

Article

Sustainable Determinants That Affect Tourist Arrival Forecasting

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Abstract: This study considers diversification effects and significant influences on tourist arrivals as a vital export direction. Different quantitative methods, namely a cointegrated-autoregressive model, panels, sentiment and sensitivity analysis, were used in this study. The time-series data for Croatia and Slovenia were isolated from several secondary sources. The variables examined in this approach are tourist arrivals, precipitations, sunny days, earthquakes, microbes and CO₂ emissions. The study results showed that there is a severe negative effect on tourist arrivals defined by viruses. Moreover, there is a significant decisive effect of weather conditions on tourist arrivals. Nevertheless, it is necessary to move past Covid-19 pandemic discussions to yield more accurate tourism supply forecasts, while demand is already somehow low since the beginning of 2020. The primary significance is to develop a broader thinking about the impacts of CO₂ emissions on the tourism escorted to official tourist websites.

Keywords: cointegration; Croatia; external factors; Slovenia; tourist arrivals; vector autoregressive model



Citation: Gricar, S.; Baldigara, T.; Šugar, V. Sustainable Determinants That Affect Tourist Arrival Forecasting. *Sustainability* **2021**, *13*, 9659. <https://doi.org/10.3390/su13179659>

Academic Editors: Paula Remoaldo, José Cadima Ribeiro and Juliana Araújo Alves

Received: 19 July 2021

Accepted: 21 August 2021

Published: 27 August 2021

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1. Introduction

The importance of tourism in small, open economies has been widely studied. It is vital to add environmental aspects to influence tourism demand and supply, confirming tourist arrivals. Tourism on the Adriatic coast has a long tradition. Moreover, in Croatia and Slovenia, the two central European tourist destinations, it is given special treatment by the government and the residents. Undoubtedly, these two countries are among the major players in European Union (EU) tourism, accounting for 6.63% of international tourist arrivals in 2019. To better understand the idea of our research, it should be noted that tourist arrivals in Croatia and Slovenia account for one-fifth of all tourist arrivals in Central Europe and the Baltics [1]. Finally, the majority of the internal tourism is not yet sustainable, and, undoubtedly, tourist seeks nice weather.

Since late 2019, tourism has experienced a crisis [2], and the vast majority of researchers [3] have been concerned with the idea of what tourism will look like after the Covid-19 pandemic [4]. It is foreseeable that the solipsism of everyday impact on the environment will be crucial for future tourism demand and, more importantly, for the supply [5]. The changes cannot be overlooked, and researching them is essential. This study examines secondary data on tourism and the environment, including microbes, following the idea of Gricar [6], who predicted the decline in tourist arrivals beforehand. On the other hand, microbes could have a significant positive effect on tourist arrivals. While some authors [7] are very sceptical that such a reset or transformation is likely as we emerge from the pandemic, others are indeed more optimistic, as shown by a literature review collage [8]. What is of great importance is that the thought, analysis and imagining

of the possibilities do occur. Sustainability, justice and fairness are not easy to give; they must be fought for and won [9].

Therefore, this is the first research that looks at the mixed type of pandemic and environmental variables to investigate the impact on tourist arrivals for a country or a pair of neighbouring countries. It is worth mentioning that this research does not address the effect of tourism on the environment, but vice-versa. The effect of the ecosystem (biotopes and biocenosis) [10–12] on tourist arrivals is essential for a sustainable tourism growth. Tourism strategies based on past models, like the three S model (sand, sun and sea), gastro tourism [13] or heritage, should be withdrawn to understand better the future dimensions of shocks, habitats and habits [14]. First, regarding the overwhelming surprises, strategic planning is crucial. Management planning should include, for example, three large global earthquakes that are likely to happen simultaneously in 2021, as reported by the authors [15]. After that, there are ongoing climate changes [16], economic threats on human neurocognitive processes [17], other economic threats [18], epidemics [19], wars connected to the post-9/11 era [20] and other threats that could be revealed by the data [21].

Second, the tourists should respect and understand natural habitats in order not to experience inconveniences or life-threatening agents such as mosquitoes [22], microbes [23] and other natural threats [24]. Finally, the pattern of tourism supply should dramatically change to reflect the new dimensions in advertising [25] and offer systems for a sustainable demand routine [26]. Overall, the economic crisis that began in 2008 [27] and the pandemic that started in 2020 have reduced supply and demand [28]. The destination management should be sustainable and not just aim to meet the tourists' needs [29]. In a nutshell, the extension of the nature shocks should be emphasised when planning tourism extensions, development and new perspectives. Economic forecasting should take into consideration all crucial variables in order to be as accurate as possible [30]. Therefore, the purpose of this paper concerns the issues of an unexpected rise in infections and diseases impacted by urbanisation (cars and concrete) and climate change [31] for sustainable tourism development.

In spite of all the mentioned shocks, tourism could be sustainable in the future [32], as services are of great importance in contemporary life and contribute to human well-being [33]. Moreover, the 17 Sustainable Development Goals (SDGs) were adopted by the United Nations in 2015 as a universal call to action to end poverty, protect the planet and ensure that by 2030 all people enjoy peace and prosperity [34]. Some forms of tourism associated with the SDGs, such as low-carbon tourism [34–36], nomadic tourism [37–39], individual tourism with discrete individual tourist systems [40] and sustainable tourism [41,42], are used as independent variables in this study, while tourist arrivals are the dependent variable [43]. In analysing Croatian and Slovenian [43] tourism further development in the long run [44–46], the imperishable employees, as well as the tourism science competencies and the everlasting tourist should be considered as key elements where a shock [47] or an interruption of rain [48] or a crisis [49] should not be crucial development issues.

If things change in Croatia and Slovenia, the non-seasonality of tourist arrivals [50] will bring higher revenues [51], higher expenses, lower seasonal waves and a sustainable approach to the domestic market [52–54].

Following the above statement and an extensive and exhaustive literature review [55–62], in which only one study [63] developing the objective of an increased sustained influence of sustained determinants [64] on post-pandemic tourism was found [65–67], the state-of-the-art hypothesis was developed. It also includes an outstanding methodological significance: a sustainable human management of the climate and ecosystems would significantly increase tourist arrivals in Croatia and Slovenia and reduce seasonal volatilities. Several subordinate-mentioned independent variables are determined to investigate the new normal [68,69].

Thus, the goal of this manuscript is twofold. First, to provide an overview of the empirical literature on the direction of tourism vs sustainability research. Second, to highlight the growing general trends in the field of tourism sustainability. In addition, it is of great importance to investigate their impact on tourists' decision-making when choosing their

destination and to highlight future trends. The researchers will evaluate at least 100 recent manuscripts published in reputed journals and publications of renowned public institutions.

On the other hand, the second goal provides multiple aims to test the hypothesis of the paper. Therefore, the first objective focuses on the variables researchers will include to determine the potential increase in tourism after the pandemic. The second objective identifies the increasing demand for differentiated tourism, including environmental and ecosystem variables. Croatia and Slovenia receive the majority of tourists from the closest north and west countries as leisure tourism: social, family and nature tourism, but also a growing trend of culinary, eco- and agro-tourism. Finally, this is the opportunity to investigate how weather conditions might influence this tourism trend in the two countries. Per the objectives, the quantitative time series method is used.

The arrival of individual tourists is one of the emerging phenomena in the tourism community. At the same time, agencies failed their clients during the Covid-19 pandemic, since large groups of tourists are undesirable because of the mandatory social distancing. All parameters of the pandemic will continue until the deep end of the current pandemic, in 2021/2023 [70,71], unless another pandemic occurs or continues until then [72]. Therefore, the statistical data should be collected so that the tourist arrivals are differentiated as individual or group visits, which is not the case now. Or, even better, by their arrival status, e.g., whether they arrived independently or in a group and whether a group was organised by a third party [73,74]. It is of enormous importance to have such data to study the effects and the relationships between variables. Tourist arrivals are a well-researched area in tourism science, but the vast majority of researchers consider these data as economic impacts and vice versa [75]; thus, the research topic of external and sustainable environmental threats on tourist arrivals is of great importance [76]. Overall, research PDQ (directly) refers to the tourist arrivals to better understand the obstacles that affect seasonality and sustainability [77].

Precipitation in millimetres of rainfall is the second factor researched and measured and the first independent variable in a collage of determinants affecting tourist arrivals as a dependent variable. A limited number of studies have been conducted considering this parameter. Perhaps the most prominent one was recently published for the mountainous regions of South Asia [78], where the authors identify a unidirectional causality from precipitation to tourist arrivals. The cornerstone is the result of [79], which shows that the amount of precipitation represented by rainfall negatively affects tourist arrivals in both the short and long term. Overall, meteorological variables are used to predict tourist arrivals in different destinations and regions, such as the Balearic Islands [80], the Pacific [81], the Philippines [82], Italy [83], Zanzibar and Tanzania [84].

