Impact of Economic Policy Uncertainty and Pandemic Uncertainty on International Tourism: What do We Learn From COVID-19?

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Abstract
Uncertainty is an overarching aspect of life that is particularly pertinent to the present COVID-19 pandemic crisis; as seen by the pandemic’s rapid worldwide spread, the nature and level of uncertainty have possibly increased due to the possible disconnects across national borders. The entire economy, especially the tourism industry, has been dramatically impacted by COVID-19. In the current study, we explore the impact of economic policy uncertainty (EPU) and pandemic uncertainty (PU) on inbound international tourism by using data gathered from Italy, Spain, and the United States for the years 1995–2021. Using the Quantile on Quantile (QQ) approach, the study confirms that EPU and PU negatively affected inbound tourism in all states. Wavelet-based Granger causality further reveals bi-directional causality running from EPU to...
inbound tourism and unidirectional causality from PU to inbound tourism in the long run. The overall findings show that COVID-19 has had a strong negative effect on tourism. So resilient skills are required to restore a sustainable tourism industry.

Keywords
economic policy uncertainty, pandemic uncertainty, international tourism, Quantile on Quantile Approach

Introduction

The world woke up to an alien and infectious coronavirus, now called COVID-19, that started spreading by mid-December 2019. Wuhan, one of China’s most populous cities, was the first to record an index case (Meo & Abd Karim, 2022; Si, Lu, & Aziz, 2021, 2021b), after which, like a wildfire, COVID-19 has spread worldwide, with only a few countries yet to record a case. Similar to severe acute respiratory syndrome (SARS), COVID-19 is an airborne infection that is highly contagious among humans. In January 2020, the Chinese government alerted the world and its citizens of the horrendous effects of the ravaging pandemic, followed by preventive measures like business and school closures, individual and community quarantines, and temporary closure of markets and leisure centers across China.

The pandemic has since metamorphosed into a global health emergency of enormous concern, to the extent of the World Health Organization (WHO) terming it an “unprecedented global pandemic.” In March 2020, the United States, Spain, Italy, and other European countries had become epicenters of COVID-19, with strict restrictions on human movement across and within countries. As of 28 April 2020, there were about 2,954,222 confirmed cases globally with 202,597 deaths, while as of 26 May 2020, there were already 5,459,528 recorded cases (European Centre for Disease Prevention and Control, 2020). Table 1 presents the number of confirmed cases and deaths by region (WHO, 2020).

For many developed and developing countries, the tourism sector is a major source of employment, government revenue, and foreign exchange earnings (Aziz et al., 2020; Zhu et al., 2021). Without this vital lifeline, many countries might experience a dramatic contraction in GDP and a rise in unemployment. However, according to the United Nations World Trade Organisation (2020), tourism was the worst hit of all major economic sectors globally. The industry is expected to have contracted by 20%–30% in 2020, which is equivalent to 300 to 450 US$ billion, about one-third of the total tourism receipt generated annually (US$ 1.5 trillion). Other sectors are
expected to recover once restrictions are eased. Still, the effect of COVID-19 is expected to be long-lasting on international tourism due to reduced consumer confidence and the possibility of longer restrictions on travel (UNCTAD, 2020).

In the 10 most visited countries, such as Spain, Italy, China, and the United States (Koçak et al., 2020), the economic shock of tourism in these countries could be far-reaching. From the Spanish Costa pubs to the chic resorts of Italy and the Grand Canyon in the United States, no one knows how tourism will fare. The losses are already alarming. According to the European Commission (2020), restaurants and hotels will lose half their income in 2020. The banking group UBS has pointed out that tourism revenue fell by 95% and 77% in March 2020 in Italy and Spain, respectively. The economic policy uncertainty (EPU) also impacts tourism development (Lim & Won, 2020), causing delays or even cancellations of travel plans due to security, safety, and stability issues, and thus periods of increasing uncertainty can discourage or make individuals reluctant to travel overseas (Demir & Gözgör et al., 2018). If uncertainty and instability are evident in a country, a household’s consumption decreases, which could reduce and delay tourism expenditure, as tourism and travels expenditures are generally very sensitive to periods of uncertainty (Balsalobre-Lorente et al., 2022a, 2022b; Chaudhry et al., 2021; Doğan et al., 2022; Jahanger et al., 2022; Jiang et al., 2022; Sinha et al., 2022; Usman & Balsalobre-Lorente, 2022).

There is uncertainty surrounding almost every aspect of the COVID-19 crisis: On the epidemiological side, uncertainties include the infectiousness and lethality of the virus (Fauci et al., 2020), the time needed to develop and deploy vaccines (Koirala et al., 2020), and the duration and effectiveness of social distancing (Anderson et al., 2020). On the economic side, uncertainties include the near-term economic impact of the pandemic and policy responses (Baqaee et al., 2020), the speed of recovery as the pandemic recedes (Congressional Budget Office, 2020), and the extent to which pandemic-induced shifts in consumer spending patterns, business travel, and

| Regions of the World          | Confirmed Cases | Deaths in Numbers |
|-------------------------------|-----------------|-------------------|
| European region               | 1386693         | 126429            |
| Region of the Americas        | 1179607         | 60211             |
| Eastern Mediterranean region  | 171238          | 7148              |
| Western pacific region        | 145385          | 5998              |
| South-east Asia region        | 48348           | 1917              |
| African region                | 22239           | 881               |

Sources: Authors computation from WHO (2020).
working from home will persist (Barrero et al., 2020). Hence, a major aspect for policy-makers of learning from this experience is the need to consider all the dimensions of uncertainty simultaneously or in sequence to ensure a more unified approach to dealing with such global disasters in the future. Therefore, the negative effect of COVID-19 on the economy makes it imperative to revisit the impact of pandemic uncertainty on tourism.

Moreover, many studies have explored the association between pandemics and tourism but ignored the non-linear trend of the variables. For instance, from the methodological perspective, most earlier studies adopted a linear approach (Sharif et al., 2021). Some merely presented information related to time while ignoring frequency-based information (Sharif et al., 2021). However, the cause of non-linearity in time series examination arises from ignoring the frequency information (Pal & Mitra, 2017). The previous studies thus yielded different results. Many other studies have employed conventional econometric approaches such as the OLS, ARDL, NARDL, VECM, pairwise granger causality. None of these traditional methods have comprehensively examined the relationships between tourism and its determinants. Furthermore, many studies are concerned with the impact of the crisis on airlines (Henderson, 2003), hotels (Chien & Law, 2003), restaurants, and travel agents (Alan et al., 2006); others have focused on the effects of pandemics like Severe Acute Respiratory Syndrome (McKercher & Chon, 2004), influenza (Monterrubio, 2010), and even bed bugs (Liu et al., 2015) but ignored the effect of economic and pandemic uncertainty on inbound international tourism in the most visited tourist destinations.

To fill this gap, the current study attempts to explore the effect of EPU and pandemic uncertainty (PU, specifically that associated with COVID-19) on tourism. The study contributes to the literature in the following ways. First, the current study is the first to estimate the relationship among the desired variables. Second, this study selects the USA, Italy, and Spain because these countries have been highly affected by COVID-19. Third, most researchers have investigated the nexus of tourism demand and its determinants in a linear framework. However, linear models cannot analyze structural changes and short-term volatilities (Po & Huang, 2008). As many macroeconomic variables exhibit non-linearities (Meo et al., 2018), the current study employs the QQ (Sim & Zhou, 2015) approach to estimate the effect of EPU and PU on tourism in quantiles following earlier researchers (Arain et al., 2020; Shahzad et al., 2017). Furthermore, the study employs a wavelet-based Granger causality test to consider the time-frequency-varying nature of the relationship between EPU, PU, and tourism, as this method aids in analyzing the association between variables within time scales and frequency bands and yields robust estimates for a small sample size (Sharif et al., 2021). Therefore, the current study explores the impact of EPU and PU on inbound tourism for the full sample ranging from 1995Q1 to 2021Q4 and then focuses on the time of
COVID-19 ranging from 01-01-2020 to 30-05-2020 to ascertain whether the relationship changed during the COVID-19 period.

