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HOW IMPORTANT ARE REGIONAL AIRPORTS TO ATTRACT FOREIGN TOURISTS?

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TÍTULO EN ESPAÑOL: ¿Cómo influyen los aeropuertos regionales en la llegada de turistas extranjeros?

RESUMEN EN ESPAÑOL:

Este trabajo hemos estudiado el efecto de la conectividad aérea en la demanda de turismo internacional en España. Utilizando un conjunto de datos de panel de las 50 provincias españoleas (nivel NUTS-3) desde 2004 hasta 2019, se estima una función de demanda con características regionales (kilómetros de playa, temperatura o dotación de infraestructuras, entre otras) y varias variables de control (tanto temporales como regionales). La principal aportación del trabajo es la creación de un índice de conectividad aérea que considera el tamaño de los aeropuertos, así como que aeropuertos en provincias limítrofes también afectan a la conectividad aérea de una provincia. Los resultados muestran el efecto positivo de albergar un aeropuerto, así como de disponer de uno en una provincia limítrofe.

TÍTULO EN INGLÉS: How important are regional airports to attract foreign tourists?

RESUMEN EN INGLÉS:

In this Final Degree Project, we have studied the effect of regional air connectivity on the demand for international tourism in Spain. Using a panel dataset of the 50 Spanish provinces (NUTS-3 level) from 2004 to 2019, we estimate a demand function with several regional characteristics that can explain the demand for tourism such as kilometres of beaches, temperature, or the endowment of infrastructure, and some control variables to account for other unobserved factors that can affect the demand for tourism (time and regional factors, among others). The main contribution is the creation of an airport connectivity index that takes into account the size of airports and considers that airports at neighbouring provinces can affect the connectivity of a province. The results show the positive effect of hosting an airport and of having one in a neighbouring province.

PALABRAS CLAVE EN ESPAÑOL: Provincias; Demanda de Turismo; Conectividad; Aeropuertos; Datos de Panel.

PALABRAS CLAVE EN INGLÉS: Regions; Tourism Demand, Connectivity; Airports; Panel Data.

SÍNTESIS DE LAS CONCLUSIONES: La conectividad aérea de una región es clave para atraer turistas extranjeros. Esta no sólo proviene de aeropuertos en la propia provincia sino también de aeropuertos en provincias limítrofes. Otras características regionales como el clima o los atractivos naturales o culturales también afectan a la demanda de turismo extranjero.

INDEX

1. INTRODUCTION

The Spanish economy is heavily dependent on international tourism. In 2019, Spain received 126 million international tourists, being the third most important destination behind France and China (UNWTO, 2020). The share of tourism in the Gross Domestic Product reached 12% of the GDP in 2019 and 2.6 million employments are directly linked to touristic activities, according to the Spanish National Statistics Institute (INE).

Given the importance of tourism for Spain, several studies have tried to understand the determinants of tourism demand (e.g.,Garín-Muñoz 2006;2007; de la Mata & Llano-Verduras, 2012). Most of them focus on typical demand variables, namely prices and income. However, far less attention has been paid to regional air connectivity.

In this study we are interested in the role played by the degree of air connectivity in attracting international tourists. A region that is not well connected is likely to attract fewer tourist than a well-connected region, given the higher costs of transportation necessary to arrive at it. Existing studies on airport connectivity mainly consider the presence of an airport (Pompili, Pisati, & Lorenzini, 2019) or the number of airports (Cafiso, Cellini, & Cuccia, 2016) inside the region. The main contribution of this study is the development of an Airport Connectivity Index that considers the size of the airport as well as the existence of airports in neighbouring provinces. We measure the size of an airport with the share of passengers arrived to it each year.

We use a panel data set consisting of monthly data for the 50 Spanish provinces over the period 2004-2019. Our empirical model is a double-log demand function with two dependent variables: the number of foreign visitors and the number of overnight stays by foreign tourists. We focus on foreign tourists since they are more affected by air connectivity, as national tourists tend to travel more by car rely more on car for interprovincial tourism. We consider a large set of explanatory variables, including the traditional demand variables, such as prices, cultural and natural amenities, or regional connectivity, as well as other control variables, namely monthly dummies to control for seasonality, yearly dummies to capture unobserved year effects, and regional dummies to account for particular characteristics of some regions: the Islands, the two main Spanish provinces (Madrid and Barcelona), Seville as an inner region with special touristic characteristics, the provinces along the Cantabrian Coast, and the those along the Mediterranean coast that receive more tourists not only because of their beaches and weather but also due to their good road connection with France, which makes them easily reachable by car, and pr.

The study is structured as follows. Section 2 provides a review of tourism demand modelling. Section 3 reviews regional connectivity and develops the Airport Connectivity Index. Section 4 presents the econometric model. Section 5 provides a description of data. Section 6 contains the econometric estimation and the discussion of the results. Lastly, section 7 concludes.

2. THE DEMAND FOR TOURISM

Understanding the determinants of the demand for tourism is crucial to address tourism planning and it is of great importance given the weight this industry has in the Spanish economy: it generates more than 12% of GDP and, in 2019, employed more than 2 million people.

With regards to the dependent variable used in tourism demand studies, there are three variables commonly used: total expenditure, tourist arrivals and overnight stays. Given the scarcity of data on tourism expenditure, particularly at the regional level, we will estimate two demand models using tourist arrivals and overnight stays as dependent variables. In fact, these are the variables most articles use, such as Garín Muñoz (2007) or Massidda & Etzo (2012), among many others.

The choice of explanatory variables varies across studies, depending not only on data availability but also on the structure of the data set. Most studies use panel data (Song & Li, 2008), which can be divided into three categories: those with a single destination and multiple origins (Garín-Muñoz, 2006), those with one place of origin and multiple destinations (Garín-Muñoz, 2007), and those that use bilateral flows (Keum, 2010).

If we were to study the difference in the number of tourists to a single destination from different origins, the push factors would be income and population of the region of origin. However, to capture why tourists choose one destination instead of another, the pull factors would be regional characteristics such as natural and cultural amenities, infrastructure, climate, etc. Since in our dataset there are multiple destinations (Spanish provinces), but the origin (different countries) is unknown, only such pull factors, and not the characteristics of the origin, will be included.

3. CONNECTIVITY

Previous authors have studied connectivity using variables that reflect the endowment of infrastructures, such as the length of highways or the presence of airports. In this study we are interested in measuring the accessibility by plane of the Spanish provinces and we depart from the endowment approach with dummy variables to develop a measure of air connectivity that better reflects how "well" the region is connected. In this sense, a province can be well communicated without having an airport if there is one in a neighbouring province.

3.1. MEASURING AIR CONNECTIVITY

Air connectivity is a key factor to attract international tourist flows. In fact, 54% of tourists travel by air (IATA, 2020). In Spain, according to FRONTUR[1], up to 82% of foreign tourists in 2019 arrived by plane, with 15% arriving by car and the rest by train or ship.

