EU, while economic growth and $CO_2$ emissions stimulate tourism in Western EU. In a related study, Zaman et al. (2016) also confirmed the negative environmental impact associated with increase in tourism in the context of 34 developed and developing countries across the world.

There have been some contradictory findings suggesting that tourism development may reduce $CO_2$ emissions. For example, Alam and Paramati (2017) investigating the impact of tourism investments on carbon emissions in a sample of 28 EU nations found that tourism decreases the carbon emissions. Lee and Brahmasrene (2013) studied the impact of tourism on $CO_2$ emission and economic growth in a panel of 27 EU countries, and they found that tourism has a statistically negative impact on $CO_2$ emissions. Dogan and Aslan (2017) provided similar evidence when they investigated the effect of energy consumption, GDP, tourist arrivals on carbon emissions in the EU countries. They found that tourism developments have a reducing effect on $CO_2$ emissions.

In addition to panel studies, a few scholars have examined the tourism-$CO_2$ nexus for individual countries. For example, Amzath and Zhao (2014) examined the relationship between carbon emission and tourism development in Maldives and found a significantly positive correlation between tourism development indicators and carbon emission. Solarin (2014) used cointegration and causality tests to examine the relationship among tourist arrivals and macroeconomic determinants of $CO_2$ emissions in Malaysia and found unidirectional causality from tourism to environmental pollution in the long run. Katircioglu et al. (2014)

investigated the impact of international tourism on $CO_2$ emissions in Cyprus, and found unidirectional causality running from $CO_2$ emissions to tourist arrivals in the short run while causality runs from tourist arrivals to $CO_2$ emissions in the long run.

Recently, some studies have estimated the impact of air pollution on international tourism based on the premise that climatic or environmental pollution changes could influence the demand for tourism. For example, Anaman and Looi (2000) analyzed the effect of haze-related air pollution on the tourism industry in Brunei Darussalam and found that air pollution led to a 3.75 percent reduction in tourist arrivals. Tang et al. (2019) assessed the impact of air quality on inbound tourist arrivals in Beijing and found that air pollution had a negative effect on tourist arrivals in the long run, but not in the short run. Also using China as a case study, Dong et al. (2019) confirmed the negative impact of air pollution on inbound tourism in China. Although most studies confirmed the existence of an empirical relationship between tourism and $CO_2$ emissions, the evidence is mixed and conflicting with respect to the direction of causation.

Epidemic and pandemic disease outbreaks[2] have affected tourism numerous times in the last 40 years. There have not been many empirical studies that confirm or quantify the relationship between disease outbreaks and tourism. Much of the literature relied on a description analysis to highlight the severe impact of infectious diseases on international tourist arrivals (Kuo et al., 2008; Gossling et al., 2020; Yang et al., 2020; Mooney & Zegarra, 2020), and few studies focused on individual country impacts (Rassy & Smith, 2013; Rossello et al., 2017; Joo et al., 2019; Karabulut et al., 2020). The evidence reported in various studies indicates that travel and tourism is both a contributor to disease spread and the economic consequences and is negatively affected by pandemics because of non-pharmaceutical interventions, such as quarantine, lockdowns, and border closures (Ryu et al., 2020).

For instance, Rassy and Smith (2013) evaluated the economic impact to the Mexican tourism sector of the 2009 H1N1 influenza pandemic, by examining tourist arrivals. The authors found that Mexico lost almost one million tourists, which amounted to roughly US$2.8 billion in losses, over a five-month period due to contagion fears of the influenza. Similarly, Rossello et al. (2017) found that the eradication of malaria, dengue, yellow fever, and Ebola in affected countries in the Americas, Asia, and Africa resulted in an increase of around 10 million additional tourists worldwide, which translated into a rise in tourism expenditure of US$12 billion. Joo et al. (2019), investigating the economic impact of the 2015 Middle East respiratory syndrome coronavirus (MERS-CoV) outbreak on the Republic of Korea's tourism-related industries found that the relatively short-lived outbreak was associated with 2.1 million fewer tourists, which corresponds to about US$2.6 billion in lost tourism revenue.

Recently, Gossling et al. (2020) compared the impacts of COVID-19 and other types of global crises in the tourism industry. The available evidence, though incomplete, suggests that the COVID-19 outbreak will have severe consequences on international tourism with concomitant effects on the economic growth and prosperity of several nations.

## METHODOLOGY AND DATA

### Empirical Methodology

To put the tourism-$CO_2$ emissions-pandemic outbreak nexus in perspective, consider the following general panel data model:

$$y_{it} = \alpha_{it} + \delta_{it} t + \beta_i^{'} X_{it} + \varepsilon_{it}; \; i = 1, 2, ..., N; t = 1, 2, ..., T \quad (1)$$

[2]For example,HIV/AID (1980-present), Severe Acute Respiratory Syndrome (SARS) outbreak (2003), Swine flu (H1N1) influenza (2009); Middle East Respiratory Syndrome (MERS-CoV) (2012); Ebola (2014-present), Zika (2015-present), Dengue fever (2016-present), and Coronavirus (COVID-19) (2019-present).

Where $y_{it}$ is the value of the dependent variable for the i-th country in the sample at the t-th time period; $X_{it}$ is $K$ x 1 vector of explanatory variables; parameters $\alpha_{it}$ $and$ $\delta_{it}$ $t$ allow for country specific fixed effects and deterministic trends; $\beta_i$ denotes slope coefficients which vary across countries; and $\varepsilon_{it}$ is the error term.

The choice of a suitable method for the analysis of causality when working with panel data requires the assessment of both cross-dependence and heterogeneity across countries because as recent world economic situation has shown, perturbations in one country can easily transmit to other countries through international trade and financial integration. Pesaran (2006) pointed out that if economic linkages between countries are relatively strong, cross-sectional dependence is likely to appear, and ignoring cross-section dependency may lead to erroneous causal inferences. Accordingly, we carried out the empirical analysis in this study in two steps. In the first step, we performed tests for cross-section dependence and slope homogeneity. In the second step, based on the results from the preliminary analysis, we determined which panel causality method would be most suitable for investigating the causality between tourism, $CO_2$ emissions, and pandemic disease outbreaks. In what follows, we outline the econometric methods employed in this study.

