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Policy debates and controversies

The relationship between tourism and air quality in five European countries

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ABSTRACT

This study aims to understand the impact of air quality on the demand of tourism destinations and the impact that tourism may have on the air quality of a specific destination.

Nights spent at tourist accommodation establishments were used as a proxy of tourism demand in each location, while PM10 concentrations were a proxy of air quality. Data for five European countries (Austria, Cyprus, Great Britain, Italy, and Switzerland), specifically monthly data from January 2008 to December 2015, was analyzed on a multivariate framework through a Vector Autoregressive Model.

Results show that for Austria and Italy tourism growth can deteriorate air quality, while for Cyprus and Great Britain, the poorer air quality of the destination may decrease tourism demand. Causality results show that tourism is a possible cause of increased PM10 levels and variance decomposition results show that shocks in PM10 levels explain a large percentage of the error variation in tourism demand.

1. Introduction

The expansion of tourism has been continuous in recent decades. It is the fastest-growing sector in the world and is estimated to be the 3rd largest employer on the planet, right after the retail and agriculture sectors (UNWTO, 2017). Despite the slight drop that the number of tourists in European establishments had in 2008 and 2009, as a result of the economic and financial crisis, this variable has been showing an upward trend since 2004 (growing at an average annual rate of 3%). In 2018, the number of overnight stays in Europe was 3.3 billion, almost 50% more than in 2004 (Eurostat, 2018).

The relation between climate change and tourism is bidirectional, that is, climate change affects tourism activities and tourism affects climate change (Tiwari et al., 2013). When tourism activities take place, the environment is inevitably changed, since tourism causes many changes and transformations in the natural environment and, therefore, several environmental impacts. With the huge increase in the tourism industry, there was a need to scale up and build infrastructures such as hotels, restaurants, and basic sanitation, sometimes without analyzing their effects on the local environment. Although they are very reliant on the natural environment (e.g. coastal zones, natural parks), tourism activities can have significant negative environmental externalities (e.g. through pollution or extraction of natural resources) (Akadiri et al., 2019; Russo et al., 2020).

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Several studies argue that it is important to address the relationship between tourism and Air quality (AQ), whose causal relationship has been widely documented in the literature (Wang et al., 2018). A suitable model to study these causal relationships is vector autoregression (VAR), which is a stochastic process model used to capture the linear interdependencies among multiple time series. VAR models generalize the univariate autoregressive model (AR model) by allowing for more than one evolving variable, therefore being the methodology employed in the present study. The studies that analyze the effect of tourism on variables such as CO_2 emissions, air pollution, climate change, and environmental variables, reach different conclusions regarding the use of different proxies to represent its effect on pollution. Most studies (e.g., Katircioglu et al., 2014; Liu et al., 2019; Zhang et al., 2019) assume that CO_2 emission is a variable that can represent air quality, though some features suggest that this variable is not the best proxy. CO_2 is a greenhouse gas, meaning that it can only be considered a pollutant because it alters the greenhouse effect of the atmosphere and contributes to climate change. However, it has a negligible effect on AQ and human health when compared to other pollutants. For this reason, this pollutant is not considered for air quality purposes, is not included in the AQ EU Directive (2008/ 50/ EC) – where limit values are defined for all the air pollutants – neither part of the European Air Quality Reports. In the most recent European air quality report (European Environment Agency, 2018), a general AQ assessment is made in Europe and the most critical pollutants (such as PM10) are identified. PM10 corresponds to the particles in the atmosphere with an aerodynamic diameter of fewer than 10 micrometers. Airborne particles are currently one of the air pollutants of greatest concern, as concentration levels continue to exceed the stipulated limit values for the protection of human health every year, at several monitoring sites throughout Europe. There are a limited number of studies using the variables PM10 or PM2.5 as representatives of AQ and studying its relationship with tourism. The existing studies are mainly for Asian countries (e.g. China and Hong Kong) (Eusébio et al., 2020; Zajchowski et al., 2018). Little is known about other regions and nations that are also affected by high levels of tourism, like Europe.

Due to the importance of studying the link between tourism and AQ, and since no studies are using adequate measures of AQ (measured trough PM10) for European countries, the present study tests the relationship between AQ and tourism demand in Austria, Cyprus, Great Britain, Italy and Switzerland (countries with available data for the study period). Our major purpose is to investigate the relationship between tourism demand and AQ using vector autoregressive models (VAR), provided these models allow us to examine simultaneous relationships among variables and their lagged values. A secondary goal is to measure the causality between these two variables by country.

This study is structured with a Literature Review presented in Section 2, a description of the Data and Methodology in Section 3. Results are presented and discussed in Section 4. Finally, the main conclusions are in Section 5, along with some limitations of the study and future research directions.

2. Literature review

Many relationships between tourism and environmental variables have been studied over time, by different authors. Most of the studies conclude that tourism can deteriorate AQ. Some authors use air pollution proxies to see the effect on tourism, or vice-versa. However, few studies analyze the causal relationship between AQ and tourism demand (e.g. Lee et al. (2009); Zhang and Gao (2016)). Moreover, a great number of published studies in this field have been carried out in Asian countries (e.g. Ahmad et al., 2018; Liu et al., 2019) and use CO_2 as an indicator of AQ (e.g. Ahmad et al., 2018; Ozturk, 2015; Paramati et al., 2017).

Ahmad et al. (2018) show a negative impact of tourism on the environment, measured by CO_2 emissions, for the regions of Ningxia, Qinghai, Gansu and Shanxi, and conclude that tourism leads to a rise in CO_2 and, consequently, greenhouse gas emissions. Additionally, Ozturk (2015) studied the relationship between energy, environment, growth, and tourism indicators for a panel of 34 countries, using CO_2 emissions as the environmental variable and concluded that these emissions have a positive relationship with tourism indicators. Also using CO_2 as a proxy of environmental quality, Tiwari et al. (2013) studied the dynamics of the relationship between climate change, energy consumption and tourism for 25 OECD countries and concluded that the response of tourism to shocks in climate change and the response of climate change to tourism are both marginally positive. Paramati et al. (2017), investigated the impact of tourism on CO_2 emissions for eastern and western European Union countries, concluding that tourism increases CO_2 emissions in the Eastern EU but decreases in the Western EU, while economic growth and CO_2 emissions lead to increased tourism in the Western EU. Overall, the results suggest that tourism plays an important role in accelerating economic growth, but its effect on CO_2 emissions largely depends on the adoption of sustainable tourism policies and efficient management of tourism development. This study suggests that the relationship between tourism and CO_2 may differ according to the level of economic development of the country, as well as the strategies adopted for tourism development. Although the studies mentioned reveal that tourism contributes to increasing CO_2, this impact may differ according to the tourism destination under analysis. Moreover, these studies are limited in terms of scope since they only use CO_2 as an indicator of AQ. CO_2 is only a component of AQ and is not the best proxy to measure AQ as explained in the introduction. Nevertheless, few studies adopt other indicators of AQ such as PM 2.5 (e.g. Liu et al., 2019) and PM10 (e.g. Lee et al., 2009; Saenz-de Miera and Rosselló, 2014).