To measure air connectivity, previous studies (Pompili, Pisati, & Lorenzini, 2019) include a dummy variable for the presence of an airport in the region. Others, such as Cafiso, Cellini, & Cuccia (2016), include the number of airports in the region. This approach has the shortcoming that it does not take into account the size of the airport.

The connectivity variables used in most of the previous studies only consider airports located in each region. However, a region's air accessibility can be also affected by airports in neighbouring regions. A clear example of this situation is Toledo, which does not host a commercial airport, but it is "well" connected since it is close to Madrid -less than one hour drive-, which hosts Adolfo Suárez Madrid-Barajas Airport, the major airport in the country.

In this study we will create two versions of an airport connectivity index (ACI) that will consider the size of the airport and the presence of an airport in the region and in neighbouring regions. The choice of the size variable is not minor, given the endogeneity issues that we face with these kinds of data. AENA provides monthly reports on the number of operations, the number of passengers, and the kilograms of freight moved at each airport. Using the number of passengers as explanatory variable will cause endogeneity given the correlation between it and the number of tourists. The number of

[1] FRONTUR is the Tourist Movement on Borders Survey carried out by the National Statistics Institute (INE). It provides monthly estimates of the number of visitors not resident in Spain that come to the country.

operations is a good indicator of the size of an airport, and we believe it will reduce the endogeneity in the model.

We only consider airports where more than 100,000 passengers have arrived each year in order to include airports where regular flights arrive, and not those dedicated mainly to charter or private flights (e.g., Burgos, Huesca or Cordoba).

We include three measures of connectivity that will allow to compare the effect that regional airports have on the arrival of foreign tourists:

Measure 1: Dummy variable

This is the most basic measure of connectivity, and the one that most previous studies have used (Algieri & Álvarez, 2022). Our binary variable takes the value 1 if the region hosts an airport with more than 100,000 arrivals, and 0 otherwise.

Measure 2: Regional Airport Index (ACI_LOCAL)

The basic index that includes the size of an airport is given by the number of operations made at the provinces' airport over the total number of operations made at all Spanish airports each month:

$$ACI\_LOCAL = s_{i\,y\,m} = \frac{Operations\ in\ regions'i\ airport}{Total\ operations\ in\ Spanish\ airports}$$

where *i* refers to a particular province, while *y* and *m* stands for year and month.

Measure 3: Neighbouring airports index (ACI_NEIGHBOUR)

To take into account the presence of an airport in a neighbouring province we sum the shares of operations made at those regions' airports:

$$ACI\_NEIGHBOUR_{i\,y\,m} = \sum_{j=1}^{J} s_{j\,y\,m}$$

where j refers to the neighbouring provinces of province i, then J refers to all the nearby regions. We consider neighbouring provinces those which share land border. We consider the two provinces of the Canary Islands to be neighbouring, given that it is easy to travel between the Islands.

We expect the local airport to have a greater effect on tourist arrivals than the neighbouring ones. For this reason, we include both indexes separately to allow for different effects.

3.2. OTHER MEANS OF TRANSPORT

Other types of transport infrastructure may also play an important role in the connectivity of a region. Even though most international visitors arrive by air, road and railway connections may matter in facilitating the movement of tourists from the arrival airport to their final destination.

Masidda & Etzo (2012) found a positive effect of the kilometres of highways of a region and its inflows of tourism. In Spain, the endowment of highways has also proven to have a positive effect on interprovincial tourism, since it is mostly done by car (Álvarez-Díaz, D'Hombres, Ghisetti, & Pontarollo, 2020). We control for the size of the provinces dividing the total kilometres of highways by the size of the province. Given the structure of the Spanish highway network, which is primarily radial with its centre in Madrid, larger inner provinces are expected to be crossed by the main highways, so they will be the ones with the greater kilometres of high-speed roads; however, smaller provinces might be as well as connected with fewer kilometres of highways. We include a variable measuring the kilometres of public and tolled highways of each region per squared kilometre of land area (HIGHW).

Spain is also known for its network of high-speed train (AVE), which connects the major cities of the country. Albalate, Campos, & Jiménez (2017) have studied the relationship between the introduction of high-speed rail services and the evolution of tourism at the local level in Spain. They find that the effects are weak or restricted to larger cities. Boto-García & Pérez (2023) study the effects of high-speed train on tourism seasonality, finding that regional accesibility through high-speed train mitigates seasonality of both national and international tourists. To control for the potential effect of the AVE, we include a dummy variable that takes the value 1 if the region is connected by high-speed train.

4. ECONOMETRIC MODEL

4.1. THE VARIABLES

We use two dependent variables to capture tourism inflows: the number of arrivals and the number of overnight stays.

As explanatory variables we include several characteristics that can explain the demand for tourism:

4.1.1. Prices

The price variable is basic in any demand function. Consumers react to higher prices by reducing the quantity demanded of the good. When it comes to tourism, measuring prices is a difficult task: they consist of several components such as the cost of transportation, the price of goods and services in the destination, travel insurance, the opportunity cost of travel time or the exchange rate (Crouch, 1992). In sum, a tourism price index is rarely available.

If we assume that the basket of goods and services consumed by tourists does not differ much from the basket measured by the Consumer Price Index, then CPI can be included as a measure of changes in the price of tourism. This is the choice made in most studies (Bujosa, Riera, & Torres, 2015; Garín-Muñoz, 2007). It is important to note that since CPI is an index, it measures price changes with respect to the base period, therefore it does not measure differences in price levels across regions which is the ideal price variable in a demand function.

Apart from the CPI, INE computes a Hotel Price Index (HPI) in order to capture the direct price of overnight stays. However, the HPI suffers from endogeneity, which is not a minor issue, since hotel prices increase during the high season due to the larger number of tourists arriving to Spain. Endogeneity causes the OLS estimators to be biased and inconsistent. We decide to use the CPI as price variable to reduce the endogeneity issue (CPI).

Another variable that affects the effective price paid by foreign tourists is the Exchange rate. Not only does it affect the effective price but also the expected price, as Gray (1966) points out:

> *"Prices are seldom completely known in advance by travellers so that the price level foreseen by the potential traveller will depend predominantly upon the rate of exchange of his domestic currency and hearsay evidence. Thus, while the influence of the price variable is undoubtedly complex, the rate of exchange can be expected to be a prime indicator of expected prices."*

Previous studies have included the exchange rate as an explanatory variable. While some authors weight the exchange rate with the CPI (Garin-Muñoz, 2007), others prefer to include it as a separate variable (Jena & Dash, 2020; Garín-Muñoz & Pérez, 2000). We will include the nominal exchange rate as an additional price variable (EXRATE).

In the case of Spain, the tourists coming from Eurozone countries are not affected due to the common currency. Since most international tourists come from the UK (21.6% in 2019), the GBP/EUR exchange rate is used.