The remainder of this study is arranged as follows: Sec. 2 reviews the literature. Methodology and data source are addressed in Sec. 3. The results are reported and discussed in Sec. 4, while Sec. 5 concludes the study with relevant policy suggestions.

**Literature Review and Theoretical Framework**

The current literature provides an exposition of the effects of EPU and PU on tourism. These uncertainties are allied with unanticipated actions that influence the demand of tourism, for example, “conflicts, terrorism, natural catastrophes, epidemics, contagions, and financial crises” (Song & Lin, 2010). Tourism is more susceptible than most industries to disasters or crises (Cró & Martins, 2017). Most studies have explored tourism’s relationship with various forms of uncertainty, such as economic uncertainty (Zaman et al., 2016) and financial uncertainty. Such uncertainties caused significant damage to international tourism by a severe decline in tourist arrivals and are a culprit in the shrinking size of overall tourism activities (Webber et al., 2010).

Moreover, regarding pandemic uncertainties, the worldwide outbreak of infectious diseases or pandemics can bring the world to a standstill. In the context of crises or pandemics, the tourism industry is predicted to be particularly vulnerable, and the UNWTO (2020), in its report, documented that pandemics caused a decline of 20%–30% in tourist arrivals. The overall evidence indicates that the pandemic led to a decrease in tourism-related expenditures due to reduced consumption by households on tourism, transportation, and leisure activities, and a higher demand for medical services. Joo et al. (2019) also found a correlation between 2.1 million drops in visitors and a US$2.6 billion loss in the 2015 MERS (Middle East respiratory syndrome) epidemic in the Republic of Korea. Likewise, in 2019, the world economy was again devastated by COVID-19 (coronavirus disease 2019), which greatly jeopardized the tourism industry. The tourism and transport-related industries were severely impacted by this pandemic. According to Baker (2020), the Chinese hotel market resulted in a decline of 71% in occupancy rate over just three days in January 2020. Yang et al. (2020) add that COVID-19 affects the health status and deteriorates the labor productivity of workers in tourism activities.

In other countries, Karim and Haque (2020) reported a negative impact of COVID-19 on the Malaysian tourism and hospitality industry and argued that as airline companies are continuing to stop all its operations to and from Malaysia, the tourism industry will continue to suffer negative effects. Wang et al. (2022) also found that pandemic risks decrease tourist arrivals. Likewise, Karabulut et al. (2020) reported that countries are
economically affected by decreasing tourist arrivals. More recently, Yan et al. (2021) reported that air quality and COVID-19 have affected Hawaii’s tourism growth. A recent study by Agboola et al. (2021) also revealed the striking impacts of COVID-19 on the economy of the Kingdom of Saudi Arabia. At the micro-level, various other studies have explored this phenomenon and proposed various suggestions to counteract the aftermath of COVID-19 (Alhassan et al., 2021a, 2021b; Rahman et al., 2021; Hossain et al., 2021). Golets et al. (2021) indicated that perceived COVID-19 severity, the perceived probability of infection, and the expected duration of the pandemic are significant predictors of travel intentions.

Based on the above discussion, worldwide tourism is clearly hit hard by pandemics; virus disease negatively affects tourism sectors, and thus affects a country’s GDP, as the tourism sector is a major earning source. History has shown that epidemics and pandemics have an immediate impact on hotels and restaurants, airline industries, travel agencies, etc., due to international travel restrictions, media coverage, and government measures. However, to the best of the authors’ knowledge, this is the first study that empirically examined the impact of EPU and PU on tourism in selected economies based on QQ and wavelet causality. Figure 1(a) illustrates the theoretical framework of economic uncertainty, pandemic, and international tourism, showing the mechanism whereby economic activities were stopped due to pandemics and uncertainty, which further affected different economic sectors, including travelling and tourism.

Modelling, Data, and Methodology

Model Specification

In specifying the theoretical models, we emphasize the objectives of the study. The study’s first objective is to examine the impact of EPU and PU on tourism, while the second objective is to investigate the effect of EPU and the COVID-19 pandemic on tourism. Hence, the theoretical models are specified as:

Model 1

\[ TOU = f(EPU, PU) \] (1)

When equation (1) is transformed into a multi-linear equation, the model becomes

\[ TOU_t = \beta_0 + \beta_1 EPU_t + \beta_2 PU_t + \epsilon_t \] (2)

Model 2
From equation (3), we have

$$TOU_t = \beta_0 + \beta_1 EPU_t + \beta_2 COVID - 19_t + \epsilon_t,$$  \hspace{1cm} (4)

Figure 1. Theoretical framework: Uncertainties, pandemic, and international tourism.
where TOU denotes inbound tourism, EPU denotes economic policy uncertainty, PU denotes pandemic uncertainty, and COVID-19 denotes the number of infected cases of a novel COVID-19 in the countries of interest.

**Data Specification**

Before pre-estimation and post-estimation analysis can be performed in any time-series study, data for the variables under investigation must be sourced. This study examines the relationship between purposed variables using the two models specified in Equations (2) and (4). The first model is designed to explore EPU and PU’s impact on TOU using a dataset of 1995Q1 to 2021Q4. In contrast, the second model is designed to examine the effects of EPU and COVID-19 on TOU based on daily observation from 2020Q1 to 2021Q4 (a period associated with the coronavirus spread). Data on tourism, EPU, PU,¹ and COVID-19 were obtained from WDI and World Uncertainty Index. Table 2 shows the sources of the data.

**Wavelet Decomposition Method**

The wavelet decomposition method helps analyze the causality between the dependent and independent variables (Sharif et al., 2017; Raza et al., 2017; Boubaker et al., 2017; Raza et al., 2017). Both the time and frequency domains are combined in wavelet analysis. Although the wavelet method allows the decomposition of time series data into different timescales, it can also preserve the time series data when the frequency of decomposition is carried out on the time data (Chu et al., 2016). Apart from these appealing merits of wavelet analysis, the primary reason for employing this econometric method is that the estimated results of the wavelet method remain unaffected by the size of the data sample. As a result, the challenge of limited data and conclusions drawn from spurious results is obviated by employing the wavelet

| Variables | Variables’ description | Measurement | Data sources |
|-----------|------------------------|-------------|--------------|
| TOU       | Tourism                | Number of tourist arrivals | WDI and tradingeconomics.com/ |
| EPU       | Economic policy uncertainty index | Index | https://worlduncertaintyindex.com/ |
| PU        | Pandemic uncertainty index | Index | https://worlduncertaintyindex.com/ |
| COVID-19  | COVID-19               | Number of infected cases | WHO |
method in this study. Following Chu et al. (2016), the wavelet decomposition method of a time series \( y(t) \) can be shown as follows

\[
y(t) = \sum_{k} d_{1,k} \psi_{1,k}(t) + \ldots + \sum_{k} d_{j-1,k} \psi_{j-1,k}(t) + \sum_{k} d_{j,k} \psi_{j,k}(t) + \sum_{k} s_{j,k} \phi_{j,k}(t)
\]

(5)

In equation (5), the scaling parameter is denoted by \( j \) while scaling coefficients are denoted by \( S_{j,k} \). \( k \) is the translation parameter ranging from 1 to the number of coefficients specified. \( d_{j,k} \) are the detail coefficients. The father wavelet and mother wavelet are represented by \( \phi \) and \( \psi \), respectively.