**Cross-Section Dependence Tests**

The general assumption in panel data econometrics is that the data used are cross-sectional independent. To test this pre-assumption, we follow Konya (2006) by looking for cross-section dependence in our data using the Lagrange Multiplier (LM) test proposed by Breusch and Pagan (1980); the Cross Dependence Lagrange Multiplier (CDLM) test and the Cross-sectional Dependence (CD) test proposed by Pesaran (2004); and the bias adjusted LM (LMadj) test proposed by Pesaran et al. (2008). For each of the tests, the null hypothesis claims "no cross sectional-dependence among countries," while the alternative hypothesis claims otherwise.

**Slope Homogeneity Tests**

The second important issue is to find out whether the slope coefficients are homogenous. As pointed out by Granger (2003), the causality from one variable to another variable by imposing the joint restriction for whole panel is a strong null hypothesis. Moreover, Breitung (2005) cautioned against assuming slope homogeneity without any empirical evidence because specific characteristics of countries included in the analysis become ignored, which could lead to inconsistent estimations.

The most common approach to testing the null hypothesis of slope homogeneity ($H_0 : \beta_i = \beta_j$ for all $i$) against the alternative hypothesis of heterogeneity ($H_1 : \beta_i \neq \beta_j$ for a non-zero fraction of pair wise slopes for ($i \neq j$) is to apply the $\hat{S}$ statistical test developed by Swamy (1970), which is however not applicable for all panel models data because of size restrictions. Pesaran and Yamagata (2008) improved on the Swamy's test and implemented the delta ($\hat{\Delta}$) homogeneity test, which is valid for large samples, and delta-adj $\left(\widehat{\Delta_{adj}}\right)$ homogeneity test which is valid for small samples.

**Bootstrap Panel Causality Test**

The existence of both cross-sectional dependence and heterogeneity across countries requires a method of analysis that will account for these dynamics. Konya (2006) presents a bootstrap panel data causality test, which allows for both slope heterogeneity and cross-sectional dependence. Konya's approach has several relevant advantages. First, the approach is based on Seemingly Unrelated Regressions (SUR), which is more efficient than Ordinary Least-Squares (OLS) if there is cross-sectional dependence (Zellner 1962). Second, the test for direction of causality is based on Wald tests with country-specific bootstrap critical values. The use of country-specific bootstrap critical values means that the Granger-causality test can be performed on each individual country separately. Third, the procedure does not require pretesting for panel unit-roots or cointegration, which could lead to pretest biases and size distortion problems. This is important because it has been widely acknowledged that the standard unit root and cointegration tests can have low power against stationary alternatives, and that different tests often lead to contradictory outcomes.

Given its advantages, we use Konya's (2006) panel data causality test approach to analyze the causal relationships between tourism, $CO_2$ emissions, and pandemic outbreak. The approach models the data as a system of two sets of the following equations:

$$
\begin{aligned}
TR_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{lTR_1} \beta_{1,1,i} TR_{1,t-i} + \sum_{i=1}^{lCE_1} \partial_{1,1,i} CE_{1,t-i} + \sum_{i=1}^{lPD_1} \gamma_{1,1,i} PD_{1,t-i} + \varepsilon_{1,1,t}, \\
TR_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{lTR_1} \beta_{1,2,i} TR_{2,t-i} + \sum_{i=1}^{lCE_1} \partial_{1,2,i} CE_{2,t-i} + \sum_{i=1}^{lPD_1} \gamma_{1,2,i} PD_{2,t-i} + \varepsilon_{1,2,t}, \\
&\vdots \\
TR_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{lTR_1} \beta_{1,N,i} TR_{N,t-i} + \sum_{i=1}^{lCE_1} \partial_{1,N,i} CE_{N,t-i} + \sum_{i=1}^{lPD_1} \gamma_{1,N,i} PD_{N,t-i} + \varepsilon_{1,N,t},
\end{aligned}
\qquad (2)
$$

and

$$
\begin{aligned}
CE_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{lTR_2} \beta_{2,1,i} TR_{1,t-i} + \sum_{i=1}^{lCE_2} \partial_{2,1,i} CE_{1,t-i} + \sum_{i=1}^{lPD_2} \gamma_{2,1,i} PD_{1,t-i} + \varepsilon_{2,1,t}, \\
CE_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{lTR_2} \beta_{2,2,i} TR_{2,t-i} + \sum_{i=1}^{lCE_2} \partial_{2,2,i} CE_{2,t-i} + \sum_{i=1}^{lPD_2} \gamma_{2,2,i} PD_{2,t-i} + \varepsilon_{2,2,t}, \\
&\vdots \\
CE_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{lTR_2} \beta_{2,N,i} TR_{N,t-i} + \sum_{i=1}^{lCE_2} \partial_{2,N,i} CE_{N,t-i} + \sum_{i=1}^{lPD_2} \gamma_{2,N,i} PD_{N,t-i} + \varepsilon_{2,N,t},
\end{aligned}
\qquad (3)
$$

where $TR_{it}$ denotes tourism in country $i$ and time period t; $CE_{it}$ refers to $CO_2$ emissions; $PD_{it}$ is pandemic disease outbreak[3]; $\alpha$ represents constant terms while $\beta, \delta$ and $\gamma$ are coefficients; N denotes the number of countries in the panel; and $lTR_{1i}, lTR_{1i}, lCE_{1i}, lTR_{2i}, lCE_{2i}$ *and* $lPD_{2i}$ indicate the lag lengths. We expect correlation across equations with respect to the error terms $\varepsilon_{1,i,t}$ *and* $\varepsilon_{2,i,t}$ due to common random shocks.