The third independent variable—identified as a factor for potentially shaken tourist arrivals in the future, not scientifically researched enough and combined with tourist arrivals—refers to earthquakes. For Croatia, after several devastating earthquakes and judging some previous results [85,86], extending the season [87] in terms of dark tourism [88] is a real possibility. At the same time, the authors found the “fortune cookie” effect when the growth of total inbound tourist arrivals to Sichuan and Nepal after earthquakes increased. It is worth noting that the catastrophic earthquakes [89] in Croatia, starting with the one in Zagreb in early 2020 [90], just as the pandemic began [91], as well as several others in the country [92], could be significant tourist attractions [93,94] in terms of dark tourism.

The number of sunny days is an important aspect that determines tourism demand [95] and the imbalance between supply and seasonality [96], which is widely recognised [97]. However, few researchers are investigating this phenomenon as an independent variable in time series data science [98]. An earlier study found that sunny days differentiate between tourist segments to an increased number of tourist arrivals [99,100]. Therefore, Croatia and Slovenia may recognise the extension of their season from cloudy weather with less sunshine in late spring and early autumn [101]. Overall, the issue of whether sunny days

are an essential variable in increasing tourist arrivals or determining seasonality [102] is debated when examining the results of this contemporary research.

Before the last independent factor, there are “microbes” that have been publicly described *ex post*, but which were less likely *ex ante*, before the Covid-19 pandemic. As a consequence of increased tourist arrivals in certain mountain regions, the secondary bacterial infections were reported [103]. Nonetheless, it is crucial to widely determine microbe threats for the tourism industry, like HIV or a brand new germ [104,105].

The last studied phenomenon that serves tourist arrivals is the idea of zero-emissions of carbon dioxide (CO₂). Contemporary tourists already choose green destinations over the smoggy ones [106,107]. Therefore, the idea is to study the opposite data, where tourist arrivals are a dependent variable instead of previous research where tourist arrivals were treated as an independent variable [108]. Overall, this variable escalated as a calculated bump in this research, while trending researchers found determinants, i.e., island travel, crisis or commuting, affecting carbon footprint [109–111]. In the EU 2030 climate and energy strategy, there are three main objectives: (1) to reduce greenhouse gas emissions by 40% (compared to 1990), (2) to increase the share of renewable energy by 32% and (3) to improve energy efficiency by 32.5%, which counts towards the overall 40% emissions reduction target [112].

The remainder of the paper is organised as follows. The following section presents the methodology and data used in the study. In the third section, the main empirical results and findings are explained. Finally, after the discussion regarding the research objectives and the hypothesis development, the most significant conclusions are provided.

2. Materials and Methods

A systematic review of previous empirical and theoretical studies has revealed that most studies have been conducted for Asian countries, where the world’s urbanisation burden is the highest. Nevertheless, precipitation and sunny days seem essential for European countries, the sparsely populated Alps and the Mediterranean region. Based on an extensive literature review, the paper discusses the methodological challenges in exploring the influence of ecosystem changes on destination choice. The researchers examined more than 100 published articles, looking for a keyword that indirectly relates to the present study. In terms of the econometric analysis, simple summary statistics is a primary method to obtain the initial information of the observed data and present the indexed results of the levels.

Given the hypothesis, the data vector in (1):

$$\Delta^{\text{HR, SI}}[\text{ARR} \cdot \text{RAI} \cdot \text{QUA} \cdot \text{SUN} \cdot \text{MIC} \cdot \text{CO}_2]_{t-1}, \quad (1)$$

provides the variables on short notice. Data were collected from secondary sources provided by national offices and other eminent national [113,114] and international institutions [115,116], as presented in Table 1. The abbreviation HR stands for Croatia and SI for Slovenia. It is crucial to produce a credible study using modern econometric tools. Therefore, the data origin and availability is presented in Table 1. The period studied in this research refers to daily, monthly or yearly sequences [117].

Table 1. The data source of the variables used in the econometric research.

Variable	Abbreviation	Source	Availability
Tourist Arrivals	ARR	Eurostat [118]	December 1999–March 2021
Precipitation	RAI	WBG [119]	January 1991–June 2021
Earthquakes	QUA	USGS [120]	December 1999–June 2021
Cloudiness	SUN	WMO [121]	January 1901–December 2018(9)
Cloudiness	SUN	CMHS [122]	January 2011–June 2021
Microbes'	MIC	ECDC [123]	January 2014–December 2019
Microbes'	MIC	NIPH [124]	January 2008–December 2019
Carbon dioxide	CO ₂	GML [125] ¹	March 1993–December 2019

Source: Different organisations. Source location: ¹—at Hegyhatsal, Hungary (HUN).

Looking at the cross-section of all available data, the final decision on a data range is from December 1999 to March 2021. In contrast, some information about the selected variables is presented below in (2), and the main data vector is:

$$\Delta^{[HR, SI]}[ARR \cdot RAI \cdot QUA \cdot SUN]^{HUN}[CO_2]_{t-1}; t = 1, 2, \dots, T; T = 256; T = 1999M12, 2000M01, \dots, 2021M03, \quad (2)$$

based on obtained, isolated or calculated monthly data. The abbreviation HUN stands for Hungary, and T is the number of observations for time t.

The supported data vector contains MIC, but the period is shortened due to the lack of data for MIC. Therefore, the supported data vector, which is analysed in the separate section, is in (3):

$$\Delta^{[HR, SI]}[ARR \cdot RAI \cdot QUA \cdot SUN \cdot MIC_{(VIR \cdot BAC)}]^{HUN}[CO_2]_{t-1}; t = 1, 2, \dots, T; T = 72; T = 2014M01, 2014M02, \dots, 2019M12; n = 1, 2 \quad (3)$$

where the abbreviation VIR stands for viruses and BAC for bacteria.

Consistency across variables is one of the advantages of a multivariate data set, which provides the ability to present, at a point in space and time, a set of variable values that are (to some degree) internally consistent. Such a step explains much of the variable production design: the ecosystem variable ARR is a dependent variable examined so it can identify the future benefits and weaknesses that determine tourism demand (pull effect). For zero ARR in Slovenia in April 2020 (Covid-19 lockdown), the missing value is replaced by the number 1.

By contrast, the independent ecosystem variables MIC and the environmental variables RAI, QUA, SUN and CO₂ have the same effect as tourism supply (push effect). The predictable result should be significant and is explained in the Results and Discussion section, while the previous empirical literature recognises singular influences. However, conducting an additional homogenisation of the dataset would be complicated due to elements such as published data. Low data coverage in some regions or for some variables is a limitation to applying neighbourhood-based homogeneity tests where some degree of homogenisation has been implemented. The multivariate nature means that homogeneities identified in mean MIC data are, for example, likely to affect other variables. Details on the source of the specified variables and homogeneity are provided in the following six paragraphs.

Eurostat and national statistical offices from a monthly dataset as a value of domestic and foreign tourists isolate the data for the variable ARR in a defined month. The values of zero events are logically numbered as 1.

The World Bank Group (WBG) Climate Change Knowledge Portal collects the data for the variable RAI on a monthly average of millimetres for the specified country.

The data for the variable QUA is obtained on individual cases from the U.S. Geological Survey (USGS) and calculated on a monthly number of observations. The months without a case of the earthquake have a value of 0.1.

SUN is used from the average monthly cloud cover factor [126]. By contrast, the World Meteorological Organization (WMO) catalogue for Climate Data covers the entire study period for Slovenia. For Croatia, the data availability is until December 2018. The missing observations from January 2019 to March 2021 are collected from the Croatian Meteorological and Hydrological Service (CMHS) using the equation specified in (4):

$$1 - (x/(y \cdot d)), \quad (4)$$

where 1 is the inverse function of a solar day, x is the cumulative hours of full sun per month, y is the maximum sun per day, and d is the number of days in the month, February having the matter of average days equal to 28.25. Overall, the data are for the Slovenian capital, Ljubljana, and for Croatia's second-largest city, Split. The choice of cities (location/destination) was made based on tourist preferences, where the Adriatic coast (Croatia) and the capital (Slovenia) are among the most popular destinations in the world.

The data for the variable MIC is obtained from two different sources: the National Institute for Public Health of the Republic of Slovenia (NIPH), which provides monthly data for Slovenia, and the European Centre for Disease Prevention and Control (ECDC), for Croatia. The annual data for Croatia are averaged per month without factor weighting. The MIC will be generally excluded from the analysis while data coverage is short. The possible significant impact will be studied and considered separately.

