Universidade de Aveiro Departamento de Economia, Gestão, Engenharia Industrial e Turismo
2019

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TURISMO E QUALIDADE DO AR: UM ESTUDO ECONOMÉTRICO PARA PAÍSES EUROPEUS

TOURISM AND AIR QUALITY: AN ECONOMETRIC STUDY FOR EUROPEAN COUNTRIES

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Economia, realizada sob a orientação científica da Professora Doutora Mara Teresa da Silva Madaleno, professora auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro, e coorientação científica da Professora Doutora Margarita Matias Robaina, professora auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro.

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palavras-chave

Turismo, Qualidade do Ar, Ambiente, PM10, Modelo de Vector Autoregressivo (VAR), Causalidade de Granger, Países Europeus

Resumo

O forte crescimento do setor do turismo em alguns países europeus, nos últimos anos, mudou a maneira como os cidadãos e os políticos encaram esse setor, em particular no que diz respeito ao seu impacto ambiental e às consequências que ele pode ter na qualidade do ar dos destinos, em particular. Recentemente, o turismo passou a ser analisado juntamente com as variáveis relacionadas com a qualidade do ar e o impacto mútuo desses conceitos passou a ser analisado, uma vez que por um lado, o turismo pode afetar o meio ambiente e, por outro, também é fortemente dependente dele para se desenvolver e crescer.

Este estudo procura entender o impacto da qualidade do ar no momento de escolher um destino turístico ou o impacto que o turismo pode ter na qualidade do ar de um local específico.

Os indicadores utilizados foram as noites em estabelecimentos turísticos, como variável representativa da procura turística, e os níveis de concentração do PM10, como variável representativa da qualidade do ar. Esses dados foram trabalhados numa estrutura multivariada e usando um modelo de vector autoregressivo (VAR), com foco em países europeus (Áustria, Chipre, Reino Unido, Itália e Suíça) para valores mensais que cobrem o período de janeiro de 2008 a janeiro de 2015.

Os resultados mostram que, na Áustria e na Itália, o crescimento do turismo pode degradar a qualidade do ar. Por outro lado, uma qualidade do ar mais baixa do destino pode diminuir a procura turística, como foi evidenciado para o Chipre e Grã-Bretanha. Em geral, os resultados de causalidade mostram que o turismo causa os níveis de PM10 e os resultados da decomposição da variância mostram que os choques nos níveis de PM10 explicam uma grande percentagem de variação nos erros da procura turística.

Os principais resultados são úteis, principalmente para a formulação de políticas ambientais sobre o turismo. As autoridades devem tomar medidas efetivas para melhorar a qualidade do ar, por exemplo, o estabelecimento de mecanismos de alerta precoce para monitorar a poluição do ar em certas regiões turísticas e a tomada de medidas efetivas para recuperar os possíveis danos à marca e imagem do destino. Além disso, as autoridades devem analisar quais as atividades turísticas ou os comportamentos do turista que podem estar a prejudicar o meio ambiente, em particular a qualidade do ar, e adotar políticas corretoras que minimizem esses impactos.

Keywords

Tourism, Air Quality, Environment, PM10, Vector Autoregressive Model (VAR), Granger Causality, European Countries

Abstract

The strong growth of the tourism sector in some European countries, in the last years, has changed the way citizens and politicians look at this sector, as regards its environmental impact and the consequences it may have on the air quality of destinations, in particular. Recently, tourism started to be analyzed together with the variables related with air quality and the true impact of these concepts on each other started to be analyzed, since tourism on the one hand can affect the environment, and on the other it is also heavily dependent on it for development and growth.

This study fetches to understand the impact of air quality in the moment of choosing a tourism destination or, the impact that tourism may have on the air quality of a specific place.

The indicators used were the nights spent at tourist accommodation establishments, as representative of tourism demand, and the PM10 concentration levels as representative of air quality. This data was worked on a Multivariate Framework and using a Vector Autoregressive Model (VAR), focusing on European countries (Austria, Cyprus, UK, Italy and Switzerland) for monthly figures that cover the period from January 2008 to January 2015.

The results show that for Austria and Italy tourism growth can deteriorate air quality. On the other hand, a poorer air quality of the destination may decrease the tourist demand, as evidenced for Cyprus and Great Britain. Overall, causality results show that tourism causes PM10 levels, and variance decomposition results show that shocks in PM10 levels explain a large percentage of the error variation in tourist demand.

The main results are useful, in particularly for environmental policy making over tourism. Authorities should provide effective measures to improve air quality, for instance through the establishment of early warning mechanisms to monitor air pollution in certain touristic regions and taking effective measures to recover the potential damage on destination’s brand and image. Moreover, authorities should analyze which tourism activities or tourist behavior can be damaging the environment, in particular air quality, and adopt corrective policies that minimize these impacts.

Index

Tables Index

List acronyms

AQ – Air Quality

T – Tourism

PM10 - particulate matter 10 micrometers or less in diameter

CO2 – Carbon Dioxide

EU – European Union

VAR – Vector Autoregressive models

VEC – Vector Error Correction models

ADF – Augmented Dickey-Fuller

KPSS – Kwiatkowski, Phillips, Schmidt, and Shin

MCE – Error Correction Mechanism

VD – Variance Decomposition

AT – Austria

CH – Switzerland

CY – Cyprus

GB – Great Britain

IT – Italy

UNWTO – United Nations World Tourism Organization

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. The World Tourism Organization, the United Nations agency that specializes in promoting responsible, sustainable and universally accessible tourism, has advanced in its annual report with some figures that give a very positive picture of developments in the tourism sector (UNWTO, 2017).