4.1.2. Climatic variables

Many studies have shown that climate is one of the main variables explaining destination choices by tourists (Goh, 2012; Priego *et al.*, 2015). The most common variable to account for climatic conditions is temperature, but there are other variables such as rain or humidity that can be considered. Tourists care about the climate of the place and not its weather[2] since they plan their trips months in advance, and they do not know the weather they will find on arrival. Therefore, we consider the average temperature of each region from 1981 until 2010, which is invariant over the sample period for each region.

Spanish inner regions experience very cold temperatures in winter and extremely hot during summer, which makes them less attractive. On the other hand, coastal regions' temperature is more constant during the whole year. Since tourists most likely dislike extreme temperatures (Muñoz, Álvarez, & Baños, 2021), it seems necessary to complement the mean of temperature with a measure of its variability. To capture this effect, following Mata & Llano (2012), we include the ratio of the monthly average temperature to its standard deviation through the year (TEMP). So that $\text{Temp}_i = {}^{\text{Monthly average temperature}}/_{\text{Standard deviation}}$ is invariant over the sample period. A region with higher temperatures and lower variability is supposed to be more attractive for tourists; also, between two regions with similar average temperatures the one with lower variability will be more pleasant for tourists. For example, Albacete and Castellón show similar average temperatures (14.3ºC) but Castellón experience lower variation around the year (5.5ºC to 6.75ºC), then, *ceteris paribus*, it will be more attractive.

4.1.3. Natural amenities

The attractiveness of tourist destinations often arises from their natural resources. Spain is known for its "Sun and beach" tourism, so we expect regions with coastline to attract more tourists. Many studies include a dummy variable for the presence of coastline or the kilometres of coastline (Priego, Rosselló, & Santana-Gallego, 2015). Given that many of the kilometres of the Spanish coastline, especially in the north, are formed by high cliffs where the sea is inaccessible to the people, the kilometres of beaches, as in Mata and Llano (2012) or Bujosa and Roselló (2013) seem more appropriate (BEACH). Also, the effect of having a beach is not the same in every season. Tourists coming in summertime are more likely to look for a destination in the coast. To account for differences between seasons, we interact the variable 'kilometres of beaches' with three dummy variables: Summer (June to September) (BEACH_S), Spring (March to May) (BEACH_P) and Autumn (October and November) (BEACH_A) in order to allow for a different effect of beaches across seasons.

In winter, tourists willing to practice ski or snowboard look for regions with ski resorts. The kilometres of ski slopes can capture this effect and, since this only matters during winter season, we create a variable multiplying the kilometres of slopes by a dummy

[2] "Weather is what conditions of the atmosphere are over a short period of time, and climate is how the atmosphere "behaves" over relatively long periods of time. (…) In short climate is the description of the long-term pattern of weather in a particular area." (National Aeronautics and Space Administration, 2005)

variable that takes the value 1 in winter months (December to March), when the practice of these sports is possible (SKI).

4.1.4. Cultural amenities

National and regional governments have made special efforts trying to obtain designations of their historical and natural attractions by UNESCO. It is thought that being included in the World Heritage Sites list will attract tourists interested in cultural amenities. This aspect is particularly important for Spain, since it is home of 45 World Heritage Sites, being the third country in the world with most sites, only below Italy and China. Patuelli *et al*. (2013), among others, have found a positive relation in the number of World Heritage Sites of a province and its tourism inflows.

Not every Site has the same capacity for attracting tourists. There are WHS which are better known and attract more tourists than others. We should not treat the Alhambra of Granada, or the Historic City of Toledo, as equally important as, for example, Risco Caído in Gran Canaria, or Las Médulas in Leon. To account for these differences, we create two categories of World Heritage Sites according to their importance. Sites included with importance 2 (WHS_2) are thought to be more important, while importance-1 Sites (WHS_1) are less well-known (see Appendix for the classification). This is a subjective categorisation that we created using our own perception of the Sites. The variables are measured as the number of WHS of each category in each region each month.

4.1.5. Connectivity

As argued in section 3, regional connectivity is key in attracting tourists. Three variables are included to account for the ease of access to the region by different means of transport: the length of highways measured as the kilometres of highways per square km of land area (HIGHW); the existence of high-speed train measured by means of a dummy variable that takes the value 1 if the region has a high-speed train station (D_AVE); and the Airport Connectivity Index that, as explained in section 3, measures the region's connectivity by air (D_AIRPORT, ACI_LOCAL, ACI_NEIGHBOUR).

4.1.6. Control variables

Apart from the previous variables that affect the demand for tourism, there are several other variables that affect the demand for tourism and must be included in the model.

4.1.6.1. Regional dummies

In order to control for the singularity of some regions, regional dummies are included following Priego, Rosselló, & Santana-Gallego (2015). Madrid and Barcelona are the two main Spanish regions, holding the two largest airports in the country, plus Madrid is where the capital of the country is located. Both regions will attract more tourists just by being the main entry points to the country. Tourists travelling to inland regions that rely on the Barcelona or Madrid airports might spend some days in those cities before going to their final destination. Two dummy variables (D_MAD, D_BCN) are included.

Additionally, the Islands have special characteristics that attract tourism. First, the touristic infrastructure they have developed makes them more attractive to tourists. The Canary Islands are known for its cool climate and sunny weather throughout the year, attracting tourists in low season, while the Balearic Islands, known by their nice coast and beaches, is the preferred destination of many European tourists looking for sunny holidays during the central months of the year. Dummy variables for the Balearic and Canary Islands are included (D_BALEAR, D_CANARY).

In 2019, more than 12 million tourists arrived to Spain via road, according to Frontur. The closer to the border a province is, the more likely tourists will arrive and stay there. In Spain, tourists are likely to enter through Girona, and continue their way into the Mediterranean coast provinces, given the good road connections to France. We expect these good connection to have a positive impact in the arrival of tourists to Girona. We control for this effect by including a dummy variable that takes value 1 for Girona (D_GIRONA).[3]

Finally, we should not treat the rest of the country equally, since there are major differences between the interior and the coastal areas. We include dummies for the Cantabrian Coast (D_CANT), the Mediterranean (D_MEDITE) and for the province of Seville (D_SEV). Therefore, the reference category is the interior provinces except Madrid and Seville.

4.1.6.2. Time dummies

Time dummies are included to control for time-varying unobserved effects that are common to all provinces.

Tourism is known for its seasonality. Since most workers have holidays during summer months, we expect more tourists in all regions during summer, even if nothing else changes. This effect is captured by the seasonal dummies (SUMMER, SPRING, AUTUMN). , which we expect to take a greater value during these months. We set Winter as the reference period.

It is also known that tourism has increased constantly worldwide, from 1.08 billion arrivals in 1995 to 2.4 billion in 2019, according to the World Bank -except for 2009 due to the global financial crisis-. We expect this positive trend to affect arrivals to Spain in the same form. To capture a potential non-linear trend, we include a trend in levels and in a squared form as additional controls.