CO₂, an all-too-human foible, is isolated in the monthly data set from GML, whose nearest reported monitoring site is in Hungary. The observatory is located on the border between Croatia and Slovenia, making it the closest observatory to provide accurate monthly data on CO₂ [127]. The data are credible, while the differences in volatility (not the amount per million (ppm) tones in the values) are similarly unsettled as those worldwide.

Croatian CO₂ emissions from significant point sources amount to about five ppm per year. The conservative estimate for storage capacity in aquifers and hydrocarbon fields is three ppm CO₂. In this respect, Croatia's storage capacity far exceeds its CO₂ emissions, compared to the total emissions from primary point sources, with conservative estimates of storage capacity of 580 years. The storage capacity estimates are based on storage efficiency factors, surface area, thickness, porosity, etc. Depending on the ranges of calculation parameters used, the lowest and highest values are obtained. The conservative estimate for aquifer storage capacity for Slovenia is 92 ppm CO₂, while the optimistic value is above 500 ppm. Slovenian CO₂ emissions from significant point sources are about 7 ppm per year, and, therefore, the available Slovenian storage capacity is sufficient to store all CO₂ [128].

The Global Monitoring Laboratory (GML) reported some details about the countries under study (Figure 1). The Republic of Croatia (Figure 1a) (HR) is one of the countries within the Adriatic-Mediterranean and Pannonian-Danube regions in Central Europe. Croatia is very sensitive to the impacts of climate change (oceanic temperature climate (spring bud (green) colour)) and sub-polar oceanic climate (dark pastel green colour), as shown in Figure 1a).

The Republic of Slovenia (SI) is located in Central Europe (Figure 1b), and the length of the coast is slightly less than 50 km. The climate in Slovenia is exceptionally diverse. It ranges from oceanic temperature climate (spring bud (green) colour) to sub-polar oceanic climate (dark pastel green) and warm-summer humid continental climate (middle sky blue colour) Figure 1b. Additionally, it has a wide range of local climatic conditions, while tourism counts for around 5% of GDP.

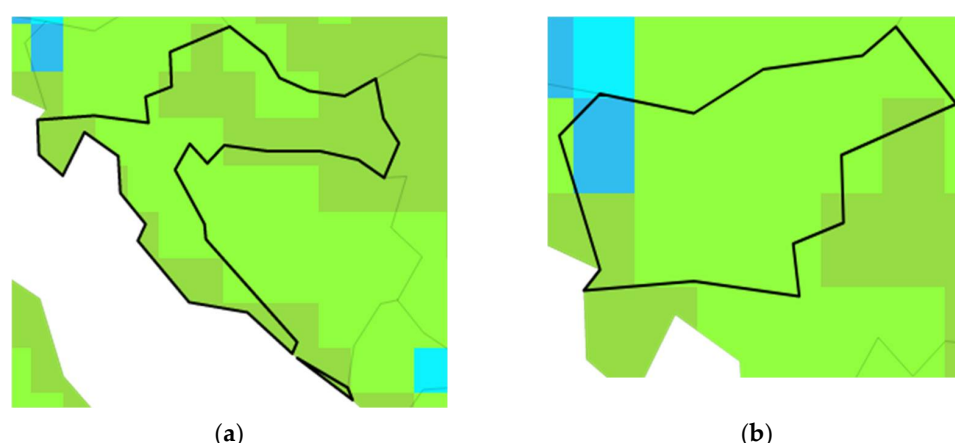


Figure 1. Köppen–Geiger Climate Classification, 1991–2020 (a) Croatia; (b) Slovenia.

The motivation for this research arose from the attempt to develop a combined vector autoregressive model (CVAR) and a panel discussion on tourism. While the United Nations World Tourist Organisation (UNWTO) has predicted the increase in tourist arrivals without interruption, but in seasonal time-series, this is a misleading idea [129]. Therefore, the sensitivity analysis will give additional input to check the robustness of the results. Finally, other variables that determine tourist arrivals, such as environmental and ecosystem, besides the obsolete microbes, will be included in the study (Table 1) for Croatia and Slovenia. Overall, the study aims to broaden the European discussion on zero emissions in tourism. At the same time, it is crucial to verify the meaning of the information behind the figures collected by different organisations. Nevertheless, this study has a significant added value, while the embedded sentiment analysis represents a significant scientific contribution to the tourism science. Due to the lack of similar studies, a separate subsection will focus on the meaning of the relevant information on the global supplier's website.

It is essential to show that past events generate future trends. Hence, CVAR econometrics is an integral part of the scientific approach to become familiar with the dispersion of data. The importance of tourism to the national economy is enormous, and policy-makers are recognised as relevant tourism industry partners. Therefore, the current research presents some aspects for further development on sustainable determinants affecting seasonality, accompanied by VAR, to identify the recent shocks that could explain the future downturn in tourism. The CVAR model is a recognised method that allows us to discover sameness in secondary quantitative time-series data. It is an econometric tool used to explore ideas that are hidden but predictable. Overall, before the sensitive and sentiment analyses, the proposal of secondary data collection and its calculation are supported by the VAR model [130].

The learning process can be based on the manual or automatic feeding of the knowledge base by developers based on user logs. Social media content is becoming increasingly essential to identify emerging trends. In this scenario, sentiment analysis has been adopted to study emotions and analyse reviews and ratings [131–133].

Sentiment analysis became popular during the pandemic while the information on tourist websites regarding actual data was not accurate and up to date [134]. Applied sentiment analysis on Twitter has measured customers' perceptions about their hospitality experience. Facebook has also been used as a source to analyse users' comments on the hospitality industry. It is compared to a machine-learning and a lexicon-based analysis method to sentiment analysis, discovering that their results are comparable and thus indicating the easiness of using sentiment analysis compared to other methods. Moreover, the simplicity in moods classification—positive, negative or neutral—suggests that sentiment analysis results should always be joined to different approaches. Anyway, the information obtained thanks to this approach provides excellent support in decision-making when defining new or reactive (to unpredicted events) strategies.

3. Results

Plotting the data at this stage is crucial in dealing with secondary data, while precluding the obstacles to the regime is a necessary econometric step in dealing with normality. The data obtained in the levels were:

- First, transferred to the Excel spreadsheet;
- Calculated, to monthly observations;
- Chained indexed (CI) in (5);

$$1. CI = X_t / X_{t-1} \cdot 100, \quad (5)$$

where X_t is the present month, X_{t-1} is the previous month;

- Indexed (I) to a constant base in (6),

$$2. I = CI_t \cdot I_{t-1} / 100, \quad (6)$$

where I for 1999 is 100 (1999 = 100) and I_{t-1} is a past index with a constant base;

Finally, the data were logarithmised and differentiated.

3.1. Familiarisation with the Data—Data Plotting in Logarithms

The need for the dispersion of data is well known in time series. Therefore the results of this step show that the obstacles are predominant in Slovenian tourism, while Croatian tourism has fewer shocks (Figure 2a). The most obvious one is the outbreak of the Covid-19 pandemic; therefore, treating these results pushes the researchers to obtain dummy variables in the other processes. On the other hand, the precipitation in Slovenia and Croatia has similar patterns (Figure 2b).

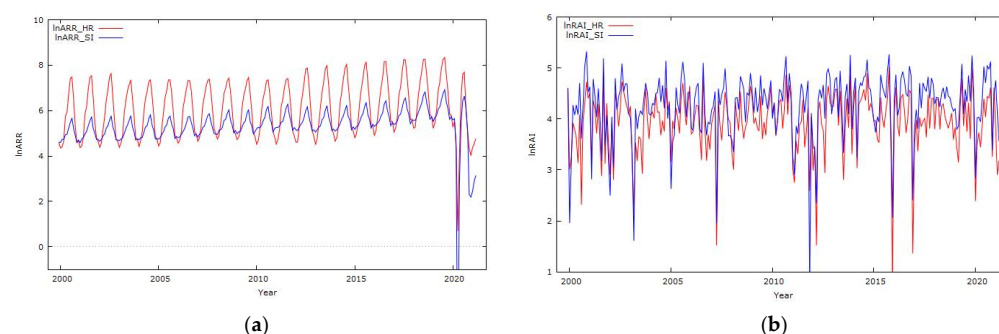


Figure 2. Spatial analysis in logarithms (ln): (a) tourist arrivals (ARR); (b) precipitation (RAI). Note: The abbreviations of variables are presented in Table 1. Source: Table 1 and data vector; authors calculations.