In recent years, the number of nights spent (tourist night) in European tourist accommodation establishments has shown an upward trend. However, there was a slight drop in 2008 and 2009 as a result of the economic and financial crisis: the number of tourists' overnight stay in the EU-28 decreased by 0.6% in 2008 and 2% in 2009. In 2010, however, the number of overnight stays began to recover and reached a peak of 2.9 billion overnight stays in 2016, an increase of 3.0% compared to 2016 (Eurostat, 2018).

When tourism activities take place, the environment is inevitably changed, as the environmental impacts of tourism are due to the changes and transformations that this activity causes in the natural environment. With the huge increase in the tourism industry, there was a need to scale up and install infrastructures such as hotels, restaurants and basic sanitation, sometimes without knowing their effects on the local environment. Tourism activities on one hand can have significant negative environmental externalities (e.g. through pollution or extraction of natural resources), but on the other hand, tourism activities are very reliant on natural environment (e.g. coastal zones, natural parks).

Air quality (AQ) can be defined as "… the composition of the air in terms of how much pollution it contains", in other words, it can be described as "…a degree to which air is suitable or clean enough for humans, animals, or plants to remain healthy" (Collins Dictionary, 2019).

The air quality is a worry in a day-to-day basis for all European citizens, and for all other persons around the world. They care more about their health conditions and the air quality has a direct impact in human health. "Poor air quality can affect or harm human health and/or the environment. Air quality can be degraded by natural or man-made sources. Natural sources include volcanic eruption, windstorm dust, and others. Man-made sources include pollution from moving vehicles, toxic gases from industries, coal powered plants, burning wood or other material in open air, landfills. Both these sources can seriously affect the overall air quality and can lead to severe health problems for humans" (Conserve Energy, 2019).

There is a series of studies that addressed the relationship between tourism and air quality. The causal relationship among tourism and air quality has been widely documented in the literature such as the study of Wang, Fang, & Law (2018). For example, the studies that related the effect of tourism on variables such as CO2 emissions, air pollution, climate change and environmental variables, may have reached different conclusions regarding the use of different variables to express the effect of pollution. However, most of the studies had made the assumption that CO2 emissions is a variable that can represent the air quality, but in reality, this variable is not the best proxy to measure air quality. CO2 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. In terms of air quality and human health, it has no effects. For this reason, this pollutant is not considered for air quality purposes and there are no legislated limiting values for its concentration in the air in terms of human exposure. CO2 is not considered an air pollutant in the Air Quality Directive (2008/ 50/ EC) or in the European Air Quality Reports. As a reference, we use the most recent European air quality reports (European Environment Agency, 2018), where a general air quality assessment is made in Europe and where the most critical pollutants (such as PM10) are identified.

PM10 are the particles in the atmosphere with an aerodynamic diameter of less than 10 micrometres. Airborne particles are currently the air pollutant of greatest concern, as concentration levels exceed the legal limit values (daily and annual average) at various locations each year.

There are a limited number of studies using variables as PM10 or PM2.5 as representative of air quality and studying its relationship with tourism. The existing studies are mainly for Asian countries (e.g. China and Hong Kong). Little is known about other regions and nations around the world where AQ levels are low or are significantly affected by high levels of tourism.

Concluding by the importance of the study of the relationship between tourism and air quality, and as there are no studies using adequate measures of air quality (measured trough PM10) for European countries, the present study tests the relationship air quality and tourism on Austria, Cyprus, UK, Italy and Switzerland. Our major purpose is to investigate the relationship between tourism demand and air quality using vector autoregressive models (VAR), provided these models allow for 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, where it is presented different studies related with tourism and its impact on air quality variables and the impact of air quality on tourism demand; afterwards we explain our Data and Methodology in a detailed way, justifying the use of each dataset and model in section 3. We apply the data and methodology approach to get our Results, discussed in section 4. Finally, in section 5 we conclude, presenting the most important findings and comparing our results with the ones that were expected previously, based on the available literature. We also present in section 5 some limitations of our work and provide future research lines that might be followed.

2. Literature Review

Tourism is a matter that is being massively talked on the last years as a consequence of the higher mobility and liberty for people to travel. Also, the topic of air quality and environmental protection is getting a large spotlight on news and political discussions over the previous months.

A deeper analysis of the available literature was performed in order to collect the necessary information for these two subjects analyzed together. The studies referred on this chapter analyzed different methods and approaches to observe the impact of different variables of tourism on environment and particularly, in air quality, but also the impact of air quality on tourism demand.

Many relationships between tourism and environmental variables have been studied among the years, by different authors. Most of these studies use CO2 emissions, climate change, environmental pollution and air quality. These variables are connected between them since CO2 emissions could impact the pollution, either the air quality and all of them have a contribution on climate change and, consequently, on environment.

A short summary of the studies analyzed could tell that we may find positive and negative associations between tourism and the referred environmental variables, and also a null effect of each other.

A first set of studies conclude for a positive relationship between tourism and environmental variables, in the sense that tourism can raise pollution, environmental footprint or climate change. Among these, the positive effect could be shown in two sides. In other words, the authors conclude that tourism could have effect on the variables, and some have even achieved that the variables have impact on tourism.