Since the causality test result is sensitive to the choice of lag length, we first determine the optimal lag length(s) for each equation in the system. Following Konya (2006), we allow maximal lags to be the same across equations but vary across variables. Assuming that the number of lags ranges from 1 to 4, we estimated all equations and then choose the combination minimizing the Schwartz Criterion (SC) and the Akaike Information Criterion (AIC)[4].

With respect to system equations (2) and (3), four different causality results can be generated for the individual country i, such as: (1) unidirectional causality runs from *CE (PD)* to *TR* if not all $\partial_{1,i,j^s}(\gamma_{1,i,j^s})$ are zero, but all $\beta_{2,j,1^s}$ are zero; (2) unidirectional causality runs from *TR* to *CE(PD)* if all $\partial_{1,j,i^s}(\gamma_{1,j,i^s})$ are zero, but not all $\beta_{2,j,1^s}$ are zero; (3) bidirectional causality relation exist between *CE* and *TR(PD)* if neither $\partial_{1,j,i^s}(\gamma_{1,j,i^s})$nor all $\beta_{2,j,1^s}$ are zero; and (4) no causality relation exist between *TR* and *CE(PD)* if all $\partial_{1,j,i^s}(\gamma_{1,j,i^s})$and $\beta_{2,j,i^s}$ are zero.

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[3] Though we have three variables in each equation, we are primarily interested in evaluating the bivariate, one-period-ahead relationship between ***TR*** and ***CE*** or ***PD***, so we will not consider the possibility of any two variables jointly causing the third one. For instance, when testing for the causality between ***TR*** and ***CE***, we consider ***PD*** as an auxiliary variable not directly involved in the Granger-causality analysis.

[4] For details and explanation of the estimation and testing procedures, see Konya (2006) and Tekin (2012).

### Data

We use annual data for the period 1995-2018 for 12 Caribbean countries (Antigua and Barbuda, The Bahamas, Barbados, Cuba, Dominican Republic, Guyana, Haiti, Jamaica, St. Kitts and Nevis, St. Lucia, Trinidad and Tobago, and British Virgin Islands) based on data availability to ensure a balanced panel structure. There are primarily two measures of tourism: tourism receipts and tourist arrivals. A potential problem with using tourism receipts as proxy for tourism is that tourism receipts data are prone to measurement errors because they are generated from bank records of foreign exchange transactions, and/or irregular survey of tourists and tourism establishments.

In contrast, data on tourist arrivals are well documented through the compulsory completion of embarkation-disembarkation cards. To avoid erroneous inferences, we measure tourism ***(TR)*** through international tourist arrivals (international visitors that stay overnight). We measure carbon dioxide emissions ***(CE)*** by $CO_2$ emissions per capita (in metric tons), which includes carbon emissions stemming from the burning of fossil fuels and the manufacture of cement. They also include carbon emissions produced during consumption of solid, liquid and gas fuels, and gas flaring. Data on international tourist arrivals are from the World Tourism Organization (UNWTO, 2020) and the Caribbean Tourism Organization (CTO) website at https://www.onecaribbean.org/. We obtain the data on $CO_2$ emissions from the World Development Indicators database and the EDGAR-Emissions Database for Global Atmospheric Research website: https://edgar.jrc.ec.europa.eu/overview.php?v=booklet2020. Data on pandemic outbreaks were taken from the World Health Organization database on disease outbreaks athttps://www.who.int/emergencies/diseases/en/.

The severity of respiratory syndromes such as COVID-19 in the Caribbean is somewhat uncertain, as cases are underreported, and accuracy of data collection varies considerably within the region. Due to lack of reliable data on spread of pandemic diseases in the Caribbean, we use a dummy variable for pandemic diseases outbreaks ***(PD)*** to estimate the impacts of pandemic diseases such as COVID-19 on the relationship between tourism and $CO_2$ emissions. The dummy variable takes the value of unity during years when there exist pandemic outbreaks and zero otherwise.

## RESULTS AND POLICY IMPLICATIONS

### Cross-Sectional Dependence and Slope Homogeneity

**Table 1** presents results of the cross-sectional dependence and slope homogeneity tests. The cross-sectional dependence statistics and associate p-values strongly reject the null of cross-section independence across the Caribbean countries, suggesting that a shock to tourism and $CO_2$ emissions in one of the countries will be transmitted to other countries. Similarly, an infectious disease outbreak in one country is likely to spread to other countries. Additionally, the statistics of the $\hat{\Delta}$ and $\hat{\Delta}_{adj}$ tests show that there is heterogeneity at a 5 percent significance level and better. This suggests that each of these countries retains their own unique characteristics; therefore, the direction of causality between tourism, $CO_2$ emission, and pandemic disease outbreak may differ across the 12 countries. Importantly, these findings prove that we chose the appropriate estimation technique.

### Panel Granger Causality

**Tables 2-4** report the results of Granger causality. We focus on pairwise Granger causal relations, conditioning on the influence from the auxiliary variable. The results of the causality running from *TR* to *PD* and from *PD* to *TR* reported in **Table 2** show unidirectional causality running from *PD* to *TR*, with no feedback, in all countries, except for St Kitts and Nevis and St. Lucia where no significant causal relation exists between *TR* and *PD*. The coefficient on the *PD* variable is negative in all cases suggesting that outbreak of COVID-19 pandemic will likely have a negative impact on tourism flows to these countries.[5]. This finding is consistent with those of Kuo et al. (2008) and Rossello (2017) regarding the negative impacts of pandemic outbreaks on the tourism industry.