Saenz-de Miera and Rosselló (2014) investigate the impact of tourism on air pollution using a different variable: PM10 concentration. Here, the daily number of tourists was shown to not only be a significant predictor of air pollution concentration levels, but also a variable whose inclusion improves the standard specification of urban AQ models that have the common feature of using meteorological conditions as main explanatory variables. Inversely, Xu and Reed (2017) reveal that air pollution may have an impact on tourism as the perceived pollution has a strong impact on inbound tourism. Zhou et al. (2018) reveal that the negative impact on tourism is higher when air pollution increases.

Liu et al. (2019) analyze different pollutants (CO_2 emissions and PM2.5 concentrations) and different tourist groups (domestic and international) for China and concluded that the impact of CO_2 on tourism is non-significant. However, the authors show that domestic tourists are very sensitive to changes in PM2.5 concentration, whereas international tourists are less sensitive. The reason for this result, according to the authors, maybe that the effect of PM2.5 on AQ is intuitive and people can perceive the negative AQ impact through personal experience or observation, which directly affects their traveling plans.

However, Zhang and Gao (2016) analyze the causal relationship between tourism and AQ, showing that tourism harms CO_2 emissions in China. The negative impact of tourism on the environment and the inverse relationship was also supported by Wang and Wang (2018), which stated that tourism growth drives to more CO_2 emissions in the future and that greater CO_2 emissions return a lagged and negative impact on tourism development (i.e. the feedback effect), thus implying that governments should implement relevant policies to maintain environmental quality and tourism development simultaneously. Also, Lee et al. (2009), show cointegration relationships between tourism and all the environmental quality variables used in their studies, such as CO_2 and PM10 emissions. However, when testing the Granger causality through the error correction model, the results indicated that tourism has significant effects on the environment, whereas the influence of the environment on tourism is not significant.

Also, Keiser et al. (2018) evaluated USA national parks and found a negative relationship between in-park ozone concentrations and park visitation. Additionally, their results also show that these may have implications for human health, as 35% of all national park visits occur when ozone levels are elevated, despite the negative association between visitation and ozone, which suggests a potential large human health benefit to further AQ improvements. Wang et al. (2018) concluded that AQ in the place of origin creates a pushing effect, and local outbound tourism demand increases as AQ deteriorates. This relationship is negatively moderated by local disposable income levels. This study also identifies a delay effect of five days in the impacts of AQ on outbound tourism demand. Studies using pollutants other than CO_2 reinforce the negative impact of tourism on AQ of the destinations. Therefore, there is a consensual conclusion that states that air pollution reduces tourism demand (Anaman and Looi, 2000; Sajjad et al., 2014; Chen et al., 2017; Deng and Xin, 2017; Keiser et al., 2018; Wang et al., 2018; Zhou et al., 2018; Liu et al., 2019). However, there are no consensual results concerning the impact of air pollution on tourism demand. For example, Xu et al. (2019) tried to assess which pollutant (PM2.5, PM10, SO_2, and NO_2) has the most negative impacts on tourism activities of 337 Chinese cities and concluded that PM2.5 had a significantly negative impact on both domestic and inbound tourist arrivals. NO_2 has a negative influence on inbound tourist arrivals but for the other two pollutants, no statistically significant impact was found. The authors also estimated an average reduction of 81,855 in annual domestic tourist arrivals and 12,269 in inbound tourist arrivals in each city due to air pollutants.

This literature review enables us to conclude that Europe is not the focus of these types of studies, and most of the studies do not analyze the relation of AQ and tourism since the majority are based on CO_2 emissions, which is not a direct indicator of AQ (EEA, 2018, 2019). Therefore, this article intends to extend knowledge in this field providing the following contributions: (i) using PM10 as a proxy of air quality, as this is a better variable for this end, while the majority of studies use CO_2 emissions, a variable not directly related to AQ, as explained in the introduction; (ii) undertaking the study in five European countries located in different European subregions, with different levels of tourism development and different tourism products, whereas existing studies are mainly for Asian countries. Little is known about other regions where tourism is an important economic activity, like Europe. Moreover, existing studies for Europe use CO_2 as a proxy for AQ; and (iii) examining the causal relationship between PM10 and tourism, since no studies are measuring the causality between these two variables for the countries under analysis. Therefore, this article will improve the knowledge of this relationship for the five European countries under analysis and provides relevant insight to define environmental and tourism policy recommendations for these specific countries.