Some authors use pollution, as an environmental variable, to see the effect on tourism, or vice-versa. An example is the study of Azam, Alam, & Haroon Hafeez (2018), where the authors conclude that tourism has a significant positive effect on environmental pollution (measured through CO2) in Malaysia and the work of Saenz-de-Miera & Rosselló (2014), that investigate the impact of tourism on air pollution, using PM10 concentration. The authors conclude that the daily stock of tourists is not only a significant predictor of air pollution concentration levels but also a variable whose inclusion improves the standard specification of urban air pollution models that have the common feature of using weather conditions as main explanatory variables.

Additionally, Xu & Reed (2017), reveal that pollution may have an impact on tourism. They conclude that the perceived pollution has a stronger impact on inbound tourism than measured pollution levels, and also that the perceived pollution level in one city could impact people's travel plans. Zhou et al. (2018), reveal that the negative impact on tourism is higher when pollution increases and the study of Ahmad, Draz, Su, Ozturk, & Rauf (2018), divulge a negative impact of tourism on environment, measured by CO2 emissions, in the regions of Ningxia, Qinghai, Gansu, and Shanxi, meaning that the tourism impact on the environment is negative, provided that the effect of tourism on CO2 is positive and the pollution will then be increased.

The CO2 emissions is a key concept that is being frequently used in the most recent works. Some studies analyzed this trend, as Bali et al. (2018), that found a positive impact of tourism on CO2 emissions in a sample of Mediterranean Countries. Wu, Han, & Tian (2015), concluded that total emissions from tourism kept increasing, while emissions per tourist dropped. Paramati, Shahbaz, & Alam (2017), investigated the impact of the effect of tourism on CO2 emissions for eastern and western European Union countries, concluding that tourism increases CO2 emissions in Eastern EU but decreases in Western EU, and that tourism causes CO2 emissions in Eastern EU, while economic growth and CO2 emissions cause tourism in Western EU (cause in the Granger sense).

Overall, the results of Paramati, Shahbaz, & Alam (2017), suggest that tourism plays an important role in accelerating economic growth; however, its role on CO2 emissions largely depends on the adaptation of sustainable tourism policies and efficient management. Liu, Pan and Zheng (2019), analyzed different pollutants (CO2 and PM2.5) and different tourist groups (domestic and international) for China and concluded that the impact of CO2 on tourism is non-significant (but negative). 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, in accordance to the authors, may be that the effect of PM2.5 on air quality is intuitive and people can perceive the negative

AQ impact through personal experience or observation, thereby directly affecting their travelling plans.

The negative impact of tourism on the environment and the inverse relationship was also supported by Wang & Wang (2018), which stated that tourism growth drives to more CO2 emissions in the future, and that greater CO2 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, Baylon Verances, & Song (2009), shown cointegration relationships between tourism and all the environmental quality variables used in their study, such as CO2 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 influences of the environment on tourism are not significant.

When we talk about environment, a concept that is necessarily associated is the climate change. Katircioglu (2014), concluded that tourism development in Turkey has resulted on considerable changes in climate. Following the 2003 Djerba Declaration, the World Tourism Organization (WTO) recognized the bidirectional relationship between tourism and climate change. Therefore, climate change has an impact on tourist destinations and tourist flows, but simultaneously, tourism is a major contributor to climate change mainly due to the use of fossil fuels (Rico et al., 2019). Peeters, Szimba, & Duijnisveld (2007), observed that climate change generates more than half of the externalities of tourist transport. The uneven distribution of emissions by type of tourism markets offers an opportunity to reduce emissions significantly, while affecting only a relatively small part of all tourism and of the tourism economy.

Other variable used by some authors, to see the impact of tourism on environment and vice-versa, is air quality. Wang, Fang, & Law (2018), explored this impact and concluded that air quality in the place of origin creates a pushing effect, and local outbound tourism demand increases as air quality deteriorates. This relationship is negatively moderated by local disposable income level. This study also identifies a delay effect of five days in the impacts of air quality on outbound tourism demand. Also, Keiser, Lade and Rudik (2018), evaluated USA national parks and found a negative relationship between in-park ozone concentrations and park visitation. Additionally, their results also point 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. A consensual conclusion is that air pollution reduces the number of tourists (Anaman and Loi, 2000; Sajjad, Noreen and Zaman, 2014; Chen, Lin and Hsu, 2017; Deng et al., 2017; Keiser, Lade and Rudik, 2018; Wang, Fang and Law, 2018; Zhou et al., 2018; Liu, Pan and Zheng, 2019).

A second set of studies reveal a negative relation of tourism with the environmental variables, meaning they are able to favor the conclusion that tourism can reduce pollution or emissions. An example is Azam, Alam, & Haroon Hafeez (2018), that conclude for a negative effect of tourism over environmental pollution observed in Thailand and Singapore. Also, Zhang & Gao (2016), shows that tourism has a negative impact on CO_2 emissions in the eastern region. Ozturk, Al-Mulali, & Saboori (2016), reveal that the number of countries that evidence a negative relationship between the ecological footprint and its determinants is more common in the upper middle and high-income countries.