The basic functions that define the sequence of coefficients are set up by the father wavelets and mother wavelets. Consequently, we have

\[
\phi_{j,k}(t) = \frac{1}{2^{j/2}} \phi_{j,k}(2^{-j} t - k) \text{ with } \int \phi(t)dt = 1
\]

(6)

The father wavelet is formally defined in equation (6). The father wavelet integrates into one, and it denotes the very long-scale smooth components of the signal

\[
\psi_{j,k}(t) = \frac{1}{2^{j/2}} \psi_{j,k}(2^{-j} t - k) \text{ with } \int \psi(t)dt = 0
\]

(7)

The mother wavelet is defined in equation (7). The deviations occurring in the smooth (scaling) components are represented by the mother wavelet. In addition, the mother wavelets integrate to zero.

\[
s_{j,k} = \int y(t) \phi_{j,k}(t)dt
\]

(8)

Equation (8) is used to approximate the scaling \( s_{j,k} \), referring to the scaling coefficients that were derived from the father wavelet. It has a maximum scale of \( 2^j \)

\[
d_{j,k} = \int y(t) \psi_{j,k}(t)dt, j = 1, 2, \ldots, J
\]

(9)

Equation (9) represents \( d_{j,k} \), the detail coefficients, which capture the higher-frequency oscillations. The detail coefficients are derived from the mother wavelet at all scales from 1 to \( j \). In this study, the Maximum Overlap Discrete Wavelet Transform (MODWT) is used to obtain the scaling and detail coefficients because of its ability to keep the sample size values in all wavelet decomposition scales, which Discrete Wavelet Transform (DWT) would have discarded. Mishra et al. (2019) also pointed out that the detail and scaling
(smooth) coefficients obtained from MODWT are related to zero phase filters. Thus, the MODWT estimator is also known to be asymptotically efficient. Besides, MODWT helps in the full utilization of information in any time series with respect to location in time and specific time horizon (Bouri et al., 2017). This implies that the application of MODWT helps to align the features of the original time series with the characteristics of Multi-Resolution Analysis (MRA). The decomposition of a time series to $J$ levels with MODWT, however, requires the application of $J$ pairs of filters, and the filtering operation at the $j$th level consists of applying a rescaled father wavelet to yield a set of detail coefficients. In contrast, the mother wavelet is rescaled to give a set of scaling coefficients (Chu et al., 2016)

$$S_{j,k} = \sum_k s_{j,k} \phi_{j,k}(t)$$  \hspace{1cm} (10)

$$D_{j,k} = \sum_k d_{j,k} \psi_{j,k}(t), j = 1, 2, \ldots, J$$  \hspace{1cm} (11)

Given these coefficients in equation (10) and (11), the wavelet series approximation of the original time series $y(t)$ defined in equation (5) becomes

$$y(t) = D_1(t) + \ldots + D_{j-1}(t) + D_j(t) + S_j(t)$$  \hspace{1cm} (12)

Equation (12) indicates that the recomposed series in the time domain of $j$ is denoted by $D_j$ and $S_j$. Equation (12) computes the $j$th level wavelet detail connected with the variations in the series at scale $\lambda_j$. $S_j$ is defined as the cumulative sum of alterations at each level. As $j$ increases, $S_j$ becomes increasingly smooth (Gencay et al., 2002). Since wavelet decomposition requires the application of filtering for a robust and reliable outcome, the least asymmetric filter of length eight (LA8) is adopted because it is widely known to yield smoother coefficients with better uncorrelatedness across scales than the Haar filter.

**Quantile-on-Quantile Approach (QQ)**

Since Koenker and Bassett (1978) officially introduced quantile regression analysis (QRA) in their seminal paper “Regression quantile” in *Econometrica* in 1978 (Merilina & Domenico, 2018), it has become one of the most widely used econometric methods because of its ability to capture different time-varying of the dependent variable. Quantile regression analysis is also widely known to perform better than the classical linear correlation/regression counterpart in the generation of a more precise and accurate result of the impact of covariates on the regress and in time-varying degree and structure of dependence (Koenker, 2005). In addition to the merit of being a median
analysis, QRA is useful in generating information on tail dependence, which aids the capturing of the normal phase of the dependent variable.

Despite the benefits of QRA as an econometric model, it cannot capture dependency in its entirety, especially in a situation of uncertainty (Sim & Zhou, 2015). Even though the heterogeneous relationship between covariates and dependent variables can be captured by quantile regression analysis, the use of the analysis is limited in this study because it neglects the possibility of uncertainty associated with the covariates on tourism. To overcome the challenges associated with the QRA and avoid making inferences from spurious estimation, QQ is employed in this study, as it enables the modelling of the quantile of tourism and its various frequencies to quantile the covariate uncertainty.

At each point of the distributions of tourism and distribution of its co-
variate, the relationship between the variables could vary across their respective distributions, allowing their dependence to be captured in its entirety. Thus, an absolute, clearer, and robust picture of dependency is obtainable with the QQ approach. Currently, there are two approaches to modelling QQ regression. The first is the triangular system equations, while the second approach is focused on a single equation regression approach. The first approach is based on Ma and Koenker’s (2005) model, the second on Sim et al. (2015). However, the single equation approach proposed by Sim et al. (2015) is adopted because it better aligns with the objectives of our study.

As previously mentioned, the specification of models for this study is purely based on its objectives. Since the primary focus is on model 1 and model 2 as stated in equations (1) and (3), respectively, “X” will be used to denote the covariate in the respective model. This will help to prevent awkwardness and unnecessary repetition in modelling the QQ approach. Given that the quantile of tourism is denoted by the superscript “θ” and the error term (with a zero θ-quantile) is denoted by $E_t^θ$, the Quantile-on-Quantile equation can be formally expressed as follows

$$\text{TOU}_t = \beta^0 X_t + E_t^0$$

In equation (13), the relationship function ($\beta^0$) remains unknown between the variables because we have neither perfect nor previous knowledge of the interlink between TOU (tourism) and changes in $X$. Thus, to examine the linkage between the $\theta$-quantile of TOU and the $\theta$-quantile of covariate $X$ (i.e., $X^\tau$), the relationship function ($\beta^0$) has to be linearized by taking its first-order Taylor expansion around $X^\tau$. As a result, we have

$$\beta^0 X_t \approx \beta^0 X^\tau + \beta^0(X^\tau)(X_t - X^\tau)$$

In line with Sim and Zhou (2015), $\beta^0 X^\tau$ and $\beta^0(X^\tau)$ can be redefined as $\beta_0(\theta X, \tau)$ and $\beta_1(\theta X, \tau)$, respectively. Thus, equation (14) can be rewritten as
\[ \beta \theta X_t \approx \beta_0 (\theta X, \tau) + \beta_1 (\theta X, \tau) (X_t - X^\tau) \]  

When equation (15) is substituted into equation (13), it becomes

\[ TOU_t = \beta_0 (\theta X, \tau) + \beta_1 (\theta X, \tau) (X_t - X^\tau) + \xi^\theta_t \]  

Equation (16) enables us to analyze the impact of various frequencies of the covariates (EPU, PU, and COVID-19) on TOU.