3. Data and methodology

This empirical research aims to estimate the relationship between inbound tourism and AQ, using cointegration and causality tests (Elliot et al., 1996; Engle and Granger, 1987; Phillips and Perron, 1988). It also aims to verify whether the direction of causality differs by country. The total number of nights spent by foreign tourists in accommodation establishments is the proxy selected to measure inbound tourism, and PM10 concentrations are the proxy selected to represent AQ. Monthly data is used, from January 2008 to December 2015. Tourism demand data is provided by Eurostat, and air quality data (PM10 concentrations) from the EMEP (European Monitoring and Evaluation Programme) network, retrieved through the EBAS database (http://ebas.nilu.no). In the framework of the EMEP program, observation data of atmospheric chemical composition is available at several background monitoring stations across Europe. Several filters were applied to select monitoring stations (such as data availability and data collection efficiency for all countries within the same period). Finally, monthly mean PM10 concentrations were calculated per country, considering all monitoring stations that met the criterion of at least 75% data availability). The analyzed countries were limited to AT — Austria (1); CH — Switzerland (5); CY — Cyprus (1); GB — Great Britain (1); IT — Italy (1) (in parentheses the number of stations that were considered). Various criteria were used to select the European countries to be analyzed in this research. Countries from different European subregions, with different tourism development levels, as well as different types of tourism products, were selected (UNWTO, 2019; WTO, 2003). Specifically, countries from three subregions were chosen — Northern Europe (Great Britain), Western Europe (Austria and Switzerland), and Southern/Mediterranean Europe (Italy and Cyprus). These countries also present different tourism development levels, with Italy and Great Britain being among the top ten worldwide tourism destinations. In contrast, Cyprus is a country with a low number of international tourism arrivals. These countries also differ concerning the tourism products offered. For example, while Great Britain is an important destination to cultural visitors, Austria and Switzerland are greatly appreciated by nature-lovers. Tourism and PM10 time series typically contain seasonal variation that is relatively constant over time, so we removed this feature by fitting a centered moving average with additive seasonality to obtain the deseasonalized tourism and PM10 series, using the method proposed by Gujarati (2003). This method uses the concept of ironing out the fluctuations of the data by calculating the means, measuring the trend by eliminating the changes or the variations using a centered moving average (Ahmed et al., 2010; Mansor et al., 2019; Sutcliffe and Sinclair, 1980). Additionally, as has often been used in similar studies, all the series are expressed in logarithms to facilitate the interpretation of coefficients (Ahmed et al., 2010; Khan et al., 2005; Kulendran and Wilson, 2000a,b; Mansor et al., 2019; Shan and Wilson, 2001) and to adequately be able to compare the variables since they were originally presented with different measurement units. We also performed descriptive statistics and pairwise Pearson correlation calculations for the different countries for both the original series and for the deseasonalized logarithmic versions.

3.1. Stationarity and cointegration analysis

In the first step of the empirical analysis, we explored the stationary properties of the data by applying the commonly used unit root test Augmented Dickey–Fuller (ADF test) (Dickey and Fuller, 1979). In the ADF test, the null hypothesis is that a time series has a unit root, against the alternative hypothesis that the time series is stationary (Dickey and Fuller, 1979; Gujarati, 2003). Identifying the order of integration of a series is a fundamental introductory step in any time series econometric study. Additionally, for unit root tests, we started by applying a common VAR model with no restrictions added to study the optimal number of lags to be included in each model by country, as well as the existence of cointegrating relationships. Only after this step was the model adjusted considering the optimal number of lags and the number of cointegrated relationships when these existed.

Before the model estimations, two important aspects need to be checked: (i) the VAR model offset order and (ii) the specification of cointegration tests related to the deterministic terms to be included in the models. Regarding (i), the VAR lag order selection tests, the Likelihood Ratio Test (LR), the Minimum Prediction Error Test (FPE), Akaike Information Criterion (AIC), Schwartz Bayesian Information Criterion (BIC) and Hannan–Quinn Information Criterion (HC), were considered. However, our choice has fallen on the AIC criteria, as in previous studies (Liu et al., 2019; Wang et al., 2018; Zhou et al., 2018). Similar to the ADF test, the AIC criteria[1] are the most used among the overall criteria for lag length selection in the literature. Moreover, it remains at the discretion of the researcher to select the maximum lags in which the adopted criterion for choosing optimal lags will use (Liew, 2004; Tang and Tan, 2015; Tang et al., 2019). Various studies already indicate that the Akaike criterion is preferable, as in Liew (2004) and Tang et al. (2019), while others develop the criteria further (Ng and Perron, 2001). Concerning (ii), the chosen model was the Johansen cointegration criteria. If the time series have a unit root, it makes sense that these variables have common dynamics that transform themselves into long-term relationships. The most appropriate methodology to estimate these long-term relationships is to investigate the presence of cointegration between the model variables and to estimate error correction models.

In the empirical literature, the most common method for cointegration testing is the method of Johansen (1988, 1995) as stated by Caiado (2002) and Mansor et al. (2019). This step was important to the second one, provided that in the presence of cointegrating relationships we need to adapt the model to be estimated from the VAR to the VEC (vector error correction model). Johansen's (1995) methodology uses the trace test and the maximum likelihood test.

3.2. VEC and VAR models

After verifying the existence of cointegration, the error correction model is estimated. The relationships between tourism demand and AQ were studied through the estimation of Vector Autoregressive Models (VAR) and Error Correction Mechanism (MCE) models (Vector Error Correction Models — VEC) to assess the existence of interdependent relationships and a long-term equilibrium relationship between tourism demand and AQ. This step was divided into three sections: (i) the estimation of VAR or VEC models; (ii) the variance decomposition (VD) and (iii) the Granger causality tests.

The VAR models help us to evaluate the relationship between variables, by looking at their lagged values, which makes it possible to anticipate their future behavior (Caiado, 2002). In a VAR or VEC model, the variables are simultaneously endogenous and exogenous and both their lagged values are used to explain the current behavior of the other. Therefore,

[1] The information criteria for optimal lag length is contingent on the number of observations. While the AIC is more appropriate when observations are less than 60, the Hannan–Quin is more efficient when observations are above 120 (Liew, 2004).

by estimating these models we are using a vector of variables to obtain a vector of coefficients and to explore their signs and significances.

The VD is a relevant analysis considering that it allows us to calculate the chain reactions of a given shock. The Granger's Causality allows us to observe whether two or more variables influence each other (bidirectional relationship) or only univocally (unidirectional relationship). Thus, they clarify a broader perception of whether the past values of a variable may influence the future behavior of a variable at the present.

The next step consists of VEC or VAR model estimation. The VEC model was used when cointegrating relationships existed. When no cointegrating relationship was found we relied on the VAR model.

The VAR model is successful and flexible for the analysis of multivariate time series, being an extension of univariate models to dynamic ones. By using VAR, we have the opportunity to estimate a system of simultaneous equations, making it easier to describe the dynamic behavior of time series and for forecasting purposes. The model is specified as in Eq. (1) when the optimal number of lags selected is two.

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \beta_{11}^1 & \beta_{12}^1 \\ \beta_{21}^1 & \beta_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \beta_{11}^2 & \beta_{12}^2 \\ \beta_{21}^2 & \beta_{22}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{1}$$

where $cov\left(\varepsilon_{1t}, \varepsilon_{2s}\right) = \sigma_{12}$ for t = s; 0 otherwise. Our VAR (p) or VEC (p) model has p lags, provided the lag length estimation criteria implemented for each model specification, and whose results are presented in the next section, provided they change depending on the country. y_{1t} and y_{2t} are simultaneously dependent and independent variables, where y_1 is in respect to tourism (T) and y_2 to PM10, in the current setting. T specifically refers to the total number of nights spent by tourists in accommodation establishments.