A third set of studies show no significant conclusions regarding the relationship between tourism and the environmental variables. For example, Paramati, Shahbaz, & Alam (2017), suggest that tourism plays an important role in accelerating economic growth. However, its role on CO_2 emissions largely depends on the adaptation of sustainable tourism policies and efficient management. Also, Azam, Alam, & Haroon Hafeez (2018), suggest that sustainable economic growth and development should be ensured by implementing prudent public policy where host governments must strive to promote socially and environmentally responsible tourism industries in their respective countries. Chen et al. (2017), evidence that the effects of air pollution and rainfall on the demand for tourism depend significantly on the phases of the business cycle. Finally, Ali & Amin (2018), indicate that a growth in tourism has not caused the observed environmental degradation in Bangladesh.

This summary of literature can enable us to conclude that Europe is not the focus on the majority of these studies. Specifically, for European countries, Rico et al.

(2019), analyzed the carbon footprint of tourism in Barcelona and Koutroulis, Grillakis, Tsanis, & Jacob (2018), studied the vulnerability of European summer tourism under climate change (global warming), but from our knowledge, studies are not so common for European countries.

Also, as shown above, most of these studies do not analyze the relation of air quality and tourism, focusing their analysis onto the relationship of tourism with other variables. When analyzing interactions between both, air quality is measured through emissions and not by real pollution variables, despite the fact that European reports state that emissions are not good measures of air quality (EEA, 2019).

In general, this literature review shows that there could be place to a relevant negative effect of the poor environmental conditions of a destination on the attractiveness of tourists. So, as the main question about the effects of the air quality over tourism destination choices is still unanswered for Europe, our study wants to mitigate these lacks, exploring this relationship through the available data for five countries of the European Union (Austria, Cyprus, Great Britain, Italy and Switzerland), using PM10 as measure of the air quality of the destination. Also, our measure of air quality represents an additional contribution for the existent literature, provided that most of the previous studies focus their analysis over other variables which they say to represent air quality, but that in reality do not, as CO2 emissions (EEA, 2019). Another contribution of the present work is related to the fact that we analyze the relationship between tourism demand and air quality but also on the other way around through the use of vector autoregressive models which permit the variables of the model to be simultaneously endogenous and exogenous.

3. Data and Methodology

This empirical research aims to estimate the relationship between inbound tourism and air quality, using cointegration and causality tests. It also aims to verify whether the direction of causality differs by country. The countries' statistical data that are used in this article are monthly figures that cover the period from January 2008 to January 2015, and that were taken from Eurostat, for tourism demand data, and EMEP network (http://ebas.nilu.no) for air quality data (PM10). EMEP is a network that has many stations across Europe (https://projects.nilu.no//ccc/sitedescriptions/index.html), furthermore while imposing the various filters (such as data quality level and data availability for all countries within the same period), the number of analyzed countries was reduced. For estimation, the Eviews Data Analysis and Statistical Software (Vol. 10) were used.

The total number of nights spent by foreign tourists in accommodation establishments is the proxy selected to measure inbound tourism, and PM10 concentrations is the proxy selected to account for air quality. Data for PM10 was selected based on a minimum availability data limit of 75% on the time horizon. Provided this, we have data for the following countries (in parentheses appears the number of stations that met the criterion of 75% data per country): AT – Austria (1); CH – Switzerland (5); CY – Cyprus (1); GB – Great Britain (1); IT – Italy (1).

Tourism series and PM10 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). We proceed by removing the seasonal effects by using the moving average technique (arithmetic means) when the number of observations is even, implemented in excel. This method uses the concept of ironing out the fluctuations of the data by taking the means, measuring the trend by eliminating the changes or the variations by means of a centered moving average (Sutcliffe & Sinclair, 1980; Ahmed et al., 2010; Mansor et al., 2019). Additionally, as has often been used in similar studies, all of the series are expressed in logarithms to facilitate the interpretation of coefficients (Khan et al., 2005; Kulendran & Wilson, 2000a; 2000b; Shan & Wilson, 2001; Ahmed et al., 2010; Mansor et al., 2019), and to turn the variables comparable since they were originally presented at different measurement units. We also performed descriptive statistics by series and Pearson correlation results among series for the different countries.

3.1. Stationarity and Cointegration Analysis

In a 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 & Fuller, 1979). We also performed other commonly reported unit root tests as that of the Kwiatkowski, Phillips, Schmidt, and Shin Test (KPSS test) (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), but we skipped to present its results in the dissertation provided that results were similar, or else, they drove in all tests to the same conclusions. Both, however, differ in the null hypothesis.

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 & Fuller, 1979; Gujarati, 2003). On the contrary, the KPSS test (Kwiatkowski et al., 1992) differs by having a null hypothesis of stationarity against the alternative hypothesis that the time series is non-stationary. At the end both tests drove us to the same conclusions. Identifying the order of integration of a series is a fundamental introductory step in any time series econometric study, since the series may not be stationary but there may be a linear combination between them. Much of the economic and financial series does not appear to be stationary and therefore needs to be transformed to become so.

Additionally to unit root tests, we have started by applying a common VAR model with no restrictions added in order to be able to study the optimal number of lags to be included in each model by country, as well as the existence of cointegrating relationships. Only afterwards, the model was adjusted considering the optimal number of lags and the number of cointegrated relationships' when these existed. If the time series under analysis 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. These models also have the advantage of incorporating the concept of error correction that can help predicting the variables in which we may have interest.

In verifying the order of integration of each set of variables, the objective is to know if there are long-term equilibrium relationships between the variables included in each model, for other words, whether they are cointegrated, or not, and what is the number of cointegrating relationships.