4.1.6.3. Size

Larger regions can host more tourists. To account for the size of regions, some authors include the regions' Area measured in squared kilometres (Bujosa & Rosselló, 2013), while others use the population of the receiving region as explanatory variable (Priego, Rosselló, & Santana-Gallego, 2015). In Spain, the largest regions are in the interior and, in general, do not attract a large share of tourists, while regions such as Madrid or the Islands are rather small and receive most of the tourists. This is an empirical rather than a methodological decision, and, since the model with the population variable fits better, we include population (POP) as a control variable for the size of the regions.

4.1.6.4. Regional holidays

Some regions celebrate traditional festivals that attract thousands of tourists every year. The most well-known are San Fermín, which is celebrated in Pamplona (Navarra) in July; Fallas, which is celebrated in Valencia in March; and Feria de Abril, which is celebrated in Seville in April. We control for the effect of these particular holidays including a dummy variable that takes the value 1 for the month and the region where the festival takes place, and 0 otherwise (D_SANFER, D_FERIA, D_FALLAS).

4.2. THE MODEL

We estimate six models, three for each of the dependent variables (visitors and overnight stays). The first model includes as connectivity variable a dummy for international airport, the second model includes the basic ACI index for regional airport (ACI_LOCAL), while in the third model we include both the regional and the neighbouring ACI index (ACI_LOCAL and ACI_NEIGHBOUR), as defined in section 3.

The subscript *i* indicates province, *m* represents month, and *y* is year. We include seasonal (μ_m) dummies with Winter as reference period, and trend variables to control for the time dimension of the panel.

[3] When Girona was not included as control variable its residual was much higher than of provinces'.

Equation 4.1. Model with regional airport dummy

$$\begin{aligned}\ln TOURISM_{i\,y\,m} &= \beta_0 + \beta_1 D\_Airport_{i\,y\,m} + \beta_2 \ln Pop_{i\,y\,m} + \beta_3 \ln Beach_i \\ &+ \beta_4 \ln Beach_i * Summer + \beta_5 \ln Beach_i * Spring \\ &+ \beta_6 \ln Beach_i * Autumn + \beta_7 \ln Ski_i * Winter + \beta_8 \ln TEMP_i \\ &+ \beta_9 \ln WHS\_2_{i\,y\,m} + \beta_{10} \ln WHS\_1_{i\,y\,m} + \beta_{11} \ln HIGHW_{i\,y\,m} \\ &+ \beta_{12} D\_AVE_{\,i\,y\,m} + \beta_{13} \ln EXRATE_{y\,m} + \beta_{14} CPI_y + \beta_{15} D\_MAD_i \\ &+ \beta_{16} D\_BCN_i + \beta_{17} D\_BALEAR_i + \beta_{18} D\_CANARY_i \\ &+ \beta_{19} D\_GIRONA_i + \beta_{20} D\_MEDITE_{i\,m} + \beta_{21} D\_CANT_{i\,m} \\ &+ \beta_{22} D\_SEV_{i\,m} + \beta_{23} D\_SANFER_{i\,m} + \beta_{24} D\_FALLAS_{i\,m} \\ &+ \beta_{25} D\_FERIA_{i\,m} + \mu_m + \delta_1 t + \delta_2 t^2 + u_{i\,y\,m}\end{aligned}$$

Equation 4.2. Model with ACI for regional airport

$$\begin{aligned}\ln TOURISM_{i\,y\,m} &= \beta_0 + \beta_1 \ln ACI\_LOCAL_{i\,y\,m} + \beta_2 \ln Pop_{i\,y\,m} + \beta_3 \ln Beach_i \\ &+ \beta_4 \ln Beach_i * Summer + \beta_5 \ln Beach_i * Spring + \beta_6 \ln Beach_i \\ &* Autumn + \beta_7 \ln Ski_i * Winter + \beta_8 \ln TEMP_i + \beta_9 \ln WHS\_2_{i\,y\,m} \\ &+ \beta_{10} \ln WHS\_1_{i\,y\,m} + \beta_{11} \ln HIGHW_{i\,y\,m} + \beta_{12} D\_AVE_{\,i\,y\,m} \\ &+ \beta_{13} \ln EXRATE_{y\,m} + \beta_{14} CPI_y + \beta_{15} D\_MAD_i + \beta_{16} D\_BCN_i \\ &+ \beta_{17} D\_BALEAR_i + \beta_{18} D\_CANARY_i + \beta_{19} D\_GIRONA_i \\ &+ \beta_{20} D\_MEDITE_{i\,m} + \beta_{21} D\_CANT_{i\,m} + \beta_{22} D\_SEV_{i\,m} \\ &+ \beta_{23} D\_SANFER_{i\,m} + \beta_{24} D\_FALLAS_{i\,m} + \beta_{25} D\_FERIA_{i\,m} + \mu_m + \delta_1 t \\ &+ \delta_2 t^2 + u_{i\,y\,m}\end{aligned}$$

Equation 4.3. Model with ACI for regional and neighbouring airports

$$\begin{aligned}\ln TOURISM_{i\,y\,m} &= \beta_0 + \beta_1 ACI\_LOCAL_{i\,y\,m} + \beta_2 ACI\_NEIGHBOUR_{i\,y\,m} \\ &+ \beta_3 \ln Pop_{i\,y\,m} + \beta_4 \ln Beach_i + \beta_5 \ln Beach_i * Summer \\ &+ \beta_6 \ln Beach_i * Spring + \beta_7 \ln Beach_i * Autumn + \beta_8 \ln Ski_i \\ &* Winter + \beta_9 \ln TEMP_i + \beta_{10} \ln WHS\_2_{i\,y\,m} + \beta_{11} \ln WHS\_1_{i\,y\,m} \\ &+ \beta_{12} \ln HIGHW_{i\,y\,m} + \beta_{13} D\_AVE_{\,i\,y\,m} + \beta_{14} \ln EXRATE_{y\,m} \\ &+ \beta_{15} CPI_y + \beta_{16} D\_MAD_i + \beta_{17} D\_BCN_i + \beta_{18} D\_BALEAR_i \\ &+ \beta_{19} D\_CANARY_i + \beta_{20} D\_GIRONA_i + \beta_{21} D\_MEDITE_{i\,m} \\ &+ \beta_{22} D\_CANT_{i\,m} + \beta_{23} D\_SEV_{i\,m} + \beta_{24} D\_SANFER_{i\,m} \\ &+ \beta_{25} D\_FALLAS_{i\,m} + \beta_{26} D\_FERIA_{i\,m} + \mu_m + \delta_1 t + \delta_2 t^2 + u_{i\,y\,m}\end{aligned}$$