**Table 1. Cross-sectional Dependence and Slope Homogeneity Tests**

| | Cross-sectional Dependency tests | | | | Slope Homogeneity tests | |
|---|---|---|---|---|---|---|
| **Variables** | $LM_{BP}$ | $CD_{LM}$ | CD | $LM_{adj}$ | $\hat{\Delta}$ | $\hat{\Delta}_{adj}$ |
| ***TR*** | 418.982*** (0.000) | 43.444*** (0.000) | 5.280*** (0.000) | 31.071*** (0.000) | 13.966*** (0.000) | 18.296*** (0.000) |
| ***CE*** | 478.008*** (0.000) | 38.178*** (0.000) | 9.425*** (0.000) | 44.924*** (0.000) | 15.883*** (0.000) | 22.426*** (0.000) |
| ***PD*** | 113.049*** (0.000) | 34.203*** (0.000) | -4.447*** (0.000) | 11.778*** (0.000) | 2.410** (0.008) | 3.499** (0.006) |

****, **, * indicate rejection of the null hypothesis at the 1, 5, and 10 % levels of significance, respectively. The probability values are in parentheses*

The results of the causality tests from *CE* to *PD* and from *PD* to *CE* are presented in **Table 3** where unidirectional causality runs from *CE* to *PD* in seven countries: The Bahamas, Barbados, Cuba, Dominican Republic, Haiti, Jamaica, and Trinidad and Tobago, thus, we infer that $CO_2$ emissions (air pollution) is a useful predictor of contagious disease outbreak. This finding can be related to the fact that these are among the larger islands in the Caribbean in terms of population and tourist arrival; and according to Razzaq et al. (2020), Hedlund et al. (2014) and He *et al*. (2013), climate change, population density, and human migration are important factors to infectious disease transmission. For the remaining five countries in **Table 3**, the results indicate no causal nexus from *CE* to *PD*. In addition, we could not reject the null of no causality running from *PD* to *CE* in any country in the sample, which suggest that pandemic outbreak does not necessarily influence the increase/decrease in the level of $CO_2$ emissions. Theoretically, it is right to assume that higher levels of carbon emissions would not be because of pandemic disease outbreaks.

The results of the causality running from *TR* to *CE* and from *CE* to *TR* presented in **Table 4** show bidirectional causality between *TR* and *CE* in Barbados, Dominican Republic, Jamaica, St. Lucia, and Trinidad and Tobago. While unidirectional causality runs from *TR* to *CE* in Antigua and Barbuda, Cuba, and Guyana, a reverse causality runs from *CE* to *TR* in The Bahamas, British Virgin Islands, and Haiti. There was no significant causal relation between *TR* and *CE* for St. Kitts and Nevis. We also observe in **Table 4** that the coefficient of the *CE* variable is negative suggesting that increased $CO_2$ emissions (air pollution) adversely affects tourism in all these countries, with the exception of St. Kitts and Nevis where we found no evidence of a causal relationship between *TR* and *CE* in either direction. In contrast, the coefficient on the *TR* variable is positive for all the countries suggesting that increased tourist arrivals increase per capita $CO_2$ emissions.

[5] The sign of the causal effect is derived from the sum of the coefficients of the variable considered as independent in a specific equation. So, in our case, the sign is based on the sum of the coefficients of the maximum number of lags of the causal variable.

**Table 2. Bootstrap panel Granger causality test results.**

| Countries | Ho: *TR* does not Granger cause *PD* (H1: *TR* causes *PD*) | | | | | Ho: *PD* does not Granger cause *TR* (H1: *PD* causes *TR*) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Wald Statistic | Bootstrap critical value | | | Coefficient | Wald Statistic | Bootstrap critical value | | |
| | | | 10% | 5% | 1% | | | 10% | 5% | 1% |
| Antigua and Barbuda | 0.142 | 5.629 | 6.717 | 10.393 | 21.365 | -0.131 | 12.882** | 5.543 | 8.164 | 14.788 |
| The Bahamas | 0.149 | 6.354 | 6.594 | 9.931 | 19.892 | -0.213 | 23.770* | 6.057 | 9.336 | 17.890 |
| Barbados | 0.150 | 6.021 | 10.372 | 14.807 | 27.747 | -0.193 | 17.073** | 9.052 | 13.407 | 23.308 |
| British Virgin Island | 0.033 | 9.770 | 10.009 | 20.954 | 39.115 | -0.149 | 20.051** | 9.644 | 14.226 | 29.012 |
| Cuba | 0.113 | 4.529 | 10.908 | 14.983 | 28.094 | -0.140 | 28.417* | 7.155 | 10.308 | 21.937 |
| Dominican Republic | 0.137 | 2.514 | 6.494 | 9.931 | 19.827 | -0.141 | 22.851* | 6.446 | 9.640 | 19.086 |
| Guyana | 0.201 | 1.924 | 5.155 | 7.392 | 14.665 | -0.119 | 17.409* | 5.443 | 8.382 | 14.812 |
| Haiti | 0.122 | 4.154 | 6.494 | 10.931 | 20.827 | -0.149 | 11.138** | 5.763 | 8.398 | 16.169 |
| Jamaica | 0.100 | 1.092 | 6.900 | 10.496 | 18.209 | -0.211 | 12.015** | 6.710 | 10.609 | 20.186 |
| St. Kitts and Nevis | 0.039 | 0.938 | 5.779 | 8.562 | 16.310 | -0.062 | 8.745 | 9.414 | 16.839 | 28.127 |
| St. Lucia | 0.104 | 4.120 | 5.643 | 8.597 | 18.462 | -0.141 | 3.981 | 6.081 | 8.752 | 16.257 |
| Trinidad and Tobago | 0.111 | 9.325 | 9.728 | 19.683 | 32.500 | -0.186 | 48.132* | 13.601 | 20.685 | 32.500 |

****, **, and * indicate significance at 1, 5, and 10% significance levels, respectively. Bootstrap critical values are based on 10,000 replications*