In the empirical literature, the most common methods for cointegration testing are the method of Engle and Granger (1987), and the method of Johansen (1988, 1995). Considering the well-known limitations in the academic literature of the Engle-Granger method, the Johansen's methodology was chosen, which tests the number of cointegrating relationships and estimates their parameters (Johansen, 1988, 1991, 1995; Johansen and Juselius, 1990). 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).

The Johansen's (1995), methodology begins with a system of identification and estimation of the VAR model on variables at level where it has been chosen, not only the deterministic component, but also the number of lags, p, common to all variables. Johansen's method uses the trace test and the maximum likelihood test, to provide information regarding the existence of cointegration between the variables. While the trace test is based on the null hypothesis of the number of distinct cointegrating vectors being less than or equal to r against a generic alternative, the maximum likelihood test is based on the null hypothesis of the number of cointegrating vectors being less than or equal to r against the alternative of r +1 cointegrating vectors.

The Eviews system calculates both statistics and the corresponding p-values. The criterion of decision follows the usual, the null hypothesis is rejected when the observed statistical value is higher than the critical value (or, when the p-value is lower than the significance level).

3.2. VEC and VAR models

After verifying the existence of cointegration through Johansen's methodology, the error correction model is included. The error correction mechanism is an essential tool for analyzing long-term relationships as it helps to reconcile short-term dynamic adjustment with long-term equilibrium relationships.

So, in a second step, the relationships between tourism demand and air quality were studied. For that, we estimated Vector Autoregressive Models (VAR), and Error Correction Mechanism (MCE) models (Vector Error Correction Models - VEC) to assess the existence of interdependent relationships between variables and a long-term equilibrium relationship between tourism demand and air quality measurement. This third step was divided on three sections: (i) the estimation of VAR or VEC models; (ii) the variance decomposition and (iii) the Granger causality tests.

The autoregressive vector models help us to evaluate the interrelationships 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, 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 variance decomposition is a very important 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 (where we say we have a bidirectional relationship) or only univocally (a unidirectional relationship). Thus, they clarify a broader perception of whether, or not, the past values of a variable may influence the future behavior of a variable at present.

Before the estimation of the models, 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), 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 over the AIC criteria. With respect to

ii) and as previously stated the chosen model was the Johansen cointegration criteria.

The next step consists in VEC or VAR models estimation. VEC model was used when cointegrating relationships existed. When no cointegrating relationship was found we relied over 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. It is useful to describe the dynamic behavior of time series and for forecasting provided it allows estimations in a system of theory-based simultaneous equations. The model is specified as in equation (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 $cov(\varepsilon_{1t}, \varepsilon_{2s}) = \sigma_{12}$ 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 to be presented in the following section, provided they change depending on the country. y_{1t} and y_{2t} are simultaneously dependent and independent variables, where y1 respects to T, and y2 to PM10, in the current setting. T refers to 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 to variable yi, where i is the variable and t-n (n = 1, 2, … lags) the lagged value of the “explanatory” variable and ε_{it} refers to the error term. VEC estimations are performed whenever it was found more than one cointegrating relationship, which in accordance to our results is used for all countries except in Switzerland, where no cointegrating relationships were found.

The results of an autoregressive vector model depend on the ordering of the variables in the estimated model, and in the present work one VAR was estimated for each of the countries under analysis and as we only included two variables in the analysis, it should also be noted that in a VAR / VEC all variables are simultaneously dependent and independent, so in the present study it will be indifferent the ordering of variables.

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 change of the next period variable. As explained before, to check if there was cointegration or not, we have used the Johansen cointegration test and results are presented in the following section. Cointegration analysis tests whether the variables trend is a random walk (sharing a common trend) and if so, at least one variable should Granger cause the other.

Firstly, introduced by Granger (1969), and later popularized by Sims (1972), it was born the concept of causality between two variables. Granger's basic idea of causation is that Xt Granger causes Yt if the past information of variable Xt allows to improve 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, using the Eviews software. This test is based on the null hypothesis of non-causality between variables, and as such, through the usual decision criterion, the null hypothesis is rejected if the p-value is lower than the significance level (for 1%, 5% or 10%).

Since the coefficients estimated by the VAR model are difficult to interpret, the impulse response functions (IRF) and the variance decomposition (VD) are regularly supportive in the interpretation of the results. In this work we use only the VD. VD is an alternative method to IRF, which examines the effects of shocks on dependent variables. This technique determines how much of the estimate 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). Each VD coefficient is interpreted as the percentage variance of the error produced in predicting a variable due to a specific shock of another variable, over a given period of time. The coefficients of this can also be interpreted as elasticities, implying that a 1% increase in one variable will have an impact, in equilibrium, of x% increase in another variable.

4. Empirical Results

On table 1 we may see the descriptive statistics of the original series and on table 2 we find the descriptive statistics of the deseasonalized series. The data suffer this transformation of dessazonalization, to remove the typical seasonal variation that is relatively constant over time.

Observing table 1, we can conclude that Italy presents the higher mean for the tourism demand as compared to the remaining countries. Also, for the values of PM10, Italy is on top of the list with the highest mean. In the other side, Austria has the lowest value presented for the mean in PM10 and Cyprus is the country with the lowest mean related to tourism demand.