We have considered a model for each of the 5 countries (Austria, Switzerland, Cyprus, Great Britain, and Italy). β_{it} refers to the estimated coefficients associated with variable y_i, where i is the variable, t-n (n = 1, 2, … lags) the lagged value of the "explanatory" variable and ε_{it} is the error term. VEC estimations are performed whenever more than one cointegrating relationship was found, which under our results is used for all countries except in Switzerland, where no cointegrating relationships were found. VAR/VEC results depend on the ordering of the variables. As we only included two variables in the analysis, the variable ordering in the present setting will be indifferent.

In the VEC model, causality is expressed by dynamics where the cointegrating equation coefficients provide long-run relationships between the variables. Therefore, coefficients show how deviations from the long-run relationship will impact the variable change of the next period.

First introduced by Granger (1969) and later popularized by Sims (1972), the concept of causality between two variables was born. Granger's basic idea of causation is that Xt Granger causes Yt if the past information of variable Xt allows improving the predictions of variable Yt. In other words, if Yt is better predicted based on past values of Xt and Yt together, than only with the past values of Yt. The formal definition of Granger causality can be found, for example, in Hamilton (1994, pp. 303). The Wald test is used to determine if there are Granger causal relationships between variables.

Since the coefficients estimated by the VAR model are difficult to interpret, the VD is regularly supportive in the interpretation of the results. The VD method examines the effects of shocks on dependent variables. This technique determines how much of the estimated error of the variance, of any variable in the system, is explained by the "innovations" or hops of each of the explanatory variables, given a series of time intervals (here from 1 to 24 months).

4. Empirical results

In Table 1 we can see the descriptive statistics of the original series and the deseasonalized series, after natural logarithms. According to these values, Italy presents the highest mean for tourism demand when compared to the remaining countries, which is also true for PM10 mean values (30.4 $\mu g/m^3$). Switzerland has the lowest value presented for PM10 mean (10.3 $\mu g/m^3$) and Cyprus is the country with the lowest mean tourism demand.

For PM10, both the lowest and highest values were registered in Great Britain, which has a range of around 66 $\mu g/m^3$.

The Pearson correlation coefficient values are presented in Table 2. This is a measure of the strength of a linear association between tourism and AQ. Results show that the strongest association of these two variables is observed in Cyprus with a strong uphill (positive) linear relationship. Austria is the only country where there is a non-significant association between variables, while the rest show a strong association among them. Also, for all the countries the correlation is positive, meaning that the variables evolve in the same direction.

The value of the probability associated with the Pearson correlation indicates the significance of the correlation found. All the countries, except for Austria, present a statistical significance of 1%.

The results in Table 3, from the ADF test, reveal that the hypothesis of non-stationarity is rejected for all studied countries. Table 4 presents, for each country, the optimal lags test results which were used in the vector autoregressive model, according to the AIC criteria.

The next step was to test the possibility of cointegration among the variables that are used. The Johansen's maximum likelihood method (ML) was applied, which tests the number of cointegrating relationships and estimates their parameters (Johansen, 1988, 1991, 1995; Johansen and Juselius, 1990). The results of this test are reported in Table 5. The null hypothesis of non-cointegration is overall rejected, with the results of the trace test statistic showing that almost all the series are cointegrated at the 10% critical value.

Table 1
Descriptive statistics of the original and deseasonalized series (log).

Countries	Descriptive statistics	Original		Deseasonalized series (log)	
		T	PM10 ($\mu g/m^3$)	T	PM10
AT	Mean	6973904	21.45	15.63	3.04
	Std. Dev.	3501196	4.76	0.55	0.23
	Min	1288469	11.59	14.07	2.45
	Max	16878220	37.20	16.64	3.62
CH	Mean	2468198	10.31	14.59	2.26
	Std. Dev.	1297254	3.70	0.53	0.40
	Min	563123.1	3.36	13.24	1.21
	Max	6359124	18.28	15.67	2.91
CY	Mean	1545147	28.10	13.81	3.24
	Std. Dev.	1181406	11.79	1.06	0.44
	Min	132215.70	9.24	11.79	2.22
	Max	3528223	73.89	15.08	4.30
GB	Mean	14665246	14.23	16.21	2.40
	Std. Dev.	12623470	11.43	0.75	0.71
	Min	2672239	2.27	14.80	0.82
	Max	67159556	68.57	18.02	4.23
IT	Mean	20533590	30.36	16.50	3.37
	Std. Dev.	16100548	8.40	0.86	0.29
	Min	4017241	13.79	15.21	2.62
	Max	54367471	48.84	17.81	3.89

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy. T — Tourism demand (Nights spent at tourist accommodation establishments — monthly data); PM10 — monthly mean concentrations of PM10.

Table 2
Pearson correlation results.

	AT	CH	CY	GB	IT
	PM10	PM10	PM10	PM10	PM10
T	0.0843	0.5416***	0.7327***	0.6584***	0.6562***
	(0.4140)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy. T — Tourism demand (Nights spent at tourist accommodation establishments — monthly data); PM10 — monthly mean concentrations of PM10. *, **, *** represents coefficient statistically significant at 10%, 5% and 1%, respectively.

Table 3
ADF tests results.

	Level *t*-Statistic	Prob.*
LDATPM10	−9.4298***	0.0000
LDATT	−2.0150***	0.0000
LDCHPM10	−5.5595***	0.0000
LDCHT	−1.4532***	0.0000
LDCYPM10	−6.5393***	0.0000
LDCYT	−2.1097***	0.0000
LDGBPM10	−3.6887***	0.0000
LDGBT	−0.6457***	0.0000
LDITPM10	−6.0932***	0.0000
LDITT	−7.6606***	0.0000

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy. LD — lagged deseasonalized *, **, *** represents coefficient statistically significant at 10%, 5% and 1%, respectively. Augmented Dickey–Fuller test statistic, Test critical values: 1% level: −3.5007; 5% level: −2.8922; 10% level: −2.5832.

When we have cointegrating relationships we need to apply a VEC model instead of VAR. The only country for which we did not find any cointegrating relationship was Switzerland, and for this case, the standard VAR was used. All the other countries demanded an econometric estimation based on the VEC model.

Estimation outputs in Table 6 consider the number of optimal lags (revealed in Table 4) provided through lag length criteria, and simultaneously, the number of cointegrating relationships in the case of the VEC model (as provided in Table 5).