**Empirical Results**

**Summary Statistics**

Table 3 reports the summary statistics of tourist arrivals, EPU, and PU from 1995Q1 to 2021Q4. The USA has the highest value of maximum tourist arrivals while Spain has the lowest. Although the Jarque–Berra test shows non-normality in the data, the QQ approach nonetheless gives robust estimates.

Further, the time paths of tourists’ arrivals, EPU, and PU for the USA, Italy, and Spain are portrayed in Figure 2. It is apparent that there is an upward trend of tourists’ arrivals in the late 2010s for all the economy, but the USA has the highest number of tourists’ arrivals. Similarly, the USA recorded the lowest tourist arrivals from 2001 to 2003. This corresponds with a period when the country experienced a recession. It was also observed that EPU is highly erratic, with periodic spikes for all the economies, but Italy records the highest spikes (in 2012) among the economies. Pandemic uncertainty plot reveals zero graphs with few plateaus. This indicates that COVID-19 is an unexpected outbreak, and the uncertainty regarding the COVID-19 epidemic is a great concern to tourists and policymakers worldwide.

**Quantile Unit Roots**

We began with a quantile unit root test before proceeding to the quantile-on-quantile regression analysis. The findings of the quantile unit root test are presented in Table 4. Traditional unit root tests yield average results, whereas the quantile unit root test yields more detailed information about the variables’ stationarity (Chowdhury et al., 2021). To overcome the issue of serial correlation, we used two lags in our analysis. The results show that at 5% level of significance, all of the variables are non-stationary.
### Table 3. Summary Statistics.

|       | USTOU | ITTOU | SPTOU | USEPU | ITEPU | SPEPU | USPU | ITPU | SPPU |
|-------|-------|-------|-------|-------|-------|-------|------|------|------|
| Mean  | 591587| 442878| 573005| 3.01  | 3.52  | 2.93  | 0.68 | 0.26 | 0.27 |
| Median| 553533| 429622| 559059| 2.00  | 2.00  | 2.00  | 0.00 | 0.00 | 0.00 |
| Maximum| 850416| 630752| 840526| 15.00 | 15.00 | 12.00 | 13.78| 20.24| 19.67|
| Minimum| 408354| 337693| 312575| 0.00  | 0.00  | 0.00  | 0.00 | 0.00 | 0.00 |
| Std. Dev.| 132979| 805125| 131046| 2.78  | 3.18  | 2.55  | 2.46 | 2.12 | 2.10 |
| Skewness| 0.44  | 0.88  | 0.58  | 1.47  | 1.08  | 1.03  | 3.78 | 8.89 | 8.54 |
| Kurtosis| 1.72  | 3.01  | 2.76  | 5.71  | 3.86  | 3.87  | 17.02| 83.04| 77.49|
| Jarque–Bera | 9.69  | 12.63 | 5.61  | 64.29 | 21.96 | 20.27 | 1015.99| 26891.15| 23364.41|
| Probability| 0.00  | 0.00  | 0.06  | 0.00  | 0.00  | 0.00  | 0.00 | 0.00 | 0.00 |

Source: Authors Computation.
Quantile-Based Granger Causality Test Results

The results of the Granger causality test in quantiles are presented in Table 5. The causality between EPU and tourist arrivals in Italy and Spain is bidirectional at 5% significant levels in all quantiles. Contrary to Italy and Spain’s economies, at the low quantiles (0.5–0.10), there is no causality between EPU and tourist arrivals in the United States of America because the economy is larger than those of its counterparts. Consequently, US policymakers’ decisions are usually delayed due to economic factors, which creates operational lags in the effect of EPU on tourism. The previous findings of Akadiri et al. (2020) also endorsed a two-way causality between EPU and tourism in the economies of France, Ireland, and the United States. Uni-directional causality runs from PU to tourist arrivals in the USA and Italy at all the quantiles (except the low quantiles 0.5 to 0.10). The unidirectional causality can be linked to a high level of information tourists acquire on the danger of the pandemic. Since health is wealth, some or most tourists minimize their travelling rate due to the rise in fear of PU. The results are in accord with the study of Nyarko et al. (2015), which found that the tourism sector is more susceptible to epidemics as tourists are unenthusiastic about traveling to countries having contagious diseases. Joo et al. (2019) and

Figure 2. Time Series trend of tourists’ arrivals, EPU, and PU for the USA, Italy, and Spain.
Wavelet-Based Granger Causality Test Results

The traditional causality and wavelet-based Granger causality are reported in Table 6. In ensuring robust estimates and unbiased inferences, the Granger causality based on wavelet analysis is also used in this study for seven frequency domains (D1 to D7). The result shows no directional causal linkage.
Table 5. Granger Causality Test in Quantiles.

Economic Policy Uncertainty and Tourist Arrivals Across Quantiles

|          | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
|----------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| USA      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ΔEPU_t to ΔTOU_t | 0.21 | 0.31 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOU_t to ΔEPU_t | 0.43 | 0.54 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Italy    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ΔEPU_t to ΔTOU_t | 0.00 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOU_t to ΔEPU_t | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Spain    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ΔEPU_t to ΔTOU_t | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOU_t to ΔEPU_t | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Pandemic uncertainty and inbound tourism across quantiles

|          | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | 0.30 | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
|----------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| USA      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ΔPU_t to ΔTOU_t | 0.14 | 0.10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOU_t to ΔPU_t | 0.76 | 0.21 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 | 0.76 |
| Italy    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ΔPU_t to ΔTOU_t | 0.45 | 0.34 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOU_t to ΔPU_t | 0.45 | 0.23 | 0.12 | 0.12 | 0.91 | 0.50 | 0.12 | 0.62 | 0.81 | 0.70 | 0.51 | 0.33 | 0.69 | 0.12 | 0.98 | 0.11 | 0.67 | 0.64 | 0.45 |
| Spain    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| ΔPU_t to ΔTOU_t | 0.21 | 0.01 | 0.02 | 0.41 | 0.34 | 0.19 | 0.52 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOU_t to ΔPU_t | 0.32 | 0.34 | 0.20 | 0.18 | 0.95 | 0.78 | 0.55 | 0.17 | 0.58 | 0.56 | 0.27 | 0.56 | 0.57 | 0.12 | 0.23 | 0.56 | 0.34 | 0.34 | 0.12 |

Note: Table 5 presents the subsampling p-values of the $S_T$ test. $\Delta EPU_t$, $\Delta TOU_t$, and $\Delta PU_t$ is economic policy uncertainty index, inbound tourism, and pandemic uncertainty index respectively.
between tourist arrivals and EPU in all the economies for domains D1 and D2. The absence of directional causal linkage between tourist arrivals and EPU implies no significant fall in tourists’ confidence in the economy; uncertainty remains low, and there are operational lags in macroeconomic policy relating to tourism in the low domain (D1 and D2). Similarly, there is no directional causality between PU and tourist arrival in domains D1 and D2 for all the economies except for Spain, where a significant effect of PU on tourism is detected in domain D2. In the third domain (D3), wavelet causality runs from PU to tourist arrivals in Italy and Spain. However, there is evidence of bi-directional causality between the United States’ variables. From the fourth domain (D4) to the seventh domain (D7), PU strongly influences tourist arrivals in the economy. At the domains D4 to D7, there is a significant rise in PU in all economies, which prompted legal restrictions on people’s movement. Moreover, travelers from highly developed countries are more sensitive to diseases and have a greater risk of PU, which pushes the tourism sector into