The “better” standard deviation listed is from Cyprus because it is the lowest one, meaning that the ‘typical’ distance from the mean is lower as compared to the other ones.

In terms of tourism demand we may conclude that the lower number of nights spent at tourist accommodation establishments (monthly data) comes from Cyprus and the higher value derives from Great Britain. The difference between the lower value and the higher one is around 67 million available beds.

For PM10 the lowest and the higher values were registered in Great Britain, which recorded a deviation between both of around 66 units.

For table 2 we have the deseasonalized data and the results obtained point into the same direction as those of the Table 1.

Table 1- Descriptive statistics of the original series

Countries	Descriptive Statistics	T	PM10
AT	Mean	6973904.	21.44744
	Std. Dev.	3501196.	4.785528
	Min	1288469.	11.59094
	Max	16878220	37.20420
CH	Mean	2468198.	10.31481
	Std. Dev.	1297254.	3.698000
	Min	563123.1	3.359029
	Max	6359124.	18.27834
CY	Mean	1545147.	28.10158
	Std. Dev.	1181406.	11.78630
	Min	132215.7	9.239657
	Max	3528223.	73.88668
GB	Mean	14665246	14.22578
	Std. Dev.	12623470	11.42971
	Min	2672239.	2.265874
	Max	67159556	68.56796
IT	Mean	20533590	30.35718
	Std. Dev.	16100548	8.402290
	Min	4017241	13.79318
	Max	54367471	48.83561

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.

Table 2 - Descriptive statistics of the deseasonalized series (log)

Countries	Descriptive Statistics	T	PM10
AT	Mean	15.62612	3.040897
	Std. Dev.	0.546756	0.225162
	Min	14.06897	2.450223
	Max	16.64153	3.616422
CH	Mean	14.58509	2.260627
	Std. Dev.	0.525225	0.400930
	Min	13.24125	1.211652
	Max	15.66540	2.905716
CY	Mean	13.81349	3.244285
	Std. Dev.	1.056043	0.442135
	Min	11.79219	2.223505
	Max	15.07630	4.302533
GB	Mean	16.21085	2.395981
	Std. Dev.	0.753588	0.706907
	Min	14.79843	0.817961
	Max	18.02258	4.227825
IT	Mean	16.49511	3.373840
	Std. Dev.	0.864261	0.285657
	Min	15.20611	2.624175
	Max	17.81128	3.888460

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.

On table 3 are represented the values for Pearson correlation coefficients. This is a measure of the strength of a linear association between tourism and air quality. Results show that the strongest association of these two variables is observed in Cyprus with a strong uphill (positive) linear relationship. Austria is the unique country with a small strength of association between the variables, and the rest of the countries shown a large strength among them. Also, for all the countries the correlation is positive, meaning that the variables go in the same direction.

The value of the probability associated to the Pearson correlation indicates the significance of the correlation founded. So, all the countries, with exception of

Austria, present a statistical significance of 1%. For Austria, the variables are not statistically significant.

Table 3 - 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 concentrations of PM10. *, **, *** represents coefficient statistically significant at 10%, 5% and 1%, respectively.

The results on table 4, from the ADF test, reveal that the hypothesis of non-stationarity is rejected, for all countries studied.

After studying the variables stationarity properties, we have applied a common VAR model to each country and pair of variables to test for possible existence of cointegrated relationships and to test the optimal number of lags to be included in each model. Only afterwards we may choose the correct model to be applied, which is to say if it should be a VAR or a VEC model depending if we do not find or find cointegrated relationships among variables, respectively. Afterwards Granger causality tests are to be presented and variance decomposition values explored.

Table 4 - 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. T – Tourism demand (Nights spent at tourist accommodation establishments - monthly data); PM10 – monthly concentrations of PM10. *, **, *** 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.

Table 5 represents, for each country, the optimal lags test determining an optimal number of lags to be used in vector autoregressive estimations, according to the AIC criteria. Similar to the ADF test, the AIC criteria is among overall criteria for lag length selection the one which is mostly used in the literature. 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. Moreover, it remains at the discretion of the researcher to select the maximum lags which the adopted criterion for choosing optimal lags will use (Liew, 2004; Tang and Tan, 2015; Tang et al., 2019).

Generally, applying a statistical technique as information criteria (AIC and BIC) to select lag length is probably less parsimonious than carrying out sound econometric judgment. This does not mean that these criteria are not sufficient in several cases. Various studies already indicate that Akaike criterion is preferable as Liew (2004) and Tang et al., (2019), others develop the criteria further (Ng and Perron, 2001).

Table 5 - 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. T – Tourism demand (Nights spent at tourist accommodation establishments - monthly data); PM10 – monthly concentrations of PM10. * means that the optimal number of lags selected by the criteria is that presented in the column lag.

The next step was to test the possibility of cointegration among the variables that are used. For that it was applied the Johansen's maximum likelihood method (ML), 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 6.

The null hypothesis of non-cointegration is rejected in general, and the results of the trace test statistic show that almost all the series are cointegrated at the 10% critical value.

Table 6 - 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

Note : The series that were used are LT and LPM10 by country

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.

Provided that in the presence of cointegrating relationships we need to adapt the model to be estimated from the VAR to the VEC, the only country for which we did not found any cointegrating relationship was Switzerland and for this the standard VAR was computed and results afterwards derived. All the other countries in our sample demanded an econometric estimation based over the VEC model.