The following spatial differences are related to the fact that fear is maintained during natural disasters and calamities. For example, Figure 3a shows that many earthquakes occurred at the beginning of the century. By contrast, the scarcity stops with the increase of events in this decade. The economic depression of 2007/2008 did not affect these types of disasters, while economic growth may have prevented the new wave of disasters that began with the Covid-19 pandemic. However, this is a hypothetical question rather than a stable result based on Figure 3a. In contrast, Figure 3b shows that CO₂ emissions increased throughout the period.

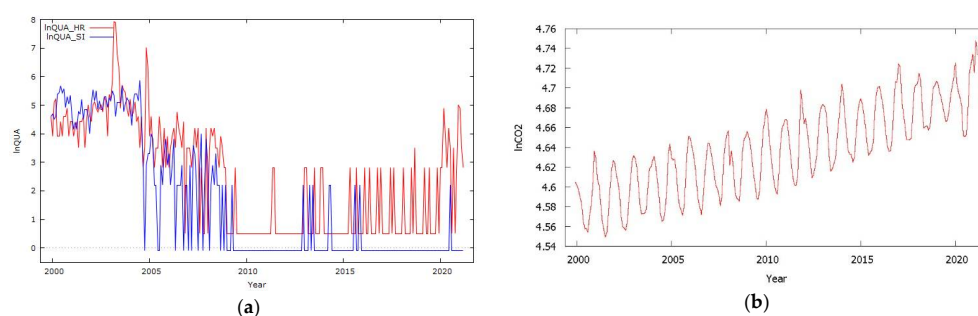


Figure 3. Spatial analysis in logarithms (ln): (a) earthquakes (QUA); (b) carbon dioxide (CO₂). Note: The abbreviations of variables are presented in Table 1. Source: Table 1 and data vector; authors calculations.

Based on the graphical design of the data in the logs, the next step in the initial analysis is to review the summary statistics. Overall, cloud cover was not represented by spatial differences in the figures, but it has an opposite effect as precipitation.

3.1.1. Data Overview

When introducing summary statistics in Table 2, the results confirm the figures, on the one hand, and add information indicating that all variables should be treated in differences; on the other hand, the normality distribution is based on skewness (standard value around 0), and kurtosis (expected value around 3) is exceeded.

Table 2. Summary statistics, using the observations 1999:12–2021:03, December 1999 = 100.

Variable	Mean	Median	Minimum	Maximum	Skewness	Ex. kurtosis	Std. Dev.
ARR_HR	780.24	399.89	1.98	4168.20	1.77	3.00	873.88
ARR_SI	252.13	212.29	0.0009	1007.40	1.83	4.70	152.38
RAI_HR	58.79	54.89	2.601	152.31	0.55	0.33	28.02
RAI_SI	82.97	81.81	2.2753	204.99	0.48	0.19	39.709
QUA_HR	71.07	16.67	1.67	2766.70	8.68	82.75	260.24
QUA_SI	40.13	0.91	0.91	354.55	1.92	2.80	72.42
SUN_HR	80.59	81.10	21.28	138.30	−0.21	−0.60	24.83
SUN_SI	76.61	76.60	38.31	116.42	0.08	−0.64	17.11
CO2_HUN	103.35	103.10	94.60	115.31	0.19	−0.66	4.52

Note: The abbreviations of variables are presented in Table 1. Source: Table 1 and data vector; authors calculations.

The highest volatility is in ARR and QUA for Croatia; by contrast, the lowest deviation is in CO₂ (Table 2). Similarly to Croatia and Slovenia, ARR and QUA are responsible for most of the differences in the data.

3.1.2. Data Plotting in First Differences

To get the most out of the data, plotting in first differences is essential. Plotting allows us to conclude that volatility and seasonality are prevalent in Croatian tourism, while Slovenian tourism shows a more stable volatility in tourism demand (Figure 4a). This step is vital to see the data distribution, while it is much easier to see obstacles in the first differences than in the levels. On the other hand, precipitation is less stable in Slovenia than in Croatia (Figure 4b).

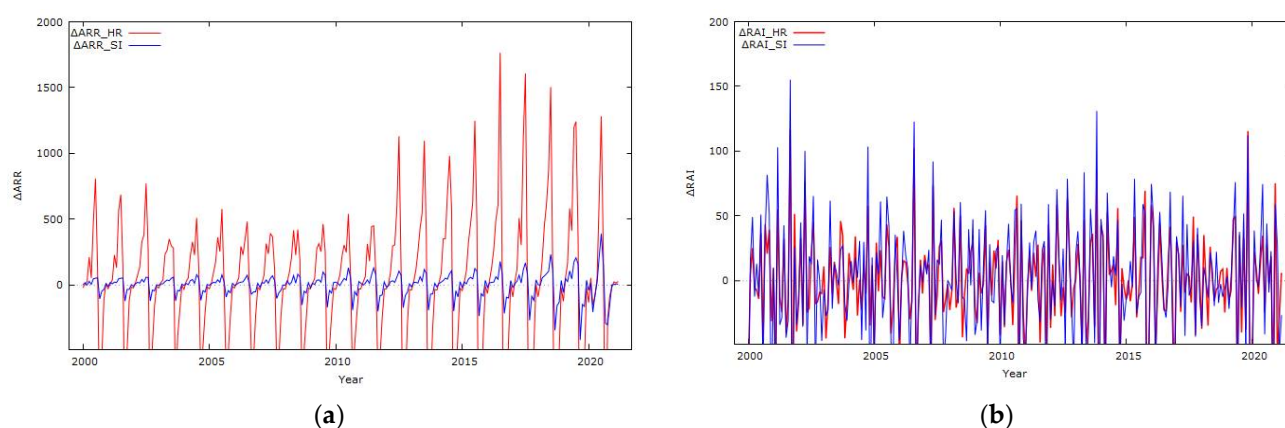


Figure 4. Spatial analysis in the first differences: (a) tourist arrivals; (b) precipitation. Note: The abbreviations of variables are presented in Table 1. Source: Table 1 and data vector; authors calculations.

Overlaying the images in Figure 5, one might conclude that there are new waves of disasters. At the beginning of the century, there were severe earthquakes in Croatia and Slovenia; on the other hand, carbon dioxide volatility was higher than in the economic expansion from 2016 to 2020. Overall, carbon dioxide volatility decreases again with crises, the Covid-19 pandemic and severe earthquakes in Croatia, starting with the one in Zagreb in March 2020. Seismicity is a hypothetical issue rather than a stable result based on Figure 5a. Nevertheless, Figure 5b confirms this statement. At the same time, in the sound economic period, when there were less earthquakes, the volatility of CO₂ emissions was higher than in the period with higher ppm amounts. Therefore, we can conclude that these two natural objects are diametrical.

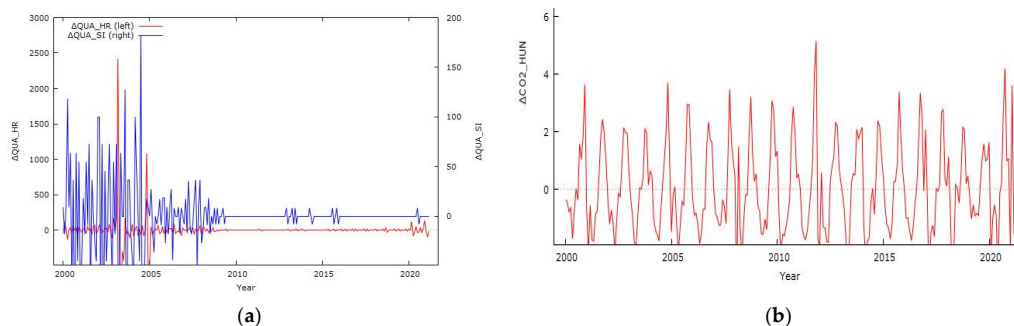


Figure 5. Spatial analysis in the first differences: (a) Earthquakes; (b) Carbon dioxide. Note: The abbreviations of variables are presented in Table 1. Source: Table 1 and data vector; authors calculations.

Based on the graphical designing of the data in differences, the next step of the initial analysis is run to check the autocorrelation. Additionally, the heteroskedasticity and normality of the variables in a VAR model is the primary treatment. Overall, the cloudiness of spatial differences was not presented in the figures while it has an opposite conclusion, like precipitation.

3.2. Results of VAR

The VAR model is a widely used method with several significant results, that could provide credible results. The calculation from the data suggests dummy variables. If one plot all the time series (Figure 6), the most obvious ones are April 2020 and May 2020 for ARR in Slovenia, so this is a transitory blip dummy $D_{tr,t} = [0,0,0,1,-1,0,0,0]$. The added form means that ARR was removed for one month and gradually restored in the next month.