**Table 3. Bootstrap panel Granger causality test results.**

| Countries | Ho: *CE* does not Granger cause *PD* (H1: *CE* causes *PD*) | | | | | Ho: *PD* does not Granger cause *CE* (H1: *PD* causes *CE*) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Wald Statistic | Bootstrap critical value | | | Coefficient | Wald Statistic | Bootstrap critical value | | |
| | | | 10% | 5% | 1% | | | 10% | 5% | 1% |
| Antigua & Barbuda | 0.022 | 4.314 | 6.431 | 9.442 | 18.388 | 0.017 | 1.986 | 3.228 | 4.907 | 8.902 |
| The Bahamas | 0.066 | 34.277*** | 9.810 | 14.601 | 28.378 | -0.028 | 3.708 | 5.294 | 13.660 | 20.175 |
| Barbados | 0.022 | 12.876*** | 3.98 | 5.71 | 10.577 | -0.014 | 6.601 | 12.442 | 19.644 | 36.332 |
| British Virgin Island | 0.039 | 5.792 | 10.344 | 14.687 | 28.022 | -0.019 | 3.094 | 8.114 | 19.290 | 33.394 |
| Cuba | 0.100 | 26.924*** | 6.328 | 13.965 | 26.043 | -0.031 | 2.341 | 6.973 | 14.238 | 33.907 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dominican Republic | 0.105 | 47.154*** | 9.667 | 14.321 | 26.443 | -0.129 | 8.410 | 10.483 | 16.552 | 32.213 |
| Guyana | 0.034 | 4.130 | 12.483 | 18.778 | 33.239 | 0.001 | 8.429 | 8.982 | 12.899 | 24.795 |
| Haiti | 0.089 | 12.746* | 9.995 | 17.332 | 38.181 | 0.013 | 2.389 | 6.445 | 9.558 | 18.245 |
| Jamaica | 0.097 | 12.773** | 8.095 | 12.449 | 30.554 | -0.102 | 7.809 | 9.010 | 24.969 | 45.295 |
| St. Kitts and Nevis | -0.008 | 5.948 | 14.022 | 21.108 | 33.574 | 0.019 | 2.853 | 6.106 | 9.034 | 16.478 |
| St. Lucia | -0.030 | 8.732 | 10.241 | 22.055 | 30.157 | 0.004 | 9.778 | 10.384 | 14.829 | 25.984 |
| Trinidad and Tobago | 0.076 | 23.510** | 9.630 | 14.267 | 36.008 | -0.024 | 2.135 | 5.373 | 7.773 | 14.098 |

****, **, and * indicate significance at 1, 5, and 10% significance levels, respectively. Bootstrap critical values are based on 10,000 replications.*

**Table 4. Bootstrap panel Granger causality test results.**

| Countries | Ho: *TR* does not Granger cause *CE* (H$_1$: *TR* causes *CE*) | | | | | Ho: *CE*does not Granger cause *TR* (H$_1$: *CE*causes *TR*) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Wald Statistic | Bootstrap critical value | | | Coefficient | Wald Statistic | Bootstrap critical value | | |
| | | | 10% | 5% | 1% | | | 10% | 5% | 1% |
| Antigua and Barbuda | 0.044 | 19.915** | 12.066 | 18.844 | 37.803 | -0.031 | 8.822 | 10.673 | 16.116 | 33.022 |
| The Bahamas | 0.081 | 8.017 | 12.700 | 18.880 | 37.613 | -0.101 | 18.011** | 11.602 | 17.332 | 36.977 |
| Barbados | 0.111 | 42.207*** | 10.034 | 17.086 | 36.053 | -0.082 | 27.004** | 10.331 | 19.108 | 39.233 |
| British Virgin Island | 0.224 | 6.929 | 11.915 | 19.077 | 34.715 | -0.133 | 23.399** | 13.024 | 19.046 | 38.729 |
| Cuba | 0.096 | 22.376** | 12.911 | 19.339 | 38.500 | -0.077 | 2.083 | 11.057 | 16.912 | 34.263 |
| Dominican Republic | 0.153 | 19.048** | 11.671 | 18.729 | 37.339 | -0.088 | 19.306** | 10.998 | 18.542 | 35.213 |
| Guyana | 0.215 | 12.223* | 9.188 | 14.662 | 29.919 | -0.058 | 6.119 | 9.807 | 13.679 | 25.496 |
| Haiti | 0.205 | 3.963 | 9.887 | 13.782 | 29.845 | -0.064 | 16.907** | 8.805 | 15.416 | 31.917 |
| Jamaica | 0.232 | 37.207** | 11.987 | 26.918 | 48.521 | -0.177 | 56.209* | 12.018 | 27.069 | 52.295 |
| St. Kitts and Nevis | 0.044 | 1.777 | 7.851 | 14.332 | 29.186 | 0.033 | 3.702 | 9.400 | 15.835 | 31.133 |
| St. Lucia | 0.311 | 24.788** | 12.741 | 21.937 | 43.193 | -0.221 | 27.315** | 11.742 | 20.470 | 41.188 |
| Trinidad and Tobago | 0.249 | 49.732*** | 10.227 | 14.236 | 39.322 | -0.144 | 37.636*** | 4.916 | 12.654 | 28.971 |

****, **, and * indicate significance at 1, 5, and 10% significance levels, respectively. Bootstrap critical values are based on 10,000 replications*

## Policy Implications

The results show unidirectional causality running from *PD* to *TR* in The Bahamas, Barbados, British Virgin Islands, Cuba, Dominica Republic, Guyana, Haiti, Jamaica, and Trinidad and Tobago, and Antigua and Barbuda; and no-causality was detected between *TR* and *PD* in St Kitts and Nevis, and St. Lucia. The coefficient on the *PD* variable was negative in all cases, implying that pandemic outbreaks impede the flow of tourism to the destinations.