Table 4
Optimal Lags by AIC criteria.

Countries	AIC	Lag
AT	0.6432*	12
CH	1.0032*	12
CY	0.9309*	10
GB	1.6529*	12
IT	0.1766*	8

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy.
* means that the optimal number of lags selected by the criteria is that presented in the column lag.

Table 5
Cointegration test results.

Country	Number of cointegrating vectors (5% critical value)	Trace Stat. (At most 1: test results)	Prob.**
AT	1	2.8240	0.0929
CH	No cointegration	1.9073	0.1673
CY	2	6.0567	0.0138
GB	1	0.0050	0.9429
IT	1	3.2912	0.0696

** MacKinnon-Haug-Michelis (1999) *p*-values.
Notes: The series that were used are LT and LPM10 by country.
Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy.

Coefficients in the cointegrating equation (CointEq1) give the estimated long-run relationship among the variables. Therefore, the coefficient on that term in the VECM shows how deviations from long-run relationships affect the variable changes in the next period. Only for Austria and Italy, both error correction terms associated with T and PM10 are significant, whereas in Cyprus and Great Britain only the PM10 coefficient reveals to be significant. In these significant values, the cointegration term, known as the error correction term, when deviating from the long-run equilibrium, is gradually corrected through a series of partial short-run adjustments, which happens most in PM10.

As seen in Table 6, there is no common pattern among countries and there are very different results both in terms of significance and coefficient signs considering the lagged effects of both T and PM10 over their current levels.

For Austria, we found a positive correlation between coefficients for lagged tourism with PM10 up to 12 lags, between tourism and tourism for the 1st and 11th lag, and from PM10 to tourism up to the 4th lagged monthly value of PM10. Lagged values of PM10 do not seem to have any statistically significant influence over current PM10, except at lag 11. To counterbalance this conclusion, we recorded that lagged tourism has a negative influence on tourism from the 9th up to its 11th lag, but only significant for the previous 11 months. All the other values for Austria are not significant according to the statistical t critical values.

Concerning Switzerland, results indicate a positive influence of PM10 on tourism for the 1st lag and positive influence of tourism demand in more tourism demand for 1st, 5th, 7th, 9th, 11th, and 12th lags, only significant in the 1st and 12th lags at 1% significance. Tourism seems to only have a positive and significant effect over pollution at its first lagged value, meaning one previous month. Therefore, we can only say that tourism can induce PM10 increase one month afterward, which can be justified by the delay on the perception of the effects of tourism over pollution. Previous months of pollution also seem to be reflected in current levels of pollution (up to 3 months) but the coefficient signs attained are mixed, for example, being negative only at the 2nd lag but positive and significant for the 1st and 3rd lags.

Considering the results attained for Cyprus and focusing on the coefficient values, there is a negative trend from tourism to PM10 for 10 lags, and from tourism to tourism for the 6th, 8th, 9th, and 10th lags, with statistical significance, being positive and significant at the 1st lag. Regarding the effects of lagged PM10 on tourism, we can observe a negative and significant effect up to eight lags, and so it seems that for Cyprus, pollution harms tourism, which is reflected through time, provided that higher levels of pollution could potentially be related to the decrease on tourism demand. The same happens when we look at the negative and significant effects of PM10 on itself up to the 8th lag. Based on these results we may argue that pollution levels observed through PM10 are reflected with a long memory, or at least up to eight lags.

Considering the estimation outcomes for Great Britain, we found a negative impact of tourism on PM10, which is significant only for the 6th lag. Regarding tourism on itself, it is also negative and significant after six months (except in the 8th and 12th lag). Besides, a negative impact for PM10 on tourism is reflected up to the 10th month (lag), but the effect of PM10 on itself does not seem to be statistically relevant at any of the 12th lag used in the estimation.

Reading the results for Italy, it is clear that previous tourism demand leads to more tourism demand in the following periods, provided that all coefficients are positive and significant (except for the 6th and 8th lags). As such, and considering the diversity of countries analyzed and results attained, we may argue that our results seem to favor those of previous authors for the consensual conclusion that air pollution has an impact on the number of tourists (Deng and Xin, 2017; Keiser et al., 2018; Liu et al., 2019; Wang et al., 2018; Zhou et al., 2018), air pollution significantly reduces international inbound tourism (Dong et al., 2019), tourism deteriorates AQ (Akadiri et al., 2019; Tang et al., 2019; Zhang and Gao,

Table 6
Estimated coefficients through VAR (if no cointegration)/VEC (with cointegration).