Table 6. Wavelets Based Causality (Granger Test in Decomposed Components).

| Quantiles | DI  | D2  | D3  | D4  | D5  | D6  | D7  | Traditional Causality |
|-----------|-----|-----|-----|-----|-----|-----|-----|------------------------|
| ΔEPUₜ ↔ ΔTOUₜ | 0.32 | 0.34 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| ΔTOUₜ ↔ ΔEPUₜ | 0.75 | 0.52 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.25 |
| ΔPUₜ ↔ ΔTOUₜ | 0.04 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOUₜ ↔ ΔPUₜ | 0.04 | 0.11 | 0.05 | 0.11 | 0.41 | 0.41 | 0.71 | 0.62 |

Italy

| Quantiles | DI  | D2  | D3  | D4  | D5  | D6  | D7  | Traditional Causality |
|-----------|-----|-----|-----|-----|-----|-----|-----|------------------------|
| ΔEPUₜ ↔ ΔTOUₜ | 0.53 | 0.45 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOUₜ ↔ ΔEPUₜ | 0.53 | 0.61 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.54 |
| ΔPUₜ ↔ ΔTOUₜ | 0.14 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 |
| ΔTOUₜ ↔ ΔPUₜ | 0.76 | 0.21 | 0.12 | 0.97 | 0.83 | 0.81 | 0.93 | 0.42 |

Spain

| Quantiles | DI  | D2  | D3  | D4  | D5  | D6  | D7  | Traditional Causality |
|-----------|-----|-----|-----|-----|-----|-----|-----|------------------------|
| ΔEPUₜ ↔ ΔTOUₜ | 0.67 | 0.54 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOUₜ ↔ ΔEPUₜ | 0.65 | 0.67 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.62 |
| ΔPUₜ ↔ ΔTOUₜ | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ΔTOUₜ ↔ ΔPUₜ | 0.32 | 0.34 | 0.20 | 0.18 | 0.95 | 0.78 | 0.55 | 0.17 |

Note: Table 6 presents the subsampling p-values of the ST test. ΔEPUₜ, ΔTOUₜ, and ΔPUₜ is the log-difference of EPU, tourism, and PU index, respectively. DI – D7 indicates the oscillations of periods 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, and 128–256 quarters. ↔ refers to null hypothesis of no-causality.
an abyss. Thus, tourism becomes highly responsive to PU. The results are analogous to the findings for previous epidemic outbreaks, such as the avian flu epidemic in Asian and Pacific countries and the UK’s foot and mouth disease (Blake et al., 2003), resulting in a sharp decline in tourism expenditures. The outcome is also supported by Joo et al.’s (2019) findings on the decline in tourist arrivals during the MERS (Middle East respiratory syndrome) outbreak, showing that infectious disease outbreak notably impacts the tourism sector. The findings also show bidirectional wavelet causality between EPU and tourist arrivals from the third frequency (D3) domain to the last frequency domain (D4). This finding corroborates the quantile

![Figure 3](image_url)

**Figure 3.** Quantile on Quantile estimates of economic policy uncertainty and inbound tourism. Note: This graph depicts the estimates of the slope coefficient, $\beta_1(\tau, \theta)$, which is placed on the z-axis against the quantiles of the EPU ($\tau$) x-axis and quantiles of the tourism (TOU) ($\theta$) on the y-axis. The color bar shows the degree of co-movement between proposed variables, dark red color indicates a strong positive relationship, and dark negative shows a strong negative relationship between proposed variables.
cointegration results. Besides, the traditional cointegration approach shows that EPU and PU Granger cause tourist arrival, and the causality is unidirectional.

**Quantile-on-Quantile Results**

**Impact of economic policy uncertainty and inbound tourism.** The quantile-on-quantile results are shown in Figure 3, which portrays the estimates of the slope coefficient, $\beta_1(\tau, \theta)$, and captures the effect of the $\tau$th quantile of EPU on the $\theta$th quantile of TOU at different values of $\tau$ and $\theta$. The QQ plots reveal interesting relations between TOU and its covariates. The results show that the co-movement between TOU and its covariate (EPU) changes under different economic conditions. Overall, a persistent negative correlation is observed between EPU and tourism in the US, Spain, and Italy at all levels of EPU. This implies that the impact of EPU on tourism demand remains negative irrespective of the US and Italy’s economic conditions. Thus, it is expected that a rise in EPU will lead to a fall in tourism demand in both the US and Italy. However, in Italy, a positive correlation is observed between the high quantiles of EPU and low quantiles of tourism. Overall, the findings imply that a high level of EPU is associated with low tourist arrivals for the economy. When EPU rises, tourists raise their precautionary demand for money and reduce their tourism expenditures because a rise in EPU reduces their trust in their economy’s condition. Other studies report the same phenomenon, such as Drakos and Kutan’s (2003) finding that EPU harms tourism in Greece. Recently, Alawin and Lila (2016) validate the economic-political uncertainty as a contributing factor leading to the drop in tourist numbers. Singh et al. (2019) also confirmed the time-frequency varying nature of the relationship between economic policy uncertainty and tourism.

**Impact of pandemic uncertainty (PU) and inbound tourism.** The study also examined the impact of PU on tourism for all the economies and presented in Figure 4. The results show that PU harms tourism demand for all the economies (US, Spain, and Italy). This is because a rise in PU usually leads to stricter restrictions on the inflow and outflow of tourists to curtail the spread of infectious diseases. Hence, a rise in PU will lead to a fall in tourism demand. Our results resonate with the previous findings of Kongoley-MIH (2015) and Novelli et al. (2018), who also evidenced the suspension of all air flights in the era of an epidemic outbreak. The outcome is also supported by Joo et al.’s (2019) findings of a decline in figures of tourist arrivals in case of MERS (Middle East respiratory syndrome) outbreak epidemic and envisages that infectious disease outbreak notably impacts the tourism sector.
Wang et al. (2022) also revealed that pandemic risks decrease tourist arrivals. Finally, the study precisely investigated the effect of EPU and COVID-19 on tourism as set out in Model 2. The results are presented in Figure 5, which shows that the effects of EPU and COVID-19 on tourism are negative in all quantiles and do not differ across the economies. This means that an increase in the EPU would lead to a decline in demand for tourism. Similarly, a decrease in tourist arrivals is expected as the number of people infected with COVID-19 increases in sampled countries. This negative relationship between COVID-19 and tourism is due to the fact that as the number of people infected increases, stricter steps are taken to limit people’s movement from one country to another. In addition, tourists become reluctant to spend on

Figure 4. QQ estimates of Pandemic Uncertainty and inbound tourism.

Wang et al. (2022) also revealed that pandemic risks decrease tourist arrivals.
tourism activities, resulting in declining demand. Balsalobre-Lorente (2020), found that China’s isolation is less responsive to its economic growth while the country’s political willpower is elastic, as demonstrated by a government commitment to dampening the effect of the COVID-19 pandemic. This confinement is marked by the aggressive response by the
government officials determined to flatten the exponential impact of the pandemic.