The findings have implications for these countries as they struggle to recover from the impact of the COVID-19 pandemic. Specifically, because tourists make rational travel choices by comparing the costs (risks associated with the experience) and the benefits (satisfaction) to be derived from the experience (Sonmez & Graefe, 1998; Hall et al., 2003), the existence of contagious disease(s) in the destination country increases the associated risks, and thus the cost. This could result in the tourist choosing other destinations perceived as safer or avoid travel altogether. The tourist's decision to avoid unsafe destinations can have profound economic consequences for the tourism sector and the overall economy of the tourism-supplying country. It is imperative therefore that, post-COVID-19, the tourism industry stakeholders initiate aggressive measures to re-establish public image of safety and attractiveness of the Caribbean, which would be required to encourage potential visitors to travel to the region and, thereby help them regain competitiveness and economic recovery.

The unidirectional causality running from *CE* to *PD* in The Bahamas, Barbados, Cuba, Dominican Republic, Haiti, Jamaica, and Trinidad and Tobago suggest that air pollution ($CO_2$ emissions) plays an important role in mediating the spread and severity of respiratory illnesses such as COVID-19 in these countries, and that measures directed to improve air quality may lead to improvements in health outcomes. The bidirectional causality between *TR* and *CE* found for Barbados, Dominican Republic, Jamaica, St. Lucia, and Trinidad and Tobago implies that tourist arrivals and $CO_2$ emissions are jointly determined and mutually influencing in these countries. This result may be explained by the green tourism hypothesis because a significant number of tourists visiting the Caribbean come for the scenic beauty, warm climate, white sand beaches, wild ecosystems, and rich biodiversity of the region. The vital revenues obtained from tourism incentivize many governments to adopt sustainable tourism policies and reduce pollution (CSTPF 2020). The reduced pollution attracts more international tourists, who can bring the foreign currency needed to finance efforts against environmental degradation.

Our finding of bidirectional causality between *TR* and *CE* is different from that by Shakouri et al. (2017), Katircioglu (2014), Solarin (2014) and Paramati et al. (2017) probably because of the uniqueness of incorporating pandemic outbreak into the tourism-$CO_2$ emissions augmented framework in this study. From a policy standpoint, our finding suggests that national policies to increase tourist arrivals should be integrated with national energy and environmental policies in order to facilitate the transition towards a more sustainable post-pandemic tourism sector. For Antigua and Barbuda, Cuba, and Guyana, there was unidirectional causality from *TR* to *CE*. This implies that the volume of tourist arrivals can predict the level of $CO_2$ emission but not the other way around. The unidirectional causality may also imply that the level of air pollution is not enough to deter tourists from coming to the islands. From the policy standpoint, this suggests that the governments could deploy environmental conservation strategies to promote energy efficiency to reduce pollutant emissions without compromising tourism growth.

In contrast, in the case of The Bahamas, British Virgin Islands and Haiti, there was unidirectional causality running from *CE* to *TR* suggesting that $CO_2$ emissions can influence tourist arrivals to the destinations, but the increase in tourist arrivals does not necessarily increase $CO_2$ emissions. From a policy standpoint, this suggests that policies in favor of protecting the environment, reducing air pollution, and limiting the spread and of contagious diseases such as COVID-19, are feasible and may be helpful in stimulating tourism flows to the destinations. Consequently, the governments and tourism stakeholders may take strategic measures that encourage the development and the use of renewable energies and increase the degree of social awareness of tourists and residents about the importance of good environmental practices for a sustainable tourism.

In St. Kitts and Nevis, the causality test results support the neutrality hypothesis between *TR* and *CE*, which implied that increased tourism activities do not necessarily influence the increase/decrease in $CO_2$ emissions and vice versa. While St. Kitts and Nevis does not seem to need to reduce tourism activities in order to reduce air pollution, or reduce air pollution in order to enhance tourism, travelers world-wide are increasingly looking for a tourist destination with a high-quality environment and they would not likely come back to and/or recommend an air-polluted destination (Hudson and Ritchie, 2001; Chen et al., 2017). This means that absence of well-planned and executed environmentally sensitive sustainable tourism policies could prove disadvantageous to the St. Kitts and Nevis tourism industry in the long run. Considering this, the government can implement policies that would encourage the use of green energy sources and energy efficiency to lower the levels of emissions. Public awareness campaigns can also be introduced to help promote a shared sense of environmental stewardship and educate all stakeholders in the tourism industry about best practices and their benefits, including attracting environment conscious tourists, better air quality and public health, and preservation of the environment on which the long-term sustainability of tourism rests.

## CONCLUSION

This study examines the relationship between tourism, $CO_2$ emissions (air pollution), and outbreak of respiratory syndromes such as COVID-19 by carrying out bootstrap panel causality tests for 12 small island states in the Caribbean between 1995 and 2018. We employ a trivariate framework that enables us to analyze the potential impact of correlations between any two variables on the third one. Applying this technique, we found strong evidence of dependency and heterogeneity across the Caribbean countries, implying that each country sustains its own dynamics.

Since each country is a special case, the shocks to tourism resulting from higher $CO_2$ emissions and pandemic outbreak are likely to be asymmetrical. Consequently, articulating "one-size-fits-all" policies for implementation throughout different countries would not be appropriate. However, because the results suggest that $CO_2$ emissions and pandemic outbreak negatively and significantly Granger-cause tourism in all the 12 countries sampled, the governments can adopt strong measures to reduce air pollution, protect the quality of the environment, and prevent the spread of respiratory illnesses such as COVID-19 to boost tourism.