5. DATA

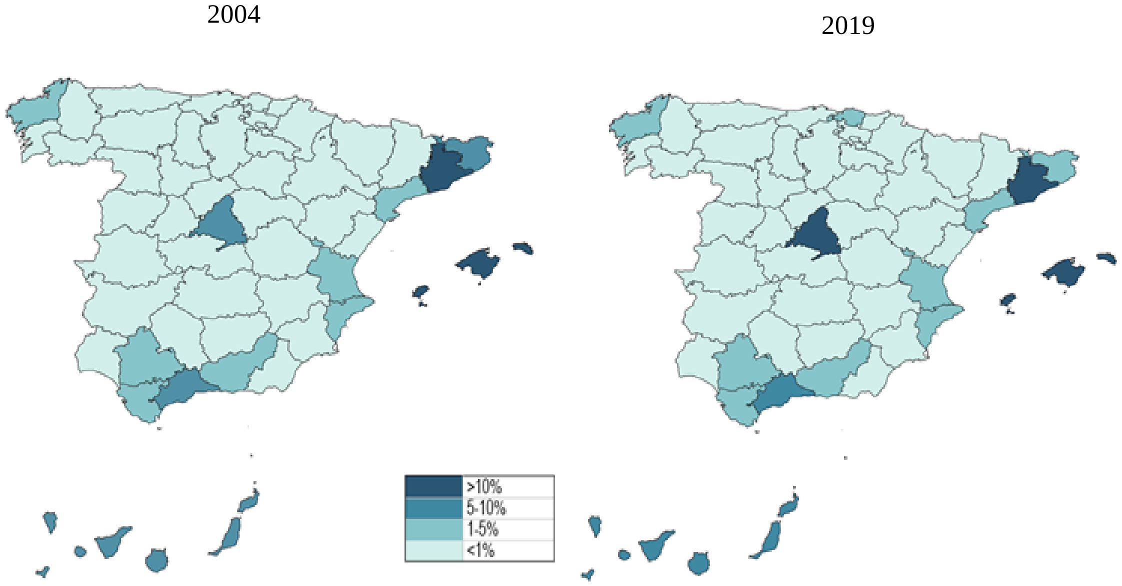
In this study, we use a panel data set consisting of monthly data on tourist arrivals to the 50 Spanish provinces over the period 2004-2019. This section contains a description of the dependent variables, as well as the data source of the explanatory variables, along with some summary statistics of all variables.

5.1. DEPENDENT VARIABLES

In section 2, we discussed that tourist activities can be measured in different ways. In this study we consider two dependent variables: the number of overnight stays and the number of tourist arrivals. The data are collected from the Hotel Occupancy Survey of the Spanish National Statistical Institute (INE). The statistical unit of a hotel establishment is understood as "all units that render hotel accommodation services (hotel, apartment hotel, motel, hostel, B&B, boarding house, guest house), […]" Therefore, we exclude one-day visitors, since by definition they are not registered in any hotel establishment, as well as those tourists that stay in alternative accommodations (e.g.: friends or relatives' homes, rented flats, campsites or rural houses). While this leads to an underestimation of the flows, the effect in our sample is probably limited since renting flats or rooms by locals has gained importance only in the last years with the expansion of platforms such as Airbnb. Additionally, the percentage of foreign tourists staying at campsites and rural accommodations during the sample period was small, accounting to 6 and 0.75 percent, respectively, according to INE.

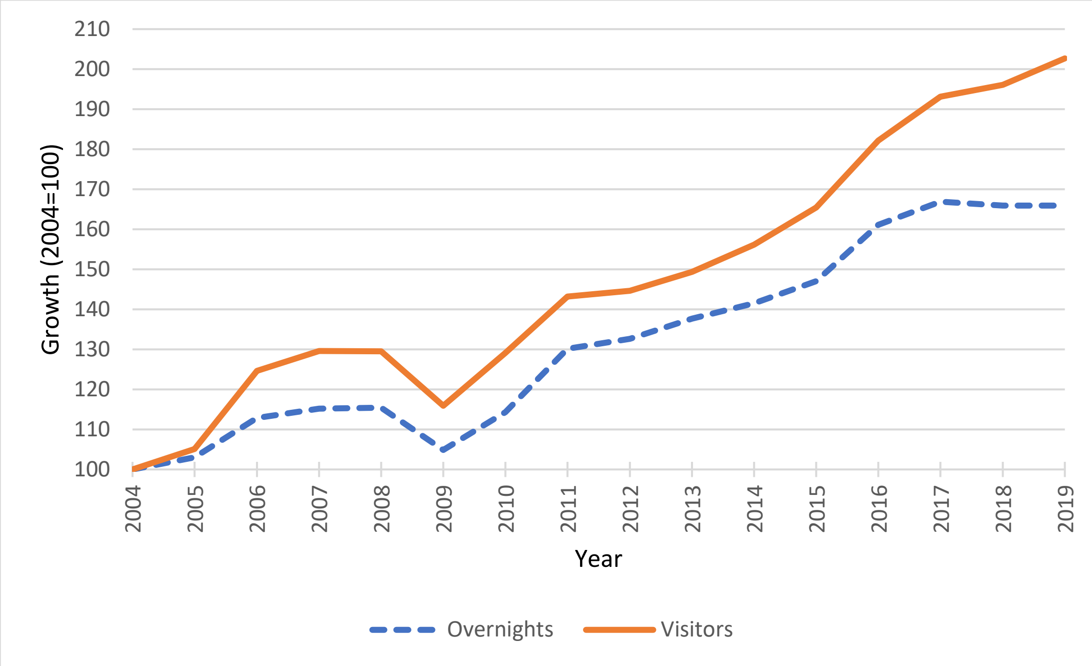
The spatial distribution of tourism in Spain is very uneven, as shown in Figure . In 2019, the main tourism provinces (Madrid, those along the Mediterranean coast, and the Islands) accounted for more than 77% of foreign visitors, with just three of the other 38 provinces receiving more than 1% of foreign tourists: Seville, Bilbao and La Coruña. Madrid grew as a touristic destination, from 9.5% in 2004 to 11% in 2019. The province of Vizcaya in the Basque Country, where Bilbao, home of the Guggenheim Museum is located, also increased its share of tourist arrivals, from 0.75% to 1.17%

Figure 5.1: Spatial distribution of foreign tourists in Spain in 2004 and 2019



The dynamics of the dependent variables are represented in Figure 5.1 . Both variables have grown during the sample period except for the year 2009 due to the global financial crisis. The number of visitors grows at a higher rate than the number of overnight stays, meaning that the average length of stay has been falling. Also, it can be noted that the number of overnight stays at hotels has declined in the last two years of the sample, even with the number of tourists rising more than 9 percentage points.