Conclusion and Policy Implications

This study is a timely addition to increasingly important strands of the tourism literature. Though tourism is a stable economic growth source (Husein et al., 2020; Wu et al., 2020), COVID-19 has drastically affected the tourism sector. Social distancing policies designed to prevent virus transmission imply a particularly negative supply shock for the tourism industry. In addition, the fear of infection significantly affects all elements of the tourism product value chain, drastically reducing its demand. Therefore, many occupations linked to tourism show significant risks of being negatively affected by the COVID-19 crisis due to both supply and demand shocks. This study explores the effects of EPU and PU on inbound tourism in the United States, Italy, and Spain. The quantile causality results indicate that EPU and inbound tourism have overall bi-directional causality across all quantiles and uni-directional causality running from PU to inbound tourism in the USA, Italy, and Spain. Moreover, Granger’s wavelet-based causality confirms bi-directional causality between EPU and inbound tourism in the long run and uni-directional causality from PU to inbound tourism. It is notable that the effects of EPU and PU have little immediate impact on tourism, while medium to long-term shocks continue due to major undesirable EPU and PU events. Finally, the QQ approach confirms that overall EPU and PU negatively influence inbound tourism in the USA, Italy, and Spain, though the strength of the relationship differs with economic conditions. In addition, the findings further indicate that during COVID-19, EPU and COVID-19 both had a strong negative effect on inbound tourism in the USA, Italy, and Spain. The association did not differ across time.

Based on the empirical findings, it is concluded that tourism responds to health and economic policy-related uncertainties. The study’s results (based on the wavelet analysis) indicate that policymakers should concentrate on long-term economic and pandemic uncertainty policies since pandemic uncertainty has a long-term impact on tourism, which requires long-term policy. In addition, it is not wise to equate COVID-19 with previous pandemics, as it is new, so policymakers should concentrate on lifting travel restrictions (applying new health protocols for safe travel), restoring traveler trust (visitor information apps and domestic tourism promotion campaigns), and rethinking (preparing detailed tourism recovery plans, encouraging innovation and investment). Another way to promote safety and health care in the studied bloc must involve smart processes. Smart tourism, related to assistive technology and augmented reality (artificial intelligence, virtual reality, speech recognition, and standardized responses), should be presented in all tourism
environments to provide quality, service, and satisfaction, thereby exceeding expectations, improving accessibility promoting heritage and culture.

The limitations of this research are mostly related to the unprecedented character of the present crisis. The COVID-19 virus is slightly less lethal but more contagious than SARS. This implies that its fear effect could be more pronounced and last longer among tourists. Therefore, future research needs to consider the latest data and could include additional measures of COVID-19. Future research should also expand the sample countries. Moreover, COVID-19 is a unique case due to the speed with which it has spread worldwide and wreaked havoc in the global economy. The evidence available indicates that most countries have taken the right steps to restrict its further spread by restricting human movement, which has had a debilitating impact on economic activity. As many of these countries are now moving toward the gradual easing of these restrictions, it would be interesting to see how quickly the tourism industry and broader economies have rebounded by sampling different countries.

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Data Availability Statement
The datasets used during the current study are available on request from corresponding or first author. The data of COVID-19 can be accessed from the European Union database (http://ec.europa.eu/eurostat/data/database).

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Note

1. “Pandemic uncertainty index is constructed by counting the number of times uncertainty is mentioned within a proximity to a word related to pandemics in the Economist Intelligence Unit (EIU) country reports. Specifically, the index is the percent of the word ‘uncertain’, and its variants, that appear near the pandemic terms in EIU country reports, multiplied by 1000. A higher number means higher uncertainty related to pandemics and vice versa.”

References

Agboola, M. O., Bekun, F. V., & Balsalobre-Lorente, D. (2021). Implications of social isolation in combating COVID-19 outbreak in kingdom of Saudi Arabia: Its consequences on the carbon emissions reduction. Sustainability, 13(16), 9476. https://doi.org/10.3390/su13169476

Akadiri, S. S., Alola, A. A., & Uzuner, G. (2020). Economic policy uncertainty and tourism: Evidence from the heterogeneous panel. Current Issues in Tourism, 23(20), 2507-2514. https://doi.org/10.1080/13683500.2019.1687662

Alan, C. B., So, S., & Sin, L. (2006). Crisis management and recovery: How restaurants in Hong Kong responded to SARS. International Journal of Hospitality Management, 25(1), 3-11. https://doi.org/10.1016/j.ijhm.2004.12.001

Alawin, M., & Abu-Lila, Z. (2016). Uncertainty and gravity model for international tourism demand in Jordan: evidence from panel-GARCH model. Applied Econometrics and International Development, 16(1), 131-146.

Alhassan, G. N., Adedoyin, F. F., Bekun, F. V., & Agabo, T. J. (2021). Does life expectancy, death rate and public health expenditure matter in sustaining economic growth under COVID-19: Empirical evidence from Nigeria? Journal of Public Affairs, 21(4), e2302. https://doi.org/10.1002/pa.2302

Alhassan, G. N., Öztürk, İ., Adedoyin, F. F., & Bekun, F. V. (2021). Telehealth as a panacea amidst global pandemic (COVID-19) in Africa. Duzce Medical Journal, 23(Special Issue), 43-47.

Anderson, R. M., Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. D. (2020). How will country-based mitigation measures influence the course of the COVID-19 epidemic? Lancet, 395(10228), 931-934. https://doi.org/10.1016/s0140-6736(20)30567-5

Arain, H., Han, L., Sharif, A., & Meo, M. S. (2020). Investigating the effect of inbound tourism on FDI: The importance of quantile estimations. Tourism Economics, 26(4), 682-703. https://doi.org/10.1177/1354816619859695

Aziz, N., Mihardjo, L. W., Sharif, A., & Jermsittiparsert, K. (2020). The role of tourism and renewable energy in testing the environmental kuznets curve in the BRICS countries: Fresh evidence from methods of moments quantile regression. Environmental Science and Pollution Research, 27(31), 39427-39441. https://doi.org/10.1007/s11356-020-10011-y
Baker, T. (2020). *Chinese hotels seeing steep declines from coronavirus*. Retrieved from http://hotelnewsnow.com/Articles/300132/Chinese-hotels-seeing-steepdeclines-from-coronavirus

Balsalobre-Lorente, D., Driha, O. M., Bekun, F. V., Sinha, A., & Adedoyin, F. F. (2020). Consequences of COVID-19 on the social isolation of the Chinese economy: Accounting for the role of reduction in carbon emissions. *Air Quality, Atmosphere & Health, 13*(12), 1439-1451. https://doi.org/10.1007/s11869-020-00898-4

Balsalobre-Lorente, D., Driha, O. M., Halkos, G., & Mishra, S. (2022). Influence of growth and urbanization on CO2 emissions: The moderating effect of foreign direct investment on energy use in BRICS. *Sustainable Development, 30*(1), 227-240. https://doi.org/10.1002/sd.2240

Balsalobre-Lorente, D., Ibáñez-Luzón, L., Usman, M., & Shahbaz, M. (2022b). The environmental Kuznets curve, based on the economic complexity, and the pollution hypothesis in PIIGS countries. *Renewable Energy, 185*, 1441-1455. https://doi.org/10.1016/j.renene.2021.10.059

Baqaee, D., Farhi, E., Mina, M., & Stock, J. H. (2020). Policies for a second wave. *Brookings Papers on Economic Activity, 2020*(2), 385-443. https://doi.org/10.1353/eca.2020.0013

Barrero, J, Bloom, N, & Davis, S J (2020). *COVID-19 and labour reallocation: Evidence from the US*. VoxEU.org.

Blake, R., Turner, L. M., Smoski, M. J., Pozdol, S. L., & Stone, W. L. (2003). Visual recognition of biological motion is impaired in children with autism. *Psychological science, 14*(2), 151-157.

Boubaker, H., & Raza, S. A. (2017). A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. *Energy Economics, 64*, 105-117. https://doi.org/10.1016/j.eneco.2017.01.026

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters, 23*, 87-95.