## REFERENCES

1. Alam, M., & Paramati, S. (2017). The dynamic role of tourism investment on tourism development and $CO_2$ emissions. Annals of Tourism Research 66, 213-215.
2. Al-Mulali, U., Fereidouni, H. & Mohammed, A. (2015). The effect of tourism arrival on $CO_2$ emissions from transportation sector. Anatolia 26(2), 230-243.
3. Amzath, A. & Zhao, L. (2014). A study of the relationship between carbon emission and tourism development in Maldives. African Journal of Business Management 8(20), 962-971.
4. Anaman, K. & Looi, C. (2000). Economic Impact of Haze-Related Air Pollution on the Tourism Industry in Brunei Darussalam. Economic Analysis and Policy 30(2), 133-143.
5. Arellano, M. & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58(2), 277-297.
6. Arellano, M. & Bover, O. (1995). Another look at the instrumental-variable estimation of error-components models. Journal of Econometrics 68(1), 29-51.
7. Blundell, R. & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87(1), 115–143.
8. Breitung, J. (2005). A parametric approach to the estimation of cointegration vectors in panel data. Econometric Reviews 24(2), 151-173.
9. Breusch, T. & Pagan, A. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. Review of Economic Studies 47(1), 239-254.
10. Bubb, A. (2017). Tourism, Growth, and the Environment in Caribbean Small Island Developing States. Master's Thesis, School of Economics, The University of Queensland, Australia.
11. Caribbean Tourism Organization (CTO) (2020). Annual Statistical Report 2020.
12. CSTPF 2020. (2020) (CTO-Caribbean Sustainable Tourism Policy Framework 2020). Avalale online at: https://www.onecaribbean.org/content/files/CbbnSustainableTourismPolicyFramework.pdf
13. Chen, C., Lin, Y. & Hsu, C. (2017). Does air pollution drive away tourists? A case study of the Sun Moon Lake National Scenic Area, Taiwan. Transportation Research Part D: Transport and Environment 53, 398-402.
14. Coccia, M. (2020). Factors determining the diffusion of COVID-19 and suggested strategy to prevent future accelerated viral infectivity similar to COVID. Science of the Total Environment 729:138474.
15. Conticini, E., Frediani, B. & Carob, D. (2020). Can atmospheric pollution be considered a co-factor in extremely high level of SARS-CoV-2 lethality in Northern Italy? Environmental Pollution 261: 114465.

16. Dogan, E. & Aslan, A. (2017). Exploring the relationship among $CO_2$ emissions, real GDP, energy consumption and tourism in the EU and candidate countries: Evidence from panel models robust to heterogeneity and cross-sectional dependence. Renewable and Sustainable Energy Reviews 77, 239-245.
17. Dong, D., Xu, X. & Wong, Y. (2019). Estimating the Impact of Air Pollution on Inbound Tourism in China: An Analysis Based on Regression Discontinuity Design. Sustainability 11(6), 1682.
18. Durbarry, R. & Seetanah, B. (2015). The impact of long-haul destinations on carbon emissions: the case of Mauritius. Journal of Hospitality Marketing & Management 24(4), 401-410.
19. Gossling, S. (2002). Global environmental consequences of tourism. Global Environmental Change 12(4): 283-302.
20. Gossling, S. (2012). Calculations of energy use in tourism for 14 Caribbean countries. CARIBSAVE Climate Change Risk Atlas (CCCRA). The CARIBSAVE Partnership: Barbados, West Indies, 2012.
21. Gossling, S., Scott, D. & Hall, C. (2020). Pandemics, tourism, and global change: A rapid assessment of COVID-19. Journal of Sustainable Tourism 1-20. Available online at: https://doi.org/10.1080/09669582.2020.1758708
22. Granger, C. (2003). Some aspects of causal relationships. Journal of Econometrics 112(1), 69-71.
23. Hall, C., Timothy, D. & Duval, D. (2003). Safety and Security in Tourism: Relationships, Management and Marketing. New York: Haworth Hospitality Press.
24. He, D., Dushoff, J., Eftimie, R. & Earn, D. (2013). Patterns of spread of influenza A in Canada. Proceedings of Royal Society B 280: 20131174.
25. Hedlund, C., Blomstedt, Y. & Schumann, B. (2014). Association of climatic factors with infectious diseases in the Arctic and subarctic region–a systematic review. Global Health Action 7, 24161.
26. Hudson, S. & Ritchie, J. (2001). Cross-cultural tourist behavior: An analysis of tourist attitudes towards the environment. Journal of Travel and Tourism Marketing 10, 1-22.
27. Inter-American Development Bank (IDB) (2020). IDB report envisions devastating tourism shocks to Latin America and the Caribbean. Available online at: https://www.iadb.org/en/news/idb-report-envisions-devastating-tourism-shocks-latin-america-and-caribbean
28. IPCC. (2013). (Intergovernmental Panel on Climate Change). 2013. Climate change 2013: The physical science basis. Working Group I contribution to the IPCC Fifth Assessment Report. Cambridge, United Kingdom: Cambridge University Press. Available online at: www.ipcc.ch/report/ar5/wg1
29. Joo, H., Maskery, B., Berro, A., Rotz, L., Lee, Y., et al. (2019). Economic Impact of the 2015 MERS Outbreak on the Republic of Korea’s Tourism-Related Industries. Health Security 17(2), 100-108.
30. Karabulut, G., Bilgin, M. & Demir, E. (2020). How Pandemics Affect Tourism: International Evidence. Available at SSRN 3579530
31. Katircioglu, S., Feridun, M. & Kilinc, C. (2014). Estimating tourism-induced energy consumption and $CO_2$ emissions: The case of Cyprus. Renewable Sustainable Energy Reviews 888, 634-640.
32. Kelly, J. & Williams, W. (2007). Modelling tourism destination energy consumption and greenhouse gas emissions: Whistler, British Columbia, Canada. Journal of Sustainable Tourism 15, 67-90.
33. Konya, L. (2006). Exports and growth: Granger causality analysis on OECD countries with a panel data approach. Economic Modelling 23(6), 978-992.
34. Kuo, H., Chen, C., Tseng, W., Ju, L.F. & Huang, B. (2008). Assessing impacts of SARS and Avian Flu on international tourism demand to Asia. Tourism Management 29, 917-928.
35. Lee, J. & Brahmasrene, T. (2013). Investigating the influence of tourism on economic growth and carbon emissions: evidence from panel analysis of the European Union. Tourism Management 38, 69-76.
36. Lin, T. (2010). Carbon dioxide emissions from transport in Taiwan's national parks. Tourism Management 31, 285-290.