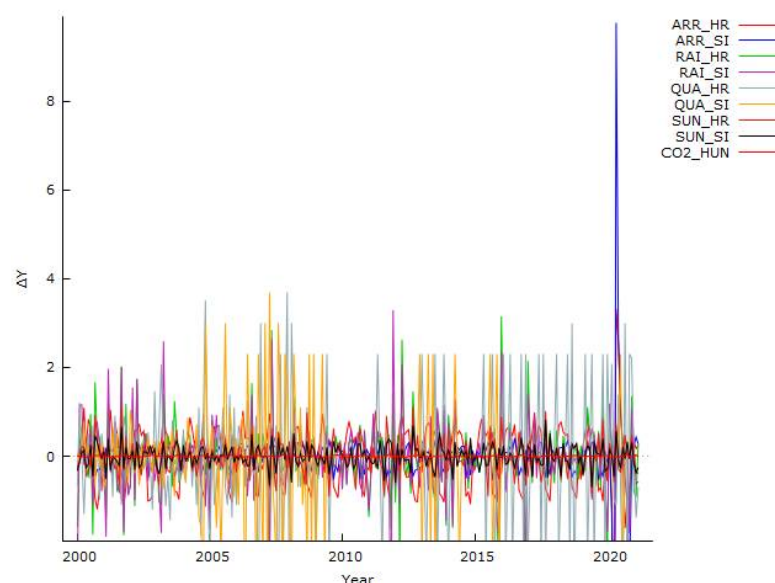


Figure 6. Illustrating a mean shift. Note: The abbreviations of variables are presented in Table 1. Source: Table 1 and data vector; authors calculations.

The estimated residual covariance matrix is shown in Table 3, where the most significant coefficients are the spatial dimensions and the correlation with carbon dioxide. Therefore, further analysis is essential, while for time series, the coefficient should be as low as possible to obtain normally distributed residuals. Therefore, several other seasonal, permanent, shift or transitory dummies are needed. At the same time, the additional performance of the misspecification test shows that only the weather variables have no ARCH effect, and the residuals are more normally distributed, accompanied by carbon dioxide. Therefore, such a model has four cointegration relations based on the Johansen trace test.

Table 3. Correlation matrix.

ARR_HR	ARR_SI	RAI_HR	RAI_SI	QUA_HR	QUA_SI	SUN_HR	SUN_SI	CO ₂	
1.0000	0.6665	−0.0088	0.0959	−0.0134	0.0520	−0.3047	−0.2300	−0.7028	ARR_HR
	1.0000	0.0154	0.0482	−0.0172	0.0137	−0.0012	0.0480	−0.1907	ARR_SI
		1.0000	0.8888	−0.0522	−0.0267	0.6390	0.6248	−0.0007	RAI_HR
			1.0000	−0.0268	−0.0647	0.4891	0.4971	−0.1451	RAI_SI
				1.0000	0.0009	−0.0456	−0.0661	−0.0277	QUA_HR
					1.0000	0.0204	−0.0079	0.0117	QUA_SI
						1.0000	0.7499	0.3136	SUN_HR
							1.0000	0.3446	SUN_SI
								1.0000	CO ₂

Note: The abbreviations of variables are presented in Table 1.

The model's misspecification tests (Table 4) rejected the null of residual normality and no autocorrelation for some variables. Moreover, the cross-correlogram showed significant correlations between the errors, which are assumed to be independent. Thus, the first set of diagnostic tests showed a clear violation of the accepted distributional assumptions. Therefore, the assumed probability model is not correctly specified; the reported statistical inference is not Maximum Likelihood, and the *p*-values calculated from standard normal distributions may be completely unreliable. The misspecification test of homoscedasticity and the normality test, accompanied by the Dickey–Fuller (ADF) test of autocorrelation, in Table 4, for each variable, separately show that the inventory variables are needed. In the right part of Table 4, the indices' distribution is conducted to understand the data's characteristics better. At the same time, we checked whether the distribution of the index in terms of height resembles a normal distribution.

Table 4. Misspecification tests and VAR.

Variable	ADF Test (Δ)	ARCH LM Test	Dummies	Jarque–Bera Test	Decision
ARR_HR	−5.52 *** I(1)	74.99 ***	$D_{tr,t}$	2.04 (−0.20; 3.20)	lnARR_HR
ARR_SI	−3.28 ** I(0)	177.17 ***	Trend, constant, $D_{tr,t}$	205.43 (−0.85; 7.06)	Δ ARR_SI
RAI_HR	−14.67 *** I(0)	6.41	Constant	3.31 (−0.08; 3.53)	Δ RAI_HR
RAI_SI	−8.08 *** I(0)	25.89 *	Constant	6.72 ** (−0.26; 3.60)	Δ RAI_SI
QUA_HR	−3.88 *** I(0)	102.86 ***	/	1.14 (−0.16; 3.12)	ln S_t QUA_HR
QUA_SI	−5.89 *** I(1)	88.84 ***	/	38.65 *** (0.86; 2.12)	lnQUA_SI
SUN_HR	−3.66 *** I(0)	38.25 ***	Constant	2.42 (0.13; 2.60)	Δ SUN_HR
SUN_SI	−4.74 *** I(0)	21.28 **	Constant	0.16 (−0.04; 2.92)	Δ SUN_SI
CO2_HUN	−4.49 *** I(1)	206.97 ***	/	5.81 ** (−0.10; 2.29)	lnCO2_HUN

Note: The abbreviations of variables are presented in Table 1; $D_{tr,t}$ —transitory dummy for the Slovenian hotels closed between April 2020 and May 2020; data in brackets—(skewness; kurtosis); ln—logarithm; Δ —one difference level; S_t —seasonally adjusted; *** significant at 1%; ** significant at 5%; * significant at 10%.

ARCH LM test for heteroskedasticity uses integration data based on the statistics of the ADF test. Since it is known that the singular ADF test is not sufficient, the supported tests were performed, along with the well-known Jarque–Bera test for the goodness-of-fit. Based on the skewness and kurtosis of the distribution of the variables and depending on the height, it is a sizeable non-symmetric distribution in most cases. Nevertheless, depending on the econometric model in 2 and based on the results of the misspecification test, the last column in Table 4 presents the decision whether to use the variable in the VAR model. The VAR model is constructed as follows. The Croatian ARR has a logarithm and a transitory dummy (0, −1, 1, 0) for April 2020 (−1) and (+1) for May 2020. This variable has only the residuals normally distributed (skewness is −0.20 and kurtosis is 3.20). On the other hand, there may be some seasonal heteroskedasticity. The decision for other variables is as follows:

- Croatian ARR is near I(0) with a transitory dummy (0, −1, 0, 0) for April 2020 (−1) and (+1) for May 2020;
- Slovenian ARR is near I(1) with a transitory dummy (0, −1, 1, 1, 1, 0) for April 2020 (−1) and (+1) for May 2020 to August 2020;
- Croatian precipitation is near I(1);
- Slovenian precipitation is near I(1);
- Croatian earthquakes variable is seasonally adjusted and has a logarithm;
- Slovenian earthquakes variable has a logarithm;
- Croatian cloud cover variable is near I(1);
- Slovenian cloud cover variable is near I(1);
- The carbon dioxide variable has a logarithm.

The VAR analysis, presented in Equation (7), assumes the following information. First, tourism demand in Croatia is significantly negatively affected by carbon dioxide (the coefficient value is −16.606) and cloudiness (the coefficient value is −0.005) in the first lagged term. On the other hand, in the second lagged term, where the lags VAR (2) were chosen based on the Schwartz Criterion, the results adjust the threat of carbon dioxide, while the effect is positive due to the coefficient value of 17.011. Moreover, cloudiness in Slovenia additionally changes tourist demand in Croatia by a weight of −0.007. Overall, Croatian tourism could extend the season through strategic decisions on carbon dioxide specifications, while all other factors are statistically insignificant.