Chauhtry, I. S., Nazar, R., Ali, S., Meo, M. S., & Faheem, M. (2021). Impact of environmental quality, real exchange rate and institutional performance on tourism receipts in East-Asia and Pacific region. *Current Issues in Tourism, 25*(4), 1-21. https://doi.org/10.1080/13683500.2021.1894101

Chien, G. C., & Law, R. (2003). The impact of the severe acute respiratory syndrome on hotels: A case study of Hong Kong. *International Journal of Hospitality Management, 22*(3), 327-332. https://doi.org/10.1016/s0278-4319(03)00041-0

Chowdhury, M. A. F., Meo, M. S., & Aloui, C. (2021). How world uncertainties and global pandemics destabilized food, energy and stock markets? Fresh evidence from quantile on quantile regressions. *International Review of Financial Analysis, 76*, 101759. https://doi.org/10.1016/j.irfa.2021.101759

Chu, X., Wu, C., & Qiu, J. (2016). A nonlinear granger causality test between stock returns and investor sentiment for Chinese stock market: A wavelet-based
approach. *Applied Economics, 48*(21), 1915-1924. https://doi.org/10.1080/00036846.2015.1109048

Congressional Budget Office (2020). *An update to the economic outlook: 2020 to 2030.*

Cró, S., & Martins, A. M. (2017). Structural breaks in international tourism demand: Are they caused by crises or disasters? *Tourism Management, 63,* 3-9. https://doi.org/10.1016/j.tourman.2017.05.009

Demir, E., & Gözgör, G. (2018). Does economic policy uncertainty affect Tourism? *Annals of Tourism Research, 69*(C), 15-17. https://doi.org/10.1016/j.annals.2017.12.005

Doğan, B., Chu, L. K., Ghosh, S., Truong, H. H. D., & Balsalobre-Lorente, D. (2022). How environmental taxes and carbon emissions are related in the G7 economies? *Renewable Energy,* 187, 645-656. https://doi.org/10.1016/j.renene.2022.01.077

Drakos, K., & Kutan, A. M. (2003). Regional effects of terrorism on tourism in three Mediterranean countries. *Journal of Conflict Resolution,* 47(5), 621-641.

European Centre for Disease Prevention and Control (2020). *COVID-19 situation update worldwide.* as of May 26 2020 https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases

European Commission (2020). *Speech by commissioner Breton on “A marshall plan for European tourism.* https://ec.europa.eu/commission/commissioners/2019-2024/breton/announcements/speech-commissioner-breton-marshall-plan-european-tourism_en (Accessed April 21, 2020).

Fauci, A S, Lane, H C, & Redfield, R R (2020). Covid-19 – navigating the uncharted. *New England Journal of Medicine,* 382(13), 1268-1269. https://doi.org/10.1056/nejme2002387

Galvao, A.F. (2009). Unit root quantile autoregression testing using covariates. *J. Econom,* 152(2), 165-178. https://doi.org/10.1016/j.jeconom.2009.01.007

Gençay, R., Selçuk, F., & Whitcher, B. (2002). *Robustness of systematic risk across time scales.* informal University of Windsor working paper.

Golets, A., Farias, J., Pilati, R., & Costa, H. (2021). COVID-19 pandemic and tourism: The impact of health risk perception and intolerance of uncertainty on travel intentions. *Current Psychology (New Brunswick, N.J.)*, 1–14, 1-14. https://doi.org/10.1007/s12144-021-02282-6

Henderson, J. C. (2003). Communicating in a crisis: Flight SQ 006. *Tourism Management,* 24(3), 279-287. https://doi.org/10.1016/s0261-5177(02)00070-5

Hossain, E., Rana, J., Islam, S., Khan, A., Chakrobortty, S., Ema, N. S., & Bekun, F. V. (2021). COVID-19 vaccine-taking hesitancy among Bangladeshi people: Knowledge, perceptions and attitude perspective. *Human Vaccines & Immunotherapeutics, 17*(11), 4028-4037. https://doi.org/10.1080/21645515.2021.1968215

Husein, J., & Kara, M. S. (2020). Examining the stability of the long-run relationship between tourism and economic growth for Puerto Rico. *Tourism Analysis,* 25(2–3), 2-3. https://doi.org/10.3727/108354220x15984191017252
Jahanger, A., Usman, M., Murshed, M., Mahmood, H., & Balsalobre-Lorente, D. (2022). The linkages between natural resources, human capital, globalization, economic growth, financial development, and ecological footprint: The moderating role of technological innovations. Resources Policy, 76, 102569. https://doi.org/10.1016/j.resourpol.2022.102569

Jiang, T., Yu, Y., Jahanger, A., & Balsalobre-Lorente, D. (2022). Structural emissions reduction of China’s power and heating industry under the goal of “double carbon”: A perspective from input-output analysis. Sustainable Production and Consumption, 31, 346-356. https://doi.org/10.1016/j.spc.2022.03.003

Joo, H., Maskery, B. A., Berro, A. D., Rotz, L. D., Lee, Y. K., & Brown, C. M. (2019). Economic impact of the 2015 MERS outbreak on the Republic of Korea’s tourism-related industries. Health Security, 17(2), 100-108. https://doi.org/10.1089/hs.2018.0115

Karabulut, G., Mehmet, H. B., Ender, D., & Asli, C. D. (2020). How pandemics affect tourism: International evidence. Annual Tourism Research, 84, 102991. https://doi.org/10.1016/j.annals.2020.102991

Karim, W., & Haque, A. (2020). The movement Control order (MCO) for COVID-19 crisis and its impact on tourism and hospitality sector in Malaysia. International Tourism and Hospitality Journal, 3(2), 1-7.

Koçak, E., Ulucak, R., & Ulucak, Z. Ş. (2020). The impact of tourism developments on CO2 emissions: An advanced panel data estimation. Tourism Management Perspectives, 33, 100611. https://doi.org/10.1016/j.tmp.2019.100611

Koenker, R. (2005). Quantile regression. New York, NY: Cambridge University Press.

Koenker, R., & Bassett, G. (1978). Regression quantiles. Econometrica, 46(1), 33-50. https://doi.org/10.2307/1913643

Koenker, R., & Xiao, Z. (2004). Unit root quantile autoregression inference. Journal of the American Statistical Association, 99(467), 775-787. https://doi.org/10.1198/016214504000001114

Koirala, A., Joo, Y. J., Khatami, A., Chiu, C., & Britton, P. N. (2020). Vaccines for COVID-19: The current state of play. Paediatric Respiratory Reviews, 35, 43-49. https://doi.org/10.1016/j.prrv.2020.06.010

Kongoley-MIH, P. S. (2015). The impact of ebola on the tourism and hospitality industry in Sierra Leone. International Journal of Scientific and Research Publications, 5(12), 542550. https://doi.org/10.29322/ijsrp.11.09.2021.p11728

Lim, J., & Won, D. (2020). How Las Vegas’ tourism could survive an economic crisis? Cities, 100, 102643. https://doi.org/10.1016/j.cities.2020.102643

Liu, B., Kim, H., & Pennington-Gray, L. (2015). Responding to the bed bug crisis in social media. International Journal of Hospitality Management, 47, 76-84. https://doi.org/10.1016/j.ijhm.2015.03.005

McKercher, B., & Chon, K. (2004). The over-reaction to SARS and the collapse of Asian tourism. Annals of Tourism Research, 31(3), 716-719. https://doi.org/10.1016/s0160-7383(04)00028-3
Meo, M. S., & Abd Karim, M. Z. (2022). The role of green finance in reducing CO2 emissions: An empirical analysis. *Borsa Istanbul Review, 22*(1), 169-178. https://doi.org/10.1016/j.bir.2021.03.002

Meo, M. S., Chowdhury, M. A. F., Shaikh, G. M., Ali, M., & Masood Sheikh, S. (2018). Asymmetric impact of oil prices, exchange rate, and inflation on tourism demand in Pakistan: New evidence from nonlinear ARDL. *Asia Pacific Journal of Tourism Research, 23*(4), 408-422. https://doi.org/10.1080/10941665.2018.1445652

Merilina, F., & Domenico, v. (2018). *Quantile regression*. West Sussex, UK: John Wiley & Sons Ltd.