Figure 5.1: Evolution of foreign tourists and overnight stays in Spain (2004 = 100)

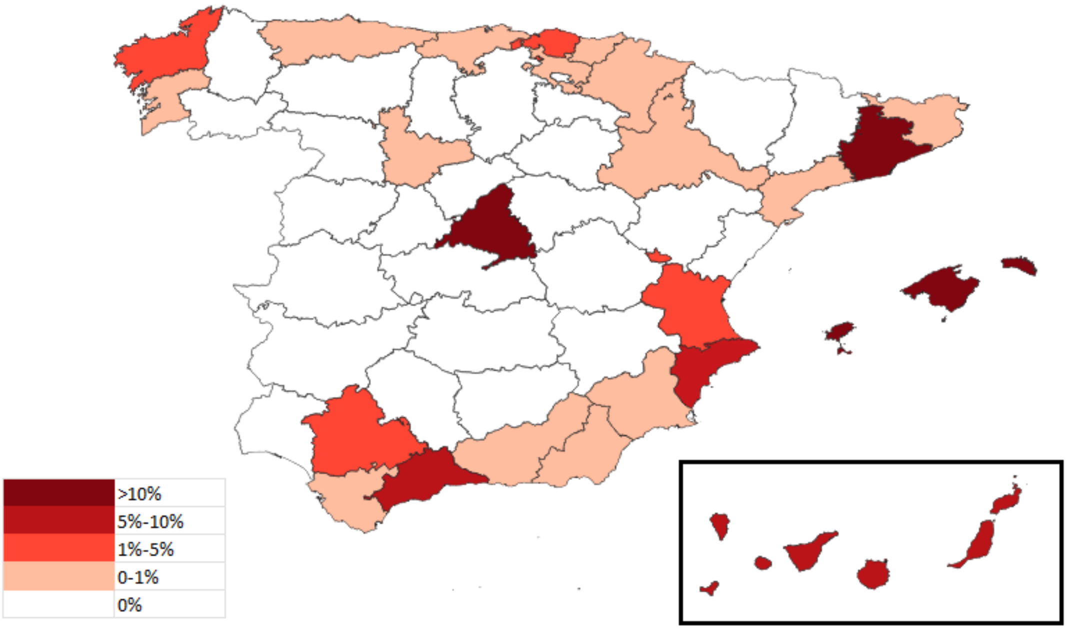


5.2. EXPLANATORY VARIABLES

Data for the explanatory variables were collected from several sources: the National Statistics Institute (INE) for population, coast and beach length, the exchange rate, and the price variables, UNESCO for the World Heritage Sites, the Spanish National Meteorology Institute (AEMET) for the weather variables, the webpage *infonieve* for the kilometres of ski resorts, the Spanish Ministry of Transport, Mobility and Urban Agenda (MITMA) for the length of highways, RENFE (National Network of Spanish Railways) for the high-speed train variable, and Spanish Airports and Air Navigation (AENA) for data to build the ACI index.

There are important differences in the air connectivity among regions. 17 provinces do not have an airport, while 7 which do host one received less than 100,000 annual passengers. Regular arrivals are concentrated in 7 regions: Madrid, Barcelona, the Balearic Islands, Alicante, Málaga, Santa Cruz de Tenerife and Las Palmas de Gran Canaria, which concentrated 86% of all passengers arriving to all Spanish airports in 2019. Seville, La Coruña, Valencia and Vizcaya received between 1 and 5 percent of passengers, according to AENA. The rest of the regions receive less than 1%.

Figure 5.3: Share of arrivals to Spanish airports, 2019.



Next, we show a table of the descriptive statistics of the variables explained above.

Table 5.1. Summary statistics of the variables used in the empirical analysis.

Variable	Description	Source	Mean	Std. Dev	Min	Max
Visitors	Thousands of monthly visitors	INE	68.02	154.8	0.249	1604.5
Stays	Thousands of monthly overnight stays	INE	296.4	884.16	0.409	10103.2
Population	Thousands of inhabitants	INE	920.57	1138.6	88.6	6663.4
Beach	Kilometres of beaches	INE	38.35	50.93	0	157.04
Ski	Kilometres of slopes	Infonieve	23.96	70.42	0	357.5
Temperature	Ratio of the monthly average temperature to its standard deviation through the year.	AEMET	2.55	1.383	0.412	8.93
WHS_2	Number of World Heritage Sites classified as more important	UNESCO	0.18	0.38	0	1
WHS_1	Number of WHS classified as less important	UNESCO	0.74	0.82	0	3
Highways	Ratio of the kilometres of public highways over the region’s area	MITMA	223.23	128.46	12	635
CPI	Consumer Price Index, base year 2016	INE	95.49	7.11	79.14	105.3
EXRATE	Sterling pound to euro exchange rate	INE	0.799	0.081	0.66	0.91

D_AVE	Dummy variable for the presence of high-speed train in the region (AVE)	RENFE	0.321	0.466	0	1
D_AIRPORT	Dummy for the presence of an international airport in the region	AENA	0.381	0.485	0	1
ACI_LOCAL	Airport Connectivity Index with regional airport		0.02	0.045	0	0.25
ACI_ NEIGHBOUR	Airport Connectivity Index with neighbouring airports		0.056	0.068	0	0.26

6. ESTIMATION AND RESULTS

The three models discussed in the previous section are estimated by Ordinary Least Squares for both dependent variables: tourist arrivals and overnight stays. We take natural logs in all the continuous variables except the CPI, so the results can be interpreted as elasticities. We take the CPI in levels so we can interpret the coefficient as the percentage variation in the number of tourists or overnight stays per unit increase in the price index.

Other tourism studies such as Patuelli, Mussoni, & Candela (2013) or Cafiso, Cellini, & Cuccia (2016) use fixed effects regression. While our model could consider fixed effects, we choose a pool model since we want to know the effect of variables that are constant over time, such as temperature or the kilometres of beaches.

In table 6.1 we show the estimation results for the dependent variable number of visitors. Model 1 includes the regional airport dummy as connectivity variable (D_AIRPORT); model 2 includes the airport index of the local airport (L_ACI_LOCAL); and model 3 includes both the index for the local airport and for airports in neighbouring provinces (L_ACI_NEIGHBOUR). Results for the dependent variable overnight stays are presented in Table 6.2.

Table 6.1. Estimation results for the dependent variable visitors.

	Model 1		Model 2		Model 3	
Variable	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Constant	-5.77***	-13.48	-3.97***	-9.57	-4.2***	-10.13
D_AIRPORT	0.25***	11.99				
L_ACI_LOCAL			0.09***	30.34	0.09***	31.07
L_ACI_NEIGHBOUR					0.02****	8.54
L_POP	0.73***	52.46	0.61***	44.37	0.64***	45.36
L_BEACH	-0.01***	-9.01	-0.01***	-16.08	-0.01***	-17
L_BEACH_S	0.03***	14.51	0.03***	15.56	0.03***	15.66
L_BEACH_P	0.02***	7.83	0.02***	8.24	0.02***	8.32
L_BEACH_A	0.01***	5.3	0.01***	5.88	0.01***	5.94
L_SKI	0.02***	10.05	0.01***	8.69	0.01***	8.64
L_TEMP	0.45***	18.02	0.48***	20.29	0.49***	20.59
L_WHS_2	0.09***	46.04	0.09***	48.18	0.09***	45.28
L_WHS_1	0.04***	26.13	0.05***	33.27	0.05***	32.42
L_HIGHW	0.34***	20.68	0.25***	15.64	0.25***	15.32
D_AVE	0.25***	16.71	0.29***	20.23	0.27***	18.14