37. Mooney, H. & Zegarra, M. A. (2020). Extreme outlier: The pandemic's unprecedented shock to tourism in Latin America and the Caribbean. COVID-19 in developing economies. CEPR Press.
38. Paramati, S., Shahbaz, M. & Alam, M. (2017). Does Tourism Degrade Environmental Quality? A Comparative Study of Eastern and Western European Union? Transportation Research Part D: Transport and Environment 50, 1-13.
39. Peeters, P. (2005). Climate change, leisure related tourism and global transport. In M. C. Hall and J. Higham (Eds.), Tourism, recreation, and climate change (pp. 247–259). Clevedon, UK: Channel View Publications, pp: 247-259.
40. Pesaran, M. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. Munich CESifo Group, CESifo Working, pp: 1233.
41. Pesaran, M. (2006). Estimation and inference in large heterogeneous panels with multifactor error structure. Econometrica, 74, 967-1012.
42. Pesaran, M., Ullah, A. & Yamagata, T. (2008). A bias adjusted LM test of error cross-section independence. The Econometrics Journal 11(1), 105-127.
43. Pesaran, M. & Yamagata, T. (2008). Testing slope homogeneity in large panels. Journal of Econometrics 142(1), 50-93.
44. Rassy, D. & Smith, R. (2013). The economic impact of H1N1 on Mexico's tourist and pork sectors. Health Economics 22(7), 824-834.
45. Razzaq, A., Sharif, A., Aziz, N., Irfan, M. & Jermsittiparsert, K. (2020). Asymmetric link between environmental pollution and COVID-19 in the top ten affected states of US: A novel estimation from quantile-on-quantile approach. Environmental Research 191: 110189.
46. Richter, L. (2003). International tourism and its global public health consequences. Journal of Travel Research 41 (4), 340-347.
47. Rossello, J., Gallego, M.S. & Awan, W. (2017). Infectious disease risk and international tourism demand. Health Policy and Planning 32(4), 538-548.
48. Ryu, S., Gao, H., Wong, J., Shiu, E., Xiao, J., et al. (2020). Nonpharmaceutical measures for pandemic influenza in nonhealthcare settings – international travel – related measures. Emerging Infectious Diseases 26(9), 961-966.
49. Shakouri, B., Yazdi, S. & Ghorchebigi, E. (2017). Does Tourism Development Promote $CO_2$ Emission? Anatolia: An International Journal of Tourism and Hospitality Research 28(3), 444-452.
50. Solarin, S. (2014). Tourist arrivals and macroeconomic determinants of $CO_2$ emissions in Malaysia. Anatolia 25(2), 228-241.
51. Sonmez, S. & Graefe, A. (1998). International vacation decision and terrorism risk. Annals of Tourism Research 25(1), 122-124.
52. Swamy, P. (1970). Efficient inference in a random coefficient regression model. Econometrica: Journal of the Econometric Society 38(2), 311-323.
53. Tang, J., Yuan, X., Ramos, V. & Sriboonchitta, S. (2019). Does air pollution decrease inbound tourist arrivals? The case of Beijing. Asia Pacific Journal of Tourism Research 24, 597-605.
54. Tekin, R. (2012). Economic growth, exports, and foreign direct investment in Least Developed Countries: A panel Granger causality analysis, Economic Modelling 29(3), 868-878.
55. Tiwari, A., Ozturk, I. & Aruna, M. (2013). Tourism, energy consumption and climate change in OECD countries. International Journal of Energy Economics and Policy 3, 247-261.
56. World Economic Forum (2019). Outbreak readiness and business impact protecting lives and livelihoods across the global economy. Available online at: http://www3.weforum.org/docs/WEF HGHI_Outbreak_Readiness_Business_Impact.pdf

57. World Tourism Organization (2020). UNWTO World Tourism Barometer and Statistical Annex, August/September 2020. Available online at: https://www.e-unwto.org/doi/abs/10.18111/wtobarometereng.2020.18.1.5

58. World Tourism Organization (2011). Tourism Towards 2030-Global Overview. Available online at: https://www.globalwellnesssummit.com/wp-content/uploads/Industry Research/Global/2011_UNWTO_Tourism_Towards_2030.pdf

59. World Travel and Tourism Council (2018). Travel and Tourism Economic Impact 2018. Caribbean. Available online at: http://www.wttc.org/research/economicimpact-research/regional-reports/caribbean/

60. World Development Indicators (2020). The World Bank. Available online at: https://databank.worldbank.org/source/world-development-indicators

61. World Health Organization (WHO) (2020). Coronavirus disease (COVID-19) Weekly Epidemiological Update and Weekly Operational Update. Available online at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.

62. World Health Organization (2018). Ambient (outdoor) air pollution: Fact Sheet. Available online at: https://www.who.int/en/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

63. Yang, Y., Zhang, H. & Chen, X. (2020). Coronavirus pandemic and tourism: Dynamic stochastic general equilibrium modeling of infectious disease outbreak. Annals of Tourism Research 83, 102913.

64. Zaman, K., Shahbaz, M., Loganathan, N. & Raza, S. (2016). Tourism development, energy consumption and environmental Kuznets curve: Trivariate analysis in the panel of developed and developing countries. Tourism Management 54, 275-283.

65. Zaman, K., Moemen, M. & Islam, T. (2017). Dynamic linkages between tourism transportation expenditures, carbon dioxide emission, energy consumption and growth factors: Evidence from the transition economies. Current Issues in Tourism 20(16), 1720-1735.

66. Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association 57(298), 348-368.

67. Zhang, L. & Zhang, J. (2020). A systematic review on tourism energy consumption, sustainable tourism and destination development: A behavioral perspective. Transport and Energy Research: A Behavioral Pesrpective, pp: 295-313.