Mishra, S., Sharif, A., Khuntia, S., Meo, M. S., & Khan, S. A. R. (2019). Does oil prices impede islamic stock indices? Fresh insights from wavelet-based quantile-on-quantile approach. *Resources Policy, 62*, 292-304. https://doi.org/10.1016/j.resourpol.2019.04.005

Monterrubio, J. C. (2010). Short-term economic impacts of influenza A (H1N1) and government reaction on the Mexican tourism industry: an analysis of the media. *International Journal of Tourism Policy, 3*(1), 1-15.

Novelli, M., Burgess, L. G., Jones, A., & Ritchie, B. W. (2018). ‘No Ebola… still doomed’—The Ebola-induced tourism crisis. *Annals of Tourism Research, 70*, 76-87.

Nyarko, Y., Goldfrank, L., Ogedegbe, G., Soghoian, S., & de-Graft Aikins, A. (2015). Preparing for Ebola Virus Disease in West African countries not yet affected: perspectives from Ghanaian health professionals. *Globalization and health, 11*(1), 1-6.

Pal, D., & Mitra, S. K. (2017). Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. *Energy Economics, 62*, 230-239.

Po, W. C., & Huang, B. N. (2008). Tourism development and economic growth—a nonlinear approach. *Physica A: Statistical mechanics and its applications, 387*(22), 5535-5542.

Rahman, M. K., Gazi, M. A. I., Bhuiyan, M. A., & Rahaman, M. A. (2021). Effect of Covid-19 pandemic on tourist travel risk and management perceptions. *Plos One, 16*(9), e0256486. https://doi.org/10.1371/journal.pone.0256486

Raza, S. A., & Shah, N. (2017). Tourism growth and income inequality: Does kuznets curve hypothesis exist in top tourist arrival countries. *Asia Pacific Journal of Tourism Research, 22*(8), 874-884. https://doi.org/10.1080/10941665.2017.1343742

Raza, S. A., Sharif, A., Wong, W. K., & Karim, M. Z. A. (2017). Tourism development and environmental degradation in the United States: Evidence from wavelet-based analysis. *Current Issues in Tourism, 20*(16), 1768-1790. https://doi.org/10.1080/13683500.2016.1192587

Shahzad, S. J. H., Shahbaz, M., Ferrer, R., & Kumar, R. R. (2017). Tourism-led growth hypothesis in the top ten tourist destinations: New evidence using the quantile-on-
quantile approach. *Tourism Management, 60*, 223-232. https://doi.org/10.1016/j.tourman.2016.12.006

Sharif, A., Jammazi, R., Raza, S. A., & Shahzad, S. J. H. (2017). Electricity and growth nexus dynamics in Singapore: Fresh insights based on wavelet approach. *Energy Policy, 110*, 686-692. https://doi.org/10.1016/j.enpol.2017.07.029

Sharif, A., Meo, M. S., Chowdhury, M. A. F., & Sohag, K. (2021). Role of solar energy in reducing ecological footprints: An empirical analysis. *Journal of Cleaner Production, 292*, 126028. https://doi.org/10.1016/j.jclepro.2021.126028

Si, R., Lu, Q., & Aziz, N. (2021). Impact of COVID-19 on peoples’ willingness to consume wild animals: Empirical insights from China. *One Health, 12*, 100240. https://doi.org/10.1016/j.onehlt.2021.100240

Si, R., Yao, Y., Zhang, X., Lu, Q., & Aziz, N. (2021b). Investigating the links between vaccination against COVID-19 and public attitudes toward protective countermeasures: Implications for public health. *Frontiers in Public Health, 9*, 1040. https://doi.org/10.3389/fpubh.2021.702699

Sim, N., & Zhou, A. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking and Finance, 55*, 1-8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Singh, R., Das, D., Jana, R. K., & Tiwari, A. K. (2019). A wavelet analysis for exploring the relationship between economic policy uncertainty and tourist footfalls in the USA. *Current Issues in Tourism, 22*(15), 1789-1796. https://doi.org/10.1080/13683500.2018.1445204

Sinha, A., Balsalobre-Lorente, D., Zafar, M. W., & Saleem, M. M. (2022). Analyzing global inequality in access to energy: Developing policy framework by inequality decomposition. *Journal of Environmental Management, 304*, 114299. https://doi.org/10.1016/j.jenvman.2021.114299

Song, H., & Lin, S. (2010). Impacts of the financial and economic crisis on tourism in Asia. *Journal of Travel Research, 49*(1), 16-30. https://doi.org/10.1177/0047287509353190

UNCTAD (2020). *Impact of COVID-19 on tourism in small island developing states*. https://unctad.org/en/pages/newsdetails.aspx?OriginalVersionID=2341

Usman, M., & Balsalobre-Lorente, D. (2022). Environmental concern in the era of industrialization: Can financial development, renewable energy and natural resources alleviate some load? *Energy Policy, 162*, 112780. https://doi.org/10.1016/j.enpol.2022.112780

Wang, H., Khan, Y. A., Mouldi, A., Abou El Khier, B. S., & Guo, W. (2022). The impact of geopolitical and pandemic risks on tourist inflows: Evidence from Asia-Pacific region. *Frontiers in Environmental Science, 70*. https://doi.org/10.3389/fenvs.2022.850729

Webber, D., Buccellato, T., & White, S. (2010). The global recession and its impact on tourist spending in the UK. *Economic and Labour Market Review, 4*(8), 65-73. https://doi.org/10.1057/elmr.2010.114
World Health Organization (2020). *Coronavirus disease 2019 (COVID-19): Situation report* (p. 73).

Wu, T. P., & Wu, H. C. (2020). Causality between tourism and economic development: The case of China. *Tourism Analysis, 25*(4), 365-381. https://doi.org/10.3727/108354220x15758301241864

Yan, R., Liao, J., Yang, J., Sun, W., Nong, M., & Li, F. (2021). Multi-hour and multi-site air quality index forecasting in Beijing using CNN, LSTM, CNN-LSTM, and spatiotemporal clustering. *Expert Systems with Applications, 169*, 114513.

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. https://doi.org/10.1016/j.annals.2020.102913

Zaman, K., Shahbaz, M., Loganathan, N., & Raza, S. A. (2016). Tourism development, energy consumption and Environmental Kuznets Curve: Trivariate analysis in the panel of developed and developing countries. *Tourism Management, 54*, 275-283. https://doi.org/10.1016/j.tourman.2015.12.001

Zhu, S., Luo, Y., Aziz, N., Jamal, A., & Zhang, Q. (2021). *Environmental impact of the tourism industry in China: Analyses based on multiple environmental factors using novel quantile autoregressive distributed lag model* (pp. 1-27). Economic Research-Ekonomska Istraživanja.