$$\begin{bmatrix} \ln ARR_{HR_t} \\ \Delta ARR_{SI_t} \\ \ln CO2_{HUN_t} \\ \ln StQUA_{HR_t} \\ \ln QUA_{SI_t} \\ \Delta RAI_{HR_t} \\ \Delta RAI_{SI_t} \\ \Delta SUN_{HR_t} \\ \Delta SUN_{SI_t} \end{bmatrix} = \begin{bmatrix} 0.86 & 0.00 & -16.61 & -0.02 & -0.01 & 0.00 & 0.00 & -0.01 & -0.00 \\ 30.91 & 0.08 & -1011.7 & -2.12 & -3.62 & 1.02 & -0.54 & -0.94 & 0.84 \\ -0.00 & -0.00 & 1.24 & 0.00 & -0.00 & -0.00 & 0.00 & 0.00 & -0.00 \\ 0.12 & 0.08 & -11.9 & 0.27 & -0.01 & 0.00 & -0.00 & 0.01 & -0.02 \\ -0.16 & 0.00 & -2.13 & 0.00 & 0.49 & 0.00 & 0.00 & -0.00 & -0.01 \\ 13.84 & -0.02 & -159.1 & 0.93 & -0.77 & -0.81 & 0.01 & 0.33 & -0.01 \\ 21.84 & -0.02 & -539.9 & 1.17 & 0.06 & -0.18 & -0.63 & 0.31 & 0.02 \\ -7.37 & -0.02 & 93.64 & 1.24 & -0.86 & -0.24 & 0.05 & -0.33 & 0.14 \\ 0.04 & -0.02 & 207.5 & 0.88 & 0.49 & -0.10 & 0.01 & 0.11 & -0.59 \\ -0.16 & -0.00 & 17.01 & -0.02 & -0.01 & 0.00 & 0.00 & -0.00 & -0.01 \\ -50.6 & -0.17 & 1037.5 & -1.22 & 2.74 & 0.24 & 0.02 & -0.03 & -0.07 \\ 0.01 & 0.00 & -0.25 & -0.00 & 0.00 & -0.00 & 0.00 & 0.00 & -0.00 \\ -0.04 & -0.00 & 11.8 & 0.19 & 0.00 & 0.01 & -0.00 & -0.00 & 0.01 \\ 0.10 & -0.00 & 2.23 & 0.03 & 0.42 & -0.00 & 0.00 & -0.00 & -0.00 \\ -5.73 & -0.02 & 148.1 & -2.08 & 1.15 & -0.50 & 0.05 & 0.20 & -0.19 \\ -13.85 & -0.01 & 529.1 & -2.19 & 0.32 & -0.12 & -0.30 & 0.08 & -0.14 \\ 11.1 & -0.02 & -96.8 & -1.40 & 1.01 & -0.22 & 0.04 & -0.11 & 0.08 \\ 6.70 & -0.04 & -216.5 & -1.20 & -0.08 & -0.06 & 0.02 & -0.02 & -0.28 \end{bmatrix} \begin{bmatrix} \ln ARR_{HR_{t-1}} \\ \Delta ARR_{SI_{t-1}} \\ \ln CO2_{HUN_{t-1}} \\ \ln StQUA_{HR_{t-1}} \\ \ln QUA_{SI_{t-1}} \\ \Delta RAI_{HR_{t-1}} \\ \Delta RAI_{SI_{t-1}} \\ \Delta SUN_{HR_{t-1}} \\ \Delta SUN_{SI_{t-1}} \end{bmatrix} + \begin{bmatrix} -1.06 & 1.58 \\ 13.44 & 95.38 \\ -0.01 & 0.01 \\ 1.65 & 0.11 \\ -0.77 & -0.05 \\ 52.47 & 24.23 \\ 79.19 & 31.81 \\ -12.11 & 21.81 \\ 4.45 & 23.86 \end{bmatrix} \begin{bmatrix} D_{tr,t} \\ HR \\ D_{tr,t} \\ SI \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ u_{5t} \\ u_{6t} \\ u_{7t} \\ u_{8t} \\ u_{9t} \end{bmatrix} \quad (7)$$

Second, tourist arrivals in Slovenia are positively associated with tourism demand in Croatia (the coefficient value is 30.907), rain in Croatia (the coefficient value is 1.020) and negatively associated with rainfall in Slovenia (the coefficient value is -0.538) and cloudiness in Croatia (the coefficient value is -0.939). On the other hand, the second lagged term establishes a significant decrease in tourist arrivals when tourist demand changes in Croatia (the coefficient value is -50.635), and demand decreases in terms of carbon dioxide, while the sum of the first and second lags is zero. In principle, Slovenia could rely on higher tourist demand during the rainy season in Croatia, but surprisingly also when the sun shines longer in Croatia. Both results could be used as a promotional tool, while the opening of the Schengen border will ensure a significant drop in tourist demand in Slovenia. In general, both countries tend to work on a carbon strategy, leading to higher demand in the long run.

Finally, the results of the VAR model (Figure 7) supported by the econometric model in (8)

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \alpha \beta' x_{t-1} - \phi_{(tr,1)} D_{tr,t,SI} Y21M04_t + \phi_{(tr,1)} D_{tr,t,SI} Y21M05_{08t} - \phi_{(tr,2)} D_{tr,t,HR} Y21M04_t + \phi_{(tr,2)} D_{tr,t,HR} Y21M05_t + \gamma_0 + \varepsilon_t, \quad (8)$$

predict an increase in tourist arrivals for both countries. At the same time, the forecasted decrease will be dramatic. The abbreviations in (8) are as follows: Y is the year, M is the month, tr is the transitory variable, ϕ is deterministic linear occasion, D is the dummy variable, Γ is the VAR matrix and $\alpha \beta'$ is an unrestricted data vector.

Note that the impact of microbes is not directly measured in this forecast. The effect of viruses is studied in Section 3.4.

3.3. Results of Cointegration

The choice of cointegration rank is likely to affect all subsequent conclusions and is, therefore, a crucial step in the empirical analysis. Unfortunately, the decision between stationary and nonstationary directions of the vector process is also often anything but straightforward. The formal test is based on the zero cases of the unit root, which is not always reasonable from an economic point of view. The LR test for cointegration rank, often called the trace test or Johansen test, is based on the VAR model in R-form, with all the short-run dynamics, dummies, and other deterministic components factored out. We estimated the model for $r = 1, 2, 3, \dots, 9$. For $r = 7$, a trace test statistic is found where the p -value is 0.003, and for $r = 6$, the p -value is 0.000. In contrast, for $r = 8$, the trace test p -value is 0.418 (Table 5).

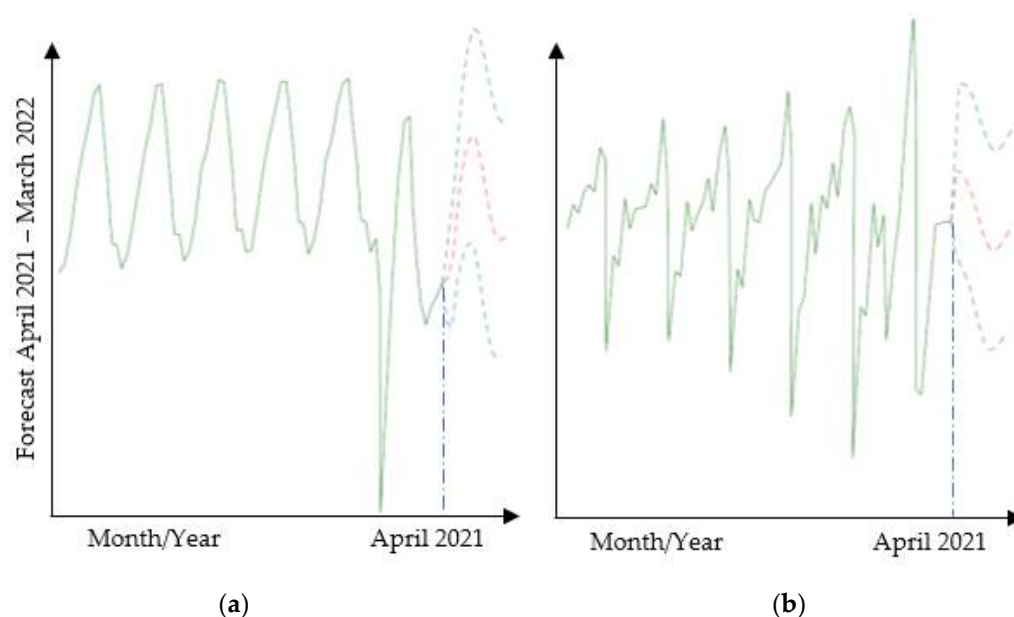


Figure 7. The VAR forecast for ARR: (a) Croatia; (b) Slovenia, from April 2021 to March 2022. Note: Source: authors calculations.

Table 5. Cointegration rank.

p-r	r	Trace	p-Value
9	0	1391.25	0.000
8	1	1118.41	0.000
7	2	871.58	0.000
6	3	647.72	0.000
5	4	440.02	0.000
4	5	265.62	0.000
3	6	115.26	0.000
2	7	57.19	0.000
1	8	18.74	0.004

Source: Authors calculations.

In the first case, an unrestricted constant term is included in the error correction (ECM) model. Since the constant term is unrestricted, it produces both a deterministic linear trend in the levels of the variables (through the gamma part) and a non-zero mean in the cointegration relations, but no linear trend in the cointegration relations, since the linear trends in the levels are cancelled. In the second case, the constant term is restricted to the cointegration relations. Thus, there are no trends in the levels, but non-zero averages are in the cointegration relations. We impose the constraint on the model that the rank of PI be r , which means that the nine variables in the model have r cointegration relationships and $p-r$ common stochastic trends. In total, by introducing two transitory dummy variables into the model, there are eventually eight cointegration relationships and one common stochastic trend.