	(VEC)	AT	(VAR)	CH	(VEC)	CY	(VEC)	GB	(VEC)	IT
	Depend.		Depend.		Depend.		Depend.		Depend.	
	X T	Y PM10	X T	Y PM10	X T	Y PM10	X T	Y PM10	X T	Y PM10
CointEq1	−1.4839***	−0.9708**			−0.0079	0.6191***	−0.1662	0.5416***	−0.0797*	−0.2706***
Lag ind.										
X (−1)	1.3242*	1.4580**	0.5352***	0.3109***	0.6164***	0.1944	0.0389	0.0865	1.1148***	0.4572***
	[1.71996]	[2.08512]	[4.49176]	[2.65408]	[3.43342]	[0.86282]	[0.27366]	[0.36661]	[5.76575]	[2.58526]
X (−2)	1.1348	1.4348**	−0.122	0.0019	0.113	−0.0377	−0.0177	−0.2626	0.7576***	0.2214
	[1.59649]	[2.22252]	[−0.85729]	[0.01373]	[0.59966]	[−0.15942]	[−0.12597]	[−1.12805]	[3.65673]	[1.16853]
X (−3)	0.9286	1.2685**	−0.0109	−0.09	0.0778	0.1755	0.031	0.0211	0.8232***	0.4686***
	[1.42331]	[2.14077]	[−0.07590]	[−0.63887]	[0.43236]	[0.77739]	[0.22114]	[0.09064]	[4.85666]	[3.02246]
X (−4)	0.7008	1.1388**	−0.0269	−0.1371	−0.0489	−0.1272	0.0317	−0.3468	0.4453	0.3549**
	[1.18537]	[2.12076]	[−0.18711]	[−0.96989]	[−0.30285]	[−0.62710]	[0.23613]	[−1.55570]	[2.53507]	[2.20892]
X (−5)	0.6107	1.0072**	0.1138	−0.1514	0.2408*	−0.0405	−0.0656	−0.0083	0.6424***	0.3853***
	[1.15951]	[2.10575]	[0.79246]	[−1.07250]	[1.66149]	[−0.22263]	[−0.48884]	[−0.03718]	[4.64191]	[3.04420]
X (−6)	0.3968	0.8943**	−0.0746	−0.0326	−0.4324***	−0.1323	−0.3321**	−0.3701*	0.0306	0.0894
	[0.85279]	[2.11597]	[−0.51963]	[−0.23139]	[−3.09325]	[−0.75401]	[−2.52194]	[−1.69447]	[0.21339]	[0.68128]
X (−7)	0.2125	0.8079**	0.0769	0.0566	0.2298*	0.1746	−0.3063**	−0.0681	0.4144***	0.1772
	[0.52606]	[2.20178]	[0.56846]	[0.42565]	[1.79055]	[1.08429]	[−2.37425]	[−0.31805]	[3.34427]	[1.56388]
X (−8)	0.0019	0.6709**	−0.1384	−0.0557	−0.2284*	−0.1447	−0.1408	−0.1119	0.075	−0.0248
	[0.00544]	[2.14296]	[−1.02792]	[−0.42075]	[−1.86309]	[−0.94065]	[−1.06606]	[−0.51052]	[0.58928]	[−0.21308]
X (−9)	−0.1742	0.4890*	0.0605	0.0049	−0.2256*	−0.1329	−0.2229*	0.2539		
	[−0.62452]	[1.93095]	[0.44613]	[0.03664]	[−1.94128]	[−0.91150]	[−1.76766]	[1.21437]		
X (−10)	−0.3544	0.4638**	−0.1163	0.0795	−0.2236**	−0.2990**	−0.1173	−0.1259		
	[−1.61280]	[2.32428]	[−0.87531]	[0.60884]	[−2.04256]	[−2.17689]	[−0.92705]	[−0.59991]		
X (−11)	−0.4913***	0.3287**	0.1161	0.0744			−0.2883**	0.0827		
	[−2.87053]	[2.11469]	[0.86672]	[0.56459]			[−2.50197]	[0.43244]		
X (−12)	0.19	0.2374*	0.4177***	0.0117			0.1099	0.0952		
	[1.39137]	[1.91394]	[3.42971]	[0.09740]			[0.91058]	[0.47560]		
Y (−1)	1.3238**	0.067	−0.0372	0.3213**	−0.5769**	−0.8235***	−0.5508***	−0.2685	0.4664***	−0.7629***
	[2.50391]	[0.13962]	[−0.27884]	[2.45031]	[−2.35596]	[−2.67992]	[−3.32638]	[−0.97753]	[2.68096]	[−4.79497]
Y (−2)	1.0442**	−0.1155	0.0685	−0.2699*	−0.6082**	−0.7344**	−0.3922**	−0.0601	0.3235	−0.7586***
	[2.00895]	[−0.24476]	[0.48898]	[−1.95964]	[−2.50180]	[−2.40726]	[−2.40114]	[−0.22189]	[1.37239]	[−3.51871]
Y (−3)	1.0305**	0.1476	0.0474	0.3542**	−0.5753**	−0.6316**	−0.2900*	−0.1761	0.1714	−0.6764***
	[2.06338]	[0.32540]	[0.32249]	[2.45062]	[−2.47599]	[−2.16642]	[−1.94457]	[−0.71191]	[0.66496]	[−2.86917]
Y (−4)	0.9250**	0.0469	−0.0923	−0.2309	−0.5419**	−0.6070**	−0.2711*	0.0201	0.1445	−0.7512***
	[1.97344]	[0.11026]	[−0.60139]	[−1.52959]	[−2.35529]	[−2.10237]	[−1.93521]	[0.08639]	[0.56480]	[−3.21106]
Y (−5)	0.7141	0.073	−0.2038	0.1538	−0.5646**	−0.6385**	−0.3757***	−0.0959	0.0016	−0.7145***
	[1.62808]	[0.18322]	[−1.32160]	[1.01449]	[−2.49811]	[−2.25120]	[−2.80034]	[−0.43114]	[0.00635]	[−3.08057]
Y (−6)	0.5689	0.0235	−0.0757	0.0652	−0.4019*	−0.6123**	−0.3930***	−0.0214	0.0965	−0.5247**
	[1.41798]	[0.06456]	[−0.47795]	[0.41840]	[−1.86052]	[−2.25875]	[−2.85913]	[−0.09375]	[0.38532]	[−2.29102]
Y (−7)	0.3739	−0.0418	−0.1802	0.0312	−0.3681*	−0.5218**	−0.3219**	0.0385	−0.1155	−0.3223
	[1.03268]	[−0.12715]	[−1.13512]	[0.19995]	[−1.90482]	[−2.15197]	[−2.42462]	[0.17473]	[−0.53399]	[−1.62880]
Y (−8)	0.4	0.0433	0.1984	0.2112	−0.3768**	−0.4810**	−0.2789**	−0.0763	−0.0988	−0.1252
	[1.24427]	[0.14818]	[1.23842]	[1.34127]	[−2.18321]	[−2.22121]	[−2.24350]	[−0.36992]	[−0.64352]	[−0.89195]
Y (−9)	0.3719	0.0105	0.0816	−0.1021	−0.1608	−0.1819	−0.2032*	−0.0491		
	[1.36017]	[0.04217]	[0.49065]	[−0.62402]	[−1.06909]	[−0.96357]	[−1.68051]	[−0.24498]		
Y (−10)	−0.0396	0.346	0.1124	−0.0627	−0.0169	−0.0603	−0.2570**	−0.1094		
	[−0.18506]	[1.46732]	[0.73147]	[−0.41528]	[−0.15424]	[−0.43743]	[−2.35954]	[−0.60567]		
Y (−11)	0.0297	0.3066*	−0.0353	0.047			−0.163	−0.0835		
	[0.18012]	[1.69092]	[−0.24612]	[0.33347]			[−1.58281]	[−0.48898]		
Y (−12)	−0.067	0.164	−0.0859	0.0505			0.0032	−0.0631		
	[−0.53086]	[1.18070]	[−0.65795]	[0.39690]			[0.03844]	[−0.45212]		
Adj. R2	0.8169	0.4482	0.74	0.5474	0.8307	0.5474	0.635	0.1856	0.7494	0.3956
F statistic	15.6323	3.6637	10.8432	5.1827	20.6249	4.0115	6.7052	1.7477	16.1241	4.3113

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy. T — Tourism demand (Nights spent at tourist accommodation establishments — monthly data); PM10 — monthly mean concentrations of PM10. *, **, *** represents coefficient statistically significant at 10%, 5% and 1%, respectively. X stands for the variable T and Y stands for variable PM10. t-statistics in [ ] and t critical values are: 1.6449 at 10%; 1.9600 at 5%; 2.5758 at 1%.