L_EXRATE	-0.24***	-3.02	-0.24***	-3.1	-0.24***	-3.22
CPI	0.004	-1.00	-0.005***	-1.09	0.005	-1.14
D_MADRID	0.98***	17.27	0.82***	14.94	0.93***	16.53
D_BCN	0.86***	15.03	0.97***	18.27	0.96***	18.09
D_BALEAR	2.85***	53.64	2.65***	53.65	2.80***	53.71
D_CANARY	2.08***	45.57	1.90***	44.83	1.83***	42.34
D_GIRONA	2.33***	43.72	2.41***	50.33	2.35***	48.52
D_MEDITE	0.81***	26.44	1.01***	37.09	0.98***	35.86
D_CANT	0.09***	2.58	0.14***	4.53	0.12***	3.94
D_SEV	0.39***	7.23	0.25***	5.04	0.19***	3.73
D_SANFER	1.03***	7.3	0.73***	5.35	0.68***	5.05
D_FERIA	0.13	0.91	0.15	1.03	0.15	1.03
D_FALLAS	-0.22	-1.53	0.36***	2.61	0.36***	2.63
T	-0.02*	-1.81	-0.02	-1.36	-0.02	-1.22
T-squared	0.004***	6.53	0.003***	6.29	0.003***	6.27
SPRING	0.52***	22.01	0.50***	22.21	0.50***	22.15
SUMMER	0.64***	20.09	0.62***	20.24	0.61***	20.15
AUTUMN	0.28***	10.32	0.28***	10.61	0.27***	10.55
R-squared	0.88		0.88		0.88	
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.						

Table 6.2. Estimation results for the dependent variable overnight stays.

	Model 1		Model 2		Model 3	
Variable	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Constant	-4.79***	-10.31	-2.43***	-5.5	-2.64***	-5.98
D_AIRPORT	0.34***	15.16				
L_ACI_LOCAL			0.11***	37.25	0.11***	37.84
L_ACI_NEIGHBOUR					0.02***	7.34
L_POP	0.64***	42.94	0.50***	33.89	0.52***	34.77
L_BEACH	-0.02***	-9.32	-0.02***	-18.21	-0.02***	-18.97
L_BEACH_S	0.05***	21.81	0.05***	23.71	0.05***	23.81
L_BEACH_P	0.03***	11.33	0.03***	12.15	0.03***	12.22
L_BEACH_A	0.02***	8.08	0.02***	9.03	0.02***	9.08
L_SKI_W	0.02***	10.49	0.02***	8.93	0.02***	8.89
L_TEMP	0.54***	20.15	0.59***	23.29	0.60***	23.54
L_WHS_2	0.07***	33.57	0.07***	34.72	0.06***	32.33
L_WHS_1	0.04***	25.19	0.05***	34.27	0.05***	33.49
L_HIGHW	0.36***	19.99	0.24***	14.21	0.24***	13.93
D_AVE	0.32***	19.15	0.37***	23.89	0.34***	21.96
L_EXRATE	-0.21***	-2.5	-0.21***	-2.59	-0.22***	-2.69
CPI	0.003***	0.67	0.003	0.65	0.003	0.61
D_MADRID	1.27***	20.57	1.06***	18.15	1.16***	19.39
D_BCN	1.44***	23.1	1.59***	28.13	1.58***	27.99
D_BALEAR	3.93***	67.92	3.67***	69.76	3.81***	68.53

D_CANARY	3.38***	68.35	3.17***	70	3.10***	67.26
D_GIRONA	2.80***	48.21	2.92***	56.99	2.85***	55.26
D_MEDITE	1.37***	41.1	1.64***	56.42	1.61***	55.2
D_CANT	0.06	1.64	0.14***	4.16	0.12***	3.65
D_SEV	0.66***	11.41	0.50***	9.41	0.44***	8.24
D_SANFER	1.11***	7.24	0.71***	4.89	0.67***	4.63
D_FERIA	0.17	1.07	0.19	1.23	0.19	1.24
D_FALLAS	-0.59***	-3.8	0.17	1.15	0.17	1.17
T	-0.06***	-3.96	-0.05***	-3.58	-0.05***	-3.46
T-squared	0.005***	7.92	0.004***	7.8	0.004***	7.79
SPRING	0.46***	17.86	0.44***	18.04	0.43***	17.97
SUMMER	0.59***	17.21	0.57***	17.38	0.56***	17.29
AUTUMN	0.24***	8.25	0.24***	8.57	0.24***	8.5
R-squared	0.88		0.87		0.88	
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.						

The estimated coefficients of the three models are similar for both dependent variables. Most of the estimated coefficients have the expected sign and are significant at 1% significance level. The R-squared is high in all estimations, around 88%. We start commenting on the estimations for the number of visitors.

The three air connectivity variables included have the expected positive sign and are significant. The presence of an airport in the region leads to more tourism there. The ACI variables can be understood as a measure of the size of the airport, -measured as the share of operations made at the airport-, the bigger the local and nearby airports, the greater the number of tourists expected to arrive to the region. The estimated coefficient of local airport variable (ACI_LOCAL) is greater than that of nearby airports (ACI_NEIGHBOUR), meaning that the effect of an airport in the region is larger than that of nearby airports. Two regions with the same characteristics (weather, size, or natural and cultural amenities) will receive different amount of tourism depending on how well the region is connected by air. The larger the airport of a region, the more tourists it will receive, ceteris paribus. The impact of an airport in a neighbouring province is also positive, but smaller.

The estimated coefficient of population (which is used as a proxy of the size) is positive and significant. Larger regions attract more tourists.

The variables accounting for the presence of beaches show both positive and negative significant coefficients. Given that the base season is Winter, while the estimated coefficient of L_BEACH is negative and significant in all six models, the effect of having more kilometres of beaches is still positive in Summer and Spring given the greater coefficient of the variables interacted with the seasonal dummy. In Autumn, the effect is closer to zero. Then, a region with more kilometres of beaches will attract more tourists during the seasons when the beach can be enjoyed. Also, as expected, the effect is greater in Summer than in Autumn or Spring. This result suggests that having more kilometres of beaches has a negative effect on tourism in Winter. The negative sign might be due to the fact that we are considering that the effect of having an extra kilometre of beaches in, for example, the Cantabrian Coast, is the same than that of having it in the Canary Islands, where tourists can enjoy the beaches even in Winter.

The effect of the ski resorts is also positive, but smaller than that of the length of beaches, which is expected given that Spain is seen as a destination for "sun and beach" tourism, rather than a winter holidays destination.

Temperature, which accounts not only for average temperatures but also for the variability, has the expected positive sign and is significant. Higher temperatures, together with lower variation throughout the year, makes the region more attractive for tourists.

The presence of World Heritage Sites (WHS) is found to have a positive and significant effect on tourism. Those WHS thought to be more important (WHS_2) have a greater effect than those included in WHS_1.

The other connectivity variables are the kilometres of highways and the presence of high-speed train. Both show the expected positive sign and are significant. The greater the endowment of highways per squared kilometre, the larger the number of tourists the region will receive, *ceteris paribus*. Also, the connectivity of the region by high-speed train (AVE) increases the amount of tourism. Model 1 shows that the presence of an airport has a greater impact on the arrival of tourists than the endowment of highways or the presence of high-speed train.