Estimation outputs in the following table (7), consider the number of optimal lags - revealed on table 5 – provided through lag length criteria, and simultaneously the number of cointegrating relationships in the case of the VEC model, as provided in table 6.

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 that long-run relationship affect the changes in the variable in the next period. Only for AT and IT, both error correction terms associated to T and PM10 are significant, whereas in CY and GB only the PM10 coefficient reveals to be significant. Merely in these significant values the cointegration term, known as the error correction term, when deviating from the long-run equilibrium is corrected gradually through a series of partial short-run adjustments, which happens more in PM10 according to our results.

It is observed from table 7 that there is no common pattern among countries and that there are very different results both in terms of significance and coefficient signs considering the lagged effects of both T and PM10 over the current levels of T and PM10.

For AT, we found a positive correlation between coefficients for lagged tourism with PM10 up to 12 lags, between tourism and tourism for 1^{st} and 11^{th} lag and from PM10 to tourism up to the 4^{th} 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^{th}. To counterbalance this conclusion, we recorded that lagged tourism has a negative influence on tourism from the 9^{th} up to its 11^{th} lag, but only significant 11^{th} months previously. All the other values for AT are not significant according to the statistical t critical values.

Table 7 - 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	Y	X	Y	X	Y	X	Y	X	Y
	T	PM10	T	PM10	T	PM10	T	PM10	T	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 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%.

With respect to country CH these results allow us to conclude for a positive influence of PM10 on tourism for 1st lag and a positive influence of tourism in tourism 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 month previously. Therefore, we can only say that tourism seems to increase PM10 one month afterwards, which seems reasonable since there is need for a delay to have real 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, being for example negative only at the 2nd lag but positive and significant also for the 1st and 3rd lags.

Considering the results attained for CY and focusing into the coefficient values we explain a negative trend from tourism to PM10 for 10 lags, and from tourism to tourism for 6th, 8th, 9th and 10th lags, with statistical significance, being positive and significant at the 1st lag. Regarding the effects of lagged PM10 over tourism we are able to observe a negative and significant effect up to eight lags, and so it seems that for CY, pollution has a negative effect over tourism which is reflected through time provided that higher levels of pollution decrease the demand for tourism, as results seem to indicate. The same happens when we look at the negative and significant effects of PM10 over PM10 up to 8th lag also. 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 GB, we found a negative impact of tourism on PM10, which is significant only for the 6th lag. On tourism over tourism it is also negative and significant after six months (except in the 8th and 12th lag). In addition, a negative impact for PM10 over tourism is reflected up to the 10th month (lag), but the effect of PM10 over this same pollutant does not seem to be statistically relevant at any of the 12th lag used in the estimation.

Reading the results for IT, it is clear that tourism has a positive influence over the tourism demand provided that all coefficients are positive and significant (except for the 6th and 8th lags). This induces a higher growth demand for tourism in IT which is enhanced through the previous demand for tourism. Moreover, the demand for tourism increases in a significant way the levels of PM10 in the Italian country at least up to 5 months. This seems a very reasonable effect regarding that it was initially expected that tourism had negative effects over pollution and in IT we observe that this really happens; meaning, the higher the demand for tourism the higher will be the pollution levels as measured through PM10 in this study. On the other way, lagged PM10 effects over tourism seem to be positive despite the fact that only significant at the first lag. This may lead us to conclude that region attractiveness may explain these undesirable 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 air quality, a result attained by Tang et al. (2019) for the Beijing region.

We can read the main results in table 8.

Table 8 – Resume of relationship of coefficients through VAR / VEC

Country	Tourism -> PM10	PM10 -> Tourism	Result
AT	Negative	(not significant)	Tourism influences negatively the PM10
CH	Negative	Positive	Tourism influences negatively the PM10; Reduced PM10 does not influence Tourism – only for the 1st month
CY	(not significant)	Negative	Tourism influences negatively the PM10
GB	Negative	Negative	Reciprocal negative relationship
IT	Negative	Positive	Tourism influences negatively the PM10; Reduced PM10 does not influence Tourism

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

Table 9 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. Therefore, and 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 CH, CY and IT being always a univariate causality. But PM10 only Granger causes tourism in GB. 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 AT.

Table 9 - 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 concentrations of PM10. *, **, *** represents coefficient statistically significant at 10%, 5% and 1%, respectively. VEC and VAR Granger Causality/Block Exogeneity Wald Tests.

In the following we decided to present also the variance decomposition results. Variance decomposition helps in the interpretation of the VAR/VEC model once it has been fitted. 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 implies its movement. The Forecast Error Variance Decomposition (FEVD) shows us how much of the future uncertainty of one time series (T or PM10) is due to future shocks into the other time series (PM10 or T, respectively) in the system. This evolves over time, so the shocks on time series may be not very important in the short-run but very important in the long run. For that we have used a total decomposition period up to 24 lags, meaning up to two years since our data is monthly. However, in terms of results and to have a good representativeness of the FEVD we have presented the results for periods 1, 6, 12, 18 and 24 months.

Given that a forecast variance decomposition 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 is able to describe a great percentage of the variance of the errors of tourism demand for almost all countries and raising over time.

Table 10 - Variance decomposition by country

	VD of T: AT			VD of T: CH			VD of T: CY	
Period	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
		VD of PM10: AT			VD of PM10: CH			VD of PM10: CY	
Period	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

		VD of T: GB			VD of T: IT	
Period	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
		VD of PM10: GB			VD of PM10: IT	
Period	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.