2016), as well as with those stating that there is no significant impact regarding the relationship between tourism and AQ (Paramati et al., 2017).

This induces a higher growth demand for tourism in Italy which is enhanced through the previous demand for tourism. Moreover, the demand for tourism can significantly impact the levels of PM10 in Italy at least up to 5 months, meaning that, the higher the demand for tourism, the higher will be the pollution levels measured through PM10 in this study. On the other hand, lagged PM10 effects on tourism seem to be positive even though they are only significant at the first lag. This may lead us to conclude that region attractiveness may explain these results, or moreover, that tourism demand may not be affected by pollution levels. Another possible explanation is that tourists who have already made their plans to visit a country are less likely to change them due to a reduction of AQ, a result attained by Tang et al. (2019) for the Beijing region. Table 7 summarizes the results discussed.

Table 8 presents the Granger causality test results by country. We fail to reject the null hypothesis (H0: X does not Granger-cause Y) whenever the *p*-value is greater than the 0.1, 0.05, or 0.01 significance level. In general terms, X is said to Granger-cause Y if Y can be better predicted using the histories of both X and Y than it can by using the history of Y alone. Looking at the attained results, we observe that tourism Granger causes PM10 in Switzerland, Cyprus, and Italy, always being a univariate causality. However, PM10 only Granger causes tourism in Great Britain. Therefore, it appears that Granger causality runs one-way from PM10 to T or from T to PM10, but never in a bivariate way. The only country for which it was impossible to find Granger causality was Austria.

VD helps in the interpretation of the VAR/VEC model as it helps to determine the proportion of variation of the error variance of the dependent variable explained by each of the independent variables, once a shock occurs. The Forecast Error Variance Decomposition (FEVD) shows us how much of the future uncertainty of one time series (T or PM10) is due to shocks into the other time series (PM10 or T, respectively) in the system. This evolves, so the shocks on time series

Table 7
Summary of relationship of coefficients through VAR/VEC.

Country	Tourism -> PM10	PM10 -> Tourism	Result
AT	Negative	(not significant)	Tourism influences negatively PM10 levels
CH	Negative	Positive	Tourism influences negatively PM10 levels; PM10 levels do not Influence Tourism significantly
CY	(not significant)	Negative	PM10 levels influences negatively Tourism
GB	Negative	Negative	Reciprocal negative relationship
IT	Negative	Positive	Tourism influences negatively PM10 levels; PM10 levels do not Influence Tourism significantly except for first lag (1 month)

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy.

Table 8
Granger causality tests between T and PM10 by country.

Dependent variable:	Country	Excluded	Chi-sq	df	Prob.
T	AT	PM10	14.0316	12	0.2987
PM10		T	10.1708	12	0.6010
T	CH	PM10	13.0595	12	0.3647
PM10		T	20.8805	12	0.0522*
T	CY	PM10	11.3744	10	0.3291
PM10		T	20.5062	10	0.0248**
T	GB	PM10	19.0090	12	0.0883*
PM10		T	14.9023	12	0.2468
T	IT	PM10	12.7375	8	0.1212
PM10		T	24.5847	8	0.0018***

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy. T — Tourism demand (Nights spent at tourist accommodation establishments — monthly data); PM10 — monthly mean concentrations of PM10. *, **, *** represents coefficient statistically significant at 10%, 5% and 1%, respectively. VEC and VAR Granger Causality/Block Exogeneity Wald Tests.

maybe not very important in the short run but very important in the long run. For that we used a total decomposition period up to 24 lags, meaning up to two years since we use monthly data. However, in terms of results and to have good representativeness of the FEVD we presented the results for periods of 1, 6, 12, 18, and 24 months.

Given that, a forecast VD measures the fraction of the overall forecast variance for a variable that can be attributed to each of the driving shocks. In Table 9 we observe that a shock of PM10 can describe a great percentage of the variance of errors of tourism demand for almost all countries and raise over time.

The only country where the percentage rounds lower is in Italy where, at the horizon of 24 months, a shock of PM10 is only able to explain 5.43% of the variance of errors of tourism demand. We also observe that a shock occurring from tourism to PM10 can describe a great percentage of the variance of PM10 errors in both the short and the long run (measured by the periods).

The country where a shock of tourism demand can explain less of the PM10 variance errors is Great Britain, where, at a horizon of 1 month, it is only able to explain 0.31%, and at 24 months the percentage is of 10.09%. From the table, we are also able to see that the explanatory capacity of PM10 on tourism increases up to the horizon of one year and a half, and decreases before reaching the two years.

Even so, we can declare that there is the ability of both PM10 and tourism demand to explain the variance of the errors of the other variable when a shock of one of the variables occurs, meaning they are both important to explain each other movements. A similar result was obtained by Tang et al. (2019), referring to the importance of pollution on inbound tourism demand in China. As such, even if it would be better to add more variables in estimates to see which other variables can influence this relationship, our results reveal that both influence each other, and it would be good to have a more generalized assessment by considering other countries into our analysis.

Also, the study of Lee et al. (2009), analyses a relationship between tourism and the environment in a famous marine destination in South Korea (Gangneung), using the cointegration and the Granger causality test. The variables considered were tourist arrivals as the measure of tourism and CO (carbon monoxide) and PM10 concentrations, for AQ proxies. The study reveals analogous conclusions to ours, revealing cointegration relationships between tourism and all the environmental quality variables. In terms of Granger causality, derived through the error correction model, their results specify that tourism has statistically significant effects on the environment, whereas the influences of the environment on tourism are not significant. Another study that reached equivalent conclusions to ours is Saenz-de Miera and Rosselló (2014). They studied the impact of tourism on air pollution from a joint perspective, analyzing in detail any

Table 9
Variance decomposition by country.