The stationarity of the variables was tested again. The most volatile variable is Slovenian ARR, but the variable remains in the model, since it is the regressed variable. In addition, variable i is stationary around a constant mean with a transitory shift; one of the cointegration relationships must be given by a linear combination of variable i , the constant term, and the level shift. When testing for the stationarity of variable i , we restrict one of the cointegration relations to the variable i , the constant term, and the level shift, while leaving the other cointegration relations unrestricted. Therefore, the hypothesis test

(a sustainable human management of climate and ecosystems would significantly increase tourist arrivals in Croatia and Slovenia, which would reduce seasonal volatilities) in (9)

$$\beta_1 C^* x_t = ARR_t + RAI_t + QUA_t + SUN_t + CO_{2t}, \quad (9)$$

allows the two spatial cointegration relations. The vector ECM (VECM) for Croatia in (10),

$$ARR_{HR,t} = 0.001 ARR_{SI,t-2} + 0.009 SUN_{SI,t-1} - 0.003 SUN_{HR,t-2}, \quad (10)$$

allows for two explanations with statistically significant coefficients. For Croatia, the sun plays an important role. It is evident that every negative change in the mean value of cloud cover in Croatia produces an increase of 0.003 in tourist arrivals. Supporting this, every positive change in cloud cover in Slovenia creates a buoyant tourism demand in Croatia. Moreover, Croatian tourism benefits when Slovenia has a greater tourist demand. A second lagged effect confirms the results. However, for Slovenia, the VECM in (11)

$$ARR_{SI,t} = 65.14 ARR_{HR,t-1} - 1.816 RAI_{HR,t-1} - 1.452 SUN_{SI,t-1} + 50.85 ARR_{HR,t-2} - 0.983 RAI_{HR,t-2} + 0.486 RAI_{SI,t-2} - 1.515 CO_{2SI,t-2}, \quad (11)$$

reports a somewhat different result. Slovenian tourism benefits when Croatian tourism is expanded by a value of 65.614 and in the first effect (one lag). In contrast, Slovenian tourism loses when it rains in Croatia and benefits when the average cloud cover declines. With a lag (second lag), Slovenian tourism benefits when Croatian tourism increases and loses when it rains in Croatia. On the other hand, demand for Slovenian tourism decreases due to carbon dioxide emissions. Surprisingly, rain in Slovenia significantly increases tourism demand in Slovenia.

In summary, supported by cointegration relationships and VECM, dark tourism associated with earthquakes is not an issue for the countries studied, as earthquakes do not significantly affect tourist arrivals. Second, Slovenian tourism benefits when Croatian tourism increases. Additionally, Slovenian tourism rises during the rainy season. On the other hand, the decrease in Croatia's rainy season is apparent (probably an effect of demand) and carbon emissions. Croatian tourism increases with fewer clouds in Slovenia, and there is a higher demand for Slovenian tourism. Overall, it can be concluded that both countries depend on tourism growth; therefore, spatial strategies should be implemented by policy-makers.

3.4. Results of the Sensitive Analysis—Pre-Pandemic Effect on a Panel

In the last part of the analysis, the microbes of great interest from 2019 are analysed. According to the ex ante research, two microbes affecting tourist arrivals were isolated by ECDC, namely *Salmonella* and *Campylobacter* (for Croatia and Slovenia) and viruses (for Slovenia). Consequently, the panel regression was estimated to obtain the robustness of the results based on a sensitivity analysis. All the variables studied in this research are included for a data vector and a defined period, as in 3. It is essential to define the sensitivity analysis to determine whether the previous methodology provides a robust result. At the same time, as suggested, due to significant volatility (see Figure 6), the variable, e.g., ARR in Slovenia, could be excluded from the analysis. Therefore, the decision is to implement microbes that generate the final shock in tourist arrivals and panels to obtain a sufficient degree of freedom while shortening the data vector in terms of a scarce disease data source. Overall, the sensitivity analysis checking the ordinary least squares parameters for a beta coefficient suggests a linear approach to fit the method's robustness [135]. In summary, the sensitivity analysis would characterise the first-class definition of the input variables in this study, i.e., the variables are sufficient to define a robust econometric model that recognises all possible obstacles and proposes a trait prediction [136].

The results of the sensitive analysis confirm the previous model strategy issues and results of the cointegration and the VAR model. The panel model with more than 10% significant coefficients for Croatia, when microbes are included, is (12):

$$ARR_{HR} = 8.35 ARR_{SI} + 4.54 RAI_{HR} - 106.06 CO2_{HR} - 6.51 SUN_{HR} + 3.91 + CAMP_{SI} - 3.13 CAM_{HR}, \quad (12)$$

where CAM is *Campylobacter*.

The panel data model for Slovenia, when microbes are included, is (13):

$$ARR_{SI} = 0.09 ARR_{HR} + 8.97 CO2_{HR} + 0.50 CAM_{HR} - 0.48 CAM_{SI} + 0.08 SAL_{HR} - 0.10 SAL_{SI} - 0.18 VIR_{SI}, \quad (13)$$

where SAL is *Salmonella*.

Based on the panel model results, the conclusion is three-dimensional. Firstly, the countries are interdependent and should cooperate. Therefore, the opening of the Schengen border could bring Croatia an even higher tourism demand. Secondly, Croatian tourism depends on the weather conditions. In contrast to the VAR model, rain also causes more demand in the panel model. On the other hand, Slovenia suffers from microbes, while only in Slovenia are viruses a factor that significantly determines tourism demand. Thirdly, both countries should keep carbon dioxide in mind, while this method has statistically significant recognised CO₂ as an important factor that causes tourist arrivals.

4. Discussion

For the first time in the tourism literature, essential variables are brought together in one study and presented. The authors found no comparative research explaining ecosystem and environmental variables in the applied econometric approach, supported by sentiment analysis, for tourism worldwide. Moreover, there is not just a research specifically for the two EU countries, in this case, Croatia and Slovenia. The relevance of the analysed variables is discussed and supported by previous research. Therefore, the main contribution of this paper is twofold—a significant scientific impact as well as a practical impact on tourism destination management.

Nevertheless, the extended development of methodology in tourism is marked. The article's idea was to discover ways to reduce the seasonality volatilities; on the other hand, the notion is widely discussed for both countries in the scientific literature and the industry. In addition, the present research examines the impact on tourist arrivals of several—let us use the term—external factors. We learned that there are no external factors, only determinants that affect tourist arrivals during the pandemic. The better the diagnosis or prediction set, the better the outcome after a devastating shock.

The objective (to evaluate at least 100 recent manuscripts) in goal one (to provide an overview of the empirical research) is achieved. It is worth mentioning that many manuscripts deal with the direct impact of tourism on the environment, while only a few deal with the opposite issue. More than 100 previous empirical results have been revised, and the main conclusion for both destinations suggests that several essential factors determine the lengthening of the seasons. Previous studies highlighted some critical findings. Firstly, cloudy days have a significant impact on higher tourist arrivals instead of sunny days. Secondly, dark tourism based on earthquakes provides a considerable increase in tourist arrivals. Thirdly, green tourism with a low carbon footprint is the determinant that positively impacts tourist arrivals. Lastly, perhaps a little surprisingly but still significantly, the bacteria studied within the determinant microbes increase tourist demand.

On the other hand, precipitation has no significant effect on tourist demand; the only possible significance relates to the tourists visiting the chosen destination for the first time. Notably, viruses cause a significant decrease in tourism demand, highlighting coronaviruses and other viruses, so the threat of viruses will most likely continue.

Independently, the second goal has (due to growing general trends in the field of tourism sustainability) been reached, and the results are presented in Table 6. All other determinants have a minor impact. The cloudiness significantly reduces tourism demand

in Croatia. In Slovenia, the top results confirm that rain in Croatia generates a higher demand in Slovenia; on the other hand, opening the border with Croatia would reduce demand in Slovenia. The empirical results of this study provide some new empirical findings that could have a significant impact on tourism theory.

Table 6. Sensitive analysis.