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

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

Even so, we are able to declare that there exists 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, turning both important to explain each other movements. A similar result was attained by Tang et al. (2019), calling our attention to the importance of pollution over inbound tourism demand in China. As such, even if it would be better to have more variables into estimations to see which other variables are able to influence this relationship, our results reveal that both influence each other, and it would be good to have a more general picture considering other countries into our analysis. Also, the study of Lee, Baylon Verances, & Song (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, and the variables were the Tourist arrival as the measure of tourism and the CO (Carbon Monoxide) emissions and the concentration of PM10 for air quality index. 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, the 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 the one of Saenz-de-Miera & Rosselló (2014). They studied the impact of tourism on air pollution from a joint perspective, looking in detail at the possible existent relationship between daily concentrations of PM10 and the number of tourists in Mallorca (Spain). The conclusions that were found were that the stock of tourists is a significant determinant of air pollution. Thus, the seasonal behavior of PM10 concentrations might be attributable not only to climatic factors but also to tourism.

5. Conclusions

The main contribution of our dissertation is in analysing the reciprocal possible existent effects between air pollution and tourism demand for five European countries. Most of previous studies concentrate their analysis into emissions which are not a good measure of air quality in accordance to European reports. Based on previous studies, it is difficult to draw conclusions on the impact of air quality on tourism and vice-versa, considering the diversity of measures for air quality. Moreover, some trends are observable after a deeper analysis of the studies. The main perception reveals that a good air quality tends to have a positive influence on tourism demand.

The studies reviewed confirm that tourists would not like to travel to places where the environment is severely polluted. The most probable reason of a high impact that it may have on tourism in a given destination is that air pollution can be perceived more easily by the public when compared to other types of pollution.

Concerning the results obtained in our study, we may conclude that air quality has an impact on tourism demand for these 5 European countries in most of the lags considered. For AT, we found a positive correlation between coefficients for lagged tourism with PM10 up to 12 lags. 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 11th months previously.

On CH, the results allow us to conclude for 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 month previously. Therefore, we can only say that tourism seems to increase PM10 one month afterward, which seems reasonable since there is the need for a delay to have real 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, being for example negative only at lag 2 but positive and significant also for the 1st and 3rd lags.

Considering the results for CY and focusing into the coefficient values we explain a negative trend from tourism to PM10 for 10 lags. Regarding the effects of lagged PM10 over tourism we are able to observe a negative and significant effect up to eight lags, and so it seems that for CY, pollution has a negative effect over tourism which is reflected through time provided that higher levels of pollution decrease the demand for tourism, as results seem to indicate. Based over 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 outcomes for GB, we describe an impact of tourism on PM10 which is negative and significant only for the 6th lag. Also, a negative impact for PM10 over tourism is reflected up to the 10th month (lag), but the effect of PM10 over this same pollutant does not seem to be statistically relevant at any of the twelve lags used in the estimation.

Reading the results for IT, the demand for tourism increases in a significant way the levels of PM10 in the Italian country at least up to 5 months. This seems a very reasonable effect regarding that it was initially expected that tourism had negative effects over pollution; meaning, the higher the demand for tourism the higher will be the pollution levels as measured through PM10 in this study. On the other way, lagged PM10 effects over tourism seem to be positive despite the fact that only significant at the first lag. This may lead us to conclude that region attractiveness may explain these undesirable results or moreover that tourism demand may not be affected by pollution levels. Similar results to the ones obtained by Saenz-de-Miera & Rosselló (2014) that found that the stock of tourists is a significant determinant of air pollution. Therefore, the seasonal behaviour of PM10 concentrations might be attributable not only to climatic factors but also to tourism demand, at some extent.

Even without very strong conclusions, in terms of policy recommendations and regarding the results achieved previously, we believe that governments from these countries should pay attention to pollution damage to tourism demand, especially in Cyprus and Great Britain. And so, to avoid greater losses, authorities should provide effective measure to control air pollution and improve air quality. This may be done through the establishment of early warning mechanisms to monitor air pollution in certain touristic regions and provide immediate reactions to the influence that air pollution might have over tourism demand. Moreover, policy makers should take effective measures to recover the potential damage on destination's brand and image. Although not so visible in IT and AT, it seems to be the case in GB and CY, and also in CH even if in this last country we did not obtained a statistically significant influence of lagged PM10 values over tourism demand. The brand and image of the country can thus be caused by air pollution, or at least is what our results seem to show even if not for all countries.

On the other side, our evidence showed that for Austria and Italy, tourism demand growth has a significant negative impact on air quality, raising PM10 levels. In these countries' authorities should analyse which tourism activities or tourist behaviour can be damaging the environment, in particular air quality.

It would be interesting to extend this study for other countries in Europe and also around the world to see if there are clear patterns among European regions at least. At the moment this was a limitation of our study provided that it is hard to collect relevant and credible data regarding pollutants. In terms of general policy directions, we advise countries governments to take advantage of the media like the internet, television, radio and other similar media platforms to propagate simultaneously the policies and measures of the destination/country, with respect to the promotion of ecology and fighting pollution. For future research also other variables like country characteristics, the quality of the destination, income per capita, tourist origin and many others should be included into the analysis to see if the local characteristics or tourist characteristics would influence the results between air quality and tourism demand.

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