Period	VD of T: AT			VD of T: CH			VD of T: CY		
	S.E.	LDATT	LDATPM10	S.E.	LDATT	LDATPM10	S.E.	LDATT	LDATPM10
1	0.2621	100.0000	0.0000	0.2780	100.0000	0.0000	0.2558	100.0000	0.0000
6	0.2980	89.9452	10.0548	0.3285	94.0903	5.9097	0.4565	99.5338	0.4662
12	0.3049	87.1512	12.8488	0.3650	83.3140	16.6860	0.5525	81.2958	18.7042
18	0.4042	86.3276	13.6724	0.4321	85.0762	14.9238	0.6700	85.6093	14.3907
24	0.4104	85.2981	14.7019	0.4644	81.5152	18.4848	0.7664	76.4849	23.5151
Period	VD of PM10: AT			VD of PM10: CH			VD of PM10: CY		
	S.E.	LDATT	LDATPM10	S.E.	LDATT	LDATPM10	S.E.	LDATT	LDATPM10
1	0.2380	0.0655	99.9345	0.2733	0.1346	99.8654	0.3210	10.8236	89.1764
6	0.2585	7.5410	92.4591	0.3302	18.7832	81.2168	0.3468	18.2880	81.7121
12	0.2725	9.9872	90.0128	0.3477	20.3938	79.6063	0.3892	17.2605	82.7395
18	0.2840	12.3420	87.6580	0.3754	28.9102	71.0898	0.4225	26.7118	73.2882
24	0.2924	13.6227	86.3773	0.3859	29.6597	70.3403	0.4595	25.7908	74.2092
Period	VD of T: GB			VD of T: IT					
	S.E.	LDATT	LDATPM10	S.E.	LDATT	LDATPM10			
1	0.2539	100.0000	0.0000	0.2679	100.0000	0.0000			
6	0.3501	71.9331	28.0669	0.4161	94.6665	5.3335			
12	0.3941	65.8959	34.1041	0.4996	93.8254	6.1746			
18	0.5741	45.3621	54.6379	0.5794	94.0437	5.9563			
24	0.6001	45.6055	54.3945	0.6441	94.5693	5.4307			
Period	VD of PM10: GB			VD of PM10: IT					
	S.E.	LDATT	LDATPM10	S.E.	LDATT	LDATPM10			
1	0.4211	0.3079	99.6921	0.2450	29.9758	70.0242			
6	0.6028	3.4586	96.5414	0.2552	33.4286	66.5715			
12	0.6524	8.0882	91.9118	0.2838	32.3548	67.6452			
18	0.7009	9.2447	90.7553	0.3066	34.9182	65.0818			
24	0.7385	10.0921	89.9079	0.3233	33.8317	66.1683			

Notes: Own elaboration. AT — Austria; CH — Switzerland; CY — Cyprus; GB — Great Britain; IT — Italy. T — Tourism demand (Nights spent at tourist accommodation establishments — monthly data); PM10 — monthly concentrations of PM10. Cholesky Ordering: T PM10. Values are presented in percentage points except S.E.

possible existing relationship between daily concentrations of PM10 and the number of tourists in Mallorca (Spain). The conclusions found were that the number of tourists is a significant determinant of air pollution.

5. Conclusions

This paper analyses the reciprocal possible existing effects of air pollution and tourism demand for five European countries (Austria, Switzerland, Cyprus, Great Britain, and Italy). Our results show that AQ has an impact on tourism demand for these countries, in most of the lags considered. For Austria, we found a positive correlation between coefficients for lagged tourism with PM10 up to 12 lags. Lagged tourism had a negative influence on tourism from the 9th up to its 11th lag, but only significant with an 11-month delay.

In Switzerland, the results show a positive influence of PM10 on tourism for its 1st lag. Tourism seems to only have a positive and significant effect over pollution at its first lagged value, meaning one previous month. Therefore, we can only say that tourism increases PM10 one month afterward, which seems reasonable since there is a delay in the real effects of tourism and tourist's perception due to pollution. Previous months of pollution also seem to be reflected in current levels of pollution (up to 3 months), but the coefficient signs attained are mixed, for example, being negative only at lag 2, but positive and significant for the 1st and 3rd lags.

Considering the results for Cyprus there seems to be an influence from tourism to PM10 for 10 lags. Regarding the effects of lagged PM10 on tourism, we can observe a negative and significant effect up to 8 lags. It seems that for Cyprus, pollution harms tourism, which is reflected through time provided that higher levels of pollution decrease the demand for tourism.

Considering the outcomes for Great Britain, we found a significant negative impact of tourism on PM10 only for the 6th lag. Also, a negative impact of PM10 on tourism is reflected up to the 10th month (lag), but the effect of PM10 over itself does not seem to be statistically relevant at any of the 12 lags used in the estimation.

Reading the results for Italy, the demand for tourism significantly increases levels of PM10 at least up to 5 months. Conversely, lagged PM10 effects on tourism seem to be positive even though they are only significant at the first lag. This may lead us to conclude that region attractiveness may explain these results. This is similar to the results obtained by Saenz-de Miera and Rosselló (2014), which found that the number of tourists is a significant determinant of air pollution.

In terms of policy recommendations and regarding the results obtained and discussed, governments from these countries should pay attention to possible damages caused by pollution in tourism demand, especially in Cyprus and Great Britain. To avoid greater losses, authorities should provide effective measures to control air pollution and improve AQ. This may be done through the establishment of early warning mechanisms to monitor air pollution in certain touristic regions and provide short-term actions to mitigate air pollution and its impact on tourism demand. Moreover, policymakers should take effective measures to recover the potential damage to their destination's brand and image. Although not so visible in Italy and Austria, this seems to be the case in Great Britain and Cyprus, and also in Switzerland, even if in the latter case we did not obtain a statistically significant influence of lagged PM10 values on tourism demand. The brand and image of the country can be influenced and deteriorated by air pollution, according to the results showed, even if not for all countries.

In contrast, our findings showed that for Austria and Italy, tourism demand growth has a significant negative impact on AQ, raising PM10 levels. In these countries, authorities should analyze which tourism activities or tourist behaviors can be damaging the environment, in particular AQ.

Governments could take the advantage of the internet, television, radio and other similar media platforms to simultaneously promote the policies and measures of some destinations and the country, for the promotion of ecology and fighting pollution.

It would be interesting and important to extend this study for other countries, modeling the relationship between tourism and AQ. Other variables like country characteristics, the quality of the destination, income per capita, tourist origin, and many others could be included in the analysis to see if the resident or tourist characteristics can influence the relationship between tourism and air quality. Additionally, indoor air quality was not included in this study, which could provide another useful research avenue in the future.

Declaration of competing interest

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