Regressor	Regressed	VAR		CVAR (ECM)		Panel (Sensitive)	
		National	Spatial	National	Spatial	National	Spatial
ARR	ARR _{HR}	/	✖	✖	✓(+)	✖	✓(+)
	ARR _{SI}	/	✓(−)	✖	✓(+)	✖	✓(+)
RAI	ARR _{HR}	✖	✖	✖	✖	✓(+)	✖
	ARR _{SI}	✓(−)	✓(+)	✓(+)	✓(−)	✖	✖
QUA	ARR _{HR}	✖	✖	✖	✖	✖	✖
	ARR _{SI}	✖	✖	✖	✖	✖	✖
SUN	ARR _{HR}	✓(+)	✓(+)	✓(+)	✓(+)	✓(+)	✖
	ARR _{SI}	✖	✓(+)	✓(+)	✓(+)	✖	✖
MIC _(VIR)	ARR _{HR}	/	/	/	/	✖	✖
	ARR _{SI}	/	/	/	/	✓(−)	✖
MIC _(BAC)	ARR _{HR}	/	/	/	/	✓(−)	✓(+)
	ARR _{SI}	/	/	/	/	✓(−)	✓(+)
CO ₂	ARR _{HR}	✓(−)	✖	✖	/	✓(−)	✖
	ARR _{SI}	✓(−)	✖	✓(−)	/	✓(+)	✖

Note: ✓—statistically significant independent beta coefficient, ✖—statistically insignificant independent beta coefficient; S—spatial influence; /—not studied or defined parameter; (+, −) the direction of the causality is in brackets, where minus is negative and plus is a positive influence on ARR.

Contrary to previous empirical findings [137], earthquake-related dark tourism has no impact on tourism in Croatia and Slovenia. The chosen variable and supported results arise from the last literature on seismicity in Croatia and Slovenia, especially in the border region of Zagreb, Krsko and Brezice [138–141], followed by the recent earthquake in Zagreb in 2020. Second, sunshine has a positive influence on both countries, while previous studies found the opposite. Finally, rain has a positive effect on Slovenian tourism, while previous results show no significant impact. Overall, previous results and this study recommend that both countries revise their carbon strategies.

Together with the empirical results of this study and previous practical achievements, the development of this research is that Croatia and Slovenia could extend the tourism season and be increased by the following instruments:

1. Carbon dioxide strategy;
2. Supply of goods and attractions for cloudy days in Croatia;
3. Supply of goods and attractions for rainy days in Slovenia;
4. Sustain with the measures developed during the pandemic to avoid further spreading of bacillus;
5. Using econometrics and predictive analysis to determine and distribute solar days. Sunshine remains a necessary demand condition in both countries.

Nonetheless, sentiment analysis could be an additional tool for policy-makers to use the accompanying method of artificial intelligence to identify future impacts. A more efficient approach is to feed the Chatbot with Machine Learning Artificial Intelligence algorithms, such as NLP (Natural Language Processing). As an example for future research, the sentiment analysis tool has performed the concept of extraction for the website of the Croatian Tourism Authority. The evaluation value ranges from −10 to +10, where the weight around 0 is considered neutral. Figure 8 shows the detected concepts and related topics with the corresponding sentiment score.



Figure 8. Sentiment evaluation for Croatian tourist board website.

The results shown in Figure 8 indicate that the general sentiment is neutral. Some positive moods related to words such as “nature”, “hope”, “events”, “sustainability”, “trip ideas” and “explore”, thus suggesting that a more balanced message should be given, also reinforce the other concepts related to tourism in Croatia.

The main limitation of the study is a limited number of independent variables. Still, due to the degrees of freedom, there is no possibility of extending this research. Researchers could add some other countries so that panel cointegration could be implemented [142,143]. Due to the significant volatility of several variables and the impossibility of achieving normalisation in the residuals, the panel cointegration is an essential formulation in the next study. Overall, it is not possible to construct a differentiated matrix of the cointegrated VAR model at this stage. At the same time, tourist arrivals in the short term are generally not normally distributed because of the Covid-19 event.

In summary, the VECM separated by a country could be a possible pre-panel solution to obtain meaningful results on the distributed variables. At the same time, there is no theoretical possibility, e.g., the theory does not provide answers to receive a correct distributional assumption on tourist arrivals in a period of significant decline due to the Covid-19 pandemic shock. The results show that not even integration or dummies could not solve the problem. Therefore, this study provides a first-rate outcome for a near-normally distributed asymptotic variable.

Nonetheless, the panel model in the sensitivity analysis, which includes microbes, highlights the importance of joint destination marketing and policy developments, and weather conditions play an even more significant positive role for Croatia. By contrast, microbes are a risk factor for Slovenian tourism.

Bottom line: leave the cars at home, travel by train, enjoy the rain, sun and green tours, and avoid microbes by washing hands. These are the factors that will increase tourism demand shortly and imperiously after the pandemic. The new normal could be a sustainable tourism strategy in the post-pandemic context. The at-a-glance results are presented in Table 6 to compare the different econometric methods used in the study that yield matching results.

The VAR model steadfastly confirms the carbon dioxide strategy. Second, the CVAR model demonstrates climate dependence and partial spatial climate dependence. Third, for Croatia, the panel ensures climate dependence (SUN, RAI), while for Slovenia, it confirms ecosystem dependence (MIC), which is also a spatially significant finding by ARR. At a glance, the results in Table 6 confirm the hypothesis that sustainable human management of climate and ecosystem would significantly increase tourism demand, where emissions are highly significant.

5. Conclusions

This pioneering research, accompanied with the selected secondary data, presented the sustainable factors influencing tourism demand and seasonality.

Based on the first goal, which is an overview of the empirical literature, the main conclusions are as follows.

1. Tourist demand is not a factual situation;
2. Quantitative analysis is essential for better planning and strategic dimensions in tourism;
3. Tourism thinking is moving towards sustainable tourism, e.g.:
 - Average temperatures should not rise above 31 degrees Celsius during the holidays;
 - Rain and cloud cover significantly affect tourism demand;
 - CO₂ emissions play an essential role for tourists;

The second goal (to highlight the growing general trends in the field of sustainability) with three objectives confirms the hypothesis that seasonality matters in tourism. Still, the results show that strategic and sustainable thinking could reduce the overwhelming demand during the summer months and reduce supply problems in the low season. In conclusion, spatial dimensions matter, so policymakers in Croatia and Slovenia need to do a thorough and coordinated job. Sustainable tourism strategies in a pandemic context are essential. Therefore, our added value to the theory is twofold—first, the use of an appropriate quantitative methodology with applied function rather than qualitative subjectification. Second, the environment and ecosystem regressors are affecting tourist arrivals. Therefore, the first objective (selection of variables) of the second goal proposes precipitation, cloud cover, earthquakes, microbes and green emissions as independent variables in a time series approach. The second objective searches for determinants of increase/decrease tourism demand in Croatia and Slovenia. It shows that the most critical determinant is CO₂. The determinant CO₂ represents a valuable strategic work for the future increase of tourism.

Moreover, the two countries depend on tourist arrivals, i.e., expected increases or decreases. In terms of tourism strategy, depending on the type of tourism, the sun is still an important issue, even more so for Croatia. At the same time, the weather conditions play a significant role for the next tourism generation, so the strategy should recognise their need and expectations. Split results of one country showed that Slovenia could gain from precipitation and lose from microbes. Therefore, Slovenian tourism should turn to these determinants and, we can say, trends that confirm the final objective (what weather conditions might influence this tourism trend) of the second goal.

Finally, the limitation of the study is that the quantitative research might be missing some essential variables. After that, additional research could improve the results. A further qualitative survey could provide insights into the mindset of tourists.

In summary, panel regression indicates that both countries have spatial benefits, i.e., greater demand. Separately, and conclusively to rivalry determinants, Croatian tourism is more likely sensitive to weather factors, i.e., less rain and clouds bring more tourists. By contrast, Slovenian tourism suffers from ecosystem determinants—with more microbes there are fewer tourists. Overall, carbon dioxide is an important strategic factor for both countries. In conclusion, the sentiment analysis has shown that more importance should be given to sustainability.

Author Contributions: Conceptualization, S.G. and T.B.; methodology, S.G. and T.B.; software, S.G.; validation, S.G.; formal analysis, S.G.; investigation, S.G.; resources, S.G.; data curation, S.G.; writing—original draft preparation, S.G.; writing—review and editing, T.B. and V.Š.; visualization, S.G. and V.Š.; supervision, T.B.; project administration, S.G.; funding acquisition, T.B., V.Š. and S.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data is in the public domain, and the relevant sources are cited in the text.

Acknowledgments: On the current occasion of tourism in Croatia and Slovenia, we are very grateful to the newspapers that disseminated the most important information about the results to the general public. The dissemination took place in August 2021 in daily newspaper Glas Istra number 217 on 8 August 2021 and weekly newspaper Dolenjski list number 31 on 5 August 2021. In addition, we would like to thank the editors and three anonymous reviewers for the critical review and comments within the scientific article.

Conflicts of Interest: The authors declare no conflict of interest.

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