The exchange rate shows the expected negative sign, and it is significant in all three models. An increase in the exchange rate (Sterling Pound to Euro) means more pounds are needed to buy a euro, so that the euro appreciates. When the euro appreciates, all the goods and services bought by British in Spain become more expensive, and the quantity consumed decreases. The Consumer Price Index is not significant in any of the models.

The regional dummies have the expected positive sign. Madrid, Barcelona, which host the largest airports in the country, receive more tourists than the provinces included in the reference category, ceteris paribus. The Islands have characteristics not included in the model that make them more attractive for tourists, thus the positive sign of the estimated coefficient, which is statistically significant. The estimated coefficients for the Balearic and Canary Islands are greater than those for Madrid and Barcelona. Girona, which was included given its proximity to the border with France and easiness to arrival by car, shows a positive coefficient and it is statistically significant. Also, its estimated coefficient is greater than the those of Madrid and Barcelona; this means that, once controlled for all other factors, being close to the border is more important than being a large city as Madrid and Barcelona. As expected, the provinces along the Mediterranean Coast also provide tourists with additional attractions and services that make them more attractive than the interior provinces. The coefficients for Seville and the Cantabrian Coast are also positive and significant, but lower in magnitude than the rest of the regional dummies.

Then, the time-dimension variables. The seasonal dummies show the preference of tourists for the summer season. The positive and significant estimators of the three seasonal dummies reflect that tourists prefer to travel during Spring, Summer or Autumn, rather than winter. This was expected given the "sun and beach" tourism typical of Spain. Holding constant everything else, more tourists are expected to come in Summer, followed by Spring, Autumn and lastly Winter.

As for the trend variables, the estimated coefficient of t is not statistically significant in any of the three models, while the coefficient for the quadratic trend is positive and statistically significant. This reflects a non-linearity in the trend, which implies that this effect increases at increasing rates. It shows that the growth of international tourism has been greater during the last years of the sample.

Lastly, as for the regional holidays included, San Fermin is estimated to have a significantly positive effect on the arrival of international tourists. The number of tourists arrived at Navarra in July is significantly higher than those which would be expected if that holiday would not be celebrated. Fallas in Valencia also show a positive sign in the most complete model (Model 3). The effect of Feria de Abril in Seville is found to be statistically insignificant.

For the dependent variable overnight stays, results are displayed in Table 6.2. The signs of the variables are the expected ones and the coefficients are similar to those of the variable visitors.

The effect of air connectivity is greater for overnight stays than for the number of visitors. As for the previous dependent variable, the estimated coefficient of the airport dummy variable is greater than that of the ACI index; also, the effect of a regional airport is greater than that of an airport in a neighbouring region. Better regional connectivity by air seems to have a positive impact in retaining the tourists for longer.

The variables measuring the kilometres of beaches show the same pattern as for the previous dependent variable. The coefficient of non-interacted variable is negative, while the interacted variables show a positive and significant sign. A region with more kilometres of beaches will make tourists to stay longer during the seasons when they can be enjoyed. Also, the effect of hosting ski resorts is greater for overnight stays than for the number of visitors. This was expected since tourists travelling to ski resorts usually stay for long periods.

The effect of temperature is positive and greater than for the number of visitors. A region with higher temperatures and/or lower variation will increase the number of overnight stays made by tourists.

Looking at other means of transport, the estimated coefficient for the endowment of highways is smaller, this could mean that those tourists travelling by car are more likely to visit more than one region, staying less nights in each destination.

The exchange rate has a negative effect on the number of overnight stays, but this effect is smaller than for the number of visitors. The Consumer Price Index is still not significant.

All the included regional dummies' coefficients are higher for overnight stays than for tourist arrivals. The islands show the highest coefficients: given the difficulty for foreign tourists to move from the islands to another province, they are likely to stay longer periods of time. Then Girona, given its characteristics, namely being close to the border, cause the number of overnight stays to be higher once everything else is controlled. Madrid and Barcelona also show a positive significant coefficient: being a large city and hosting the largest helps to retain tourists longer. Tourists staying at coastal areas (Mediterranean and Cantabrian) also stay longer periods than those staying at the interior provinces, *ceteris paribus*. The estimated coefficient for Seville is also significant and greater than that the one for tourist arrivals.

The time dimension variables are now both significant. The coefficient of t is negative, while the quadratic term is still positive. Again, this shows that the trend is non-linear.

Seasonal dummies' coefficients are similar than for the number of visitors. All three variables are positive and significant, meaning that we expect more overnight stays outside Winter months. Also, Summer shows the greatest coefficient, while Spring and Autumn estimated coefficients are similar.

As for the regional holidays, the effect for San Fermin is still significant and similar than for tourists' arrivals. The estimated coefficients for Fallas and Feria de Abril are not significant.

7. CONCLUSION

In this study we have studied the effect of regional air connectivity in the arrival of tourists to the 50 Spanish regions. We have used a monthly dataset between 2004 and 2019 including the number of foreign tourists and the number of overnight stays, and several regional characteristics that can explain the demand for tourism such as kilometres of beaches, temperature, or the endowment of infrastructure. To measure air connectivity, we have created an index that measures the size of an airport as the share of arrivals to the airport over the total arrivals at Spanish commercial airports.

Differently from previous studies, we acknowledge that regional connectivity does not only come from the presence of airports in the region, but also from airports in neighbouring ones. We included a separate index summing up the size of neighbouring regions' airports.

The estimated coefficients of the index show that the size of airports is positive correlated to the arrival of tourists. The effect of hosting an airport is greater than that of having an airport in a neighbouring province, and both are positive and significant. That is, we find that the positive effect of air connectivity on tourism does not only come from the fact of having an airport in the region, but also from having one in a neighbouring province.

Regarding the pull factors that affect the demand for tourism, our findings confirm the previous studies on the importance of natural amenities (beaches and ski resorts), temperatures, cultural amenities -measured by the number of WHS- and transport connectivity by road and railway.

These results suggest that there is no need for building airports in every region in order to increase the arrival of tourists to each of them. A region's air connectivity can be boosted with connections via an airport at a neighbouring province.

REFERENCES

Albalate, D., Campos, J., & Jiménez, J. (2017). Tourism and high speed rail in Spain: Does the AVE increase local visitors? *Annals of Tourism Research*, 71-82. doi:https://doi.org/10.1016/j.annals.2017.05.004

Algieri, B., & Álvarez, A. (2022). Assessing the ability of regions to attract foreign tourists: The case of Italy. *Tourism Economics*, 1-24.

Álvarez-Díaz, M., D'Hombres, B., Ghisetti, C., & Pontarollo, N. (2020). Analysing domestic torusim flows at the provincial level in Spain by using spatial gravity models. *International Journal of Tourism Research*, 403-415. doi:https://doi.org/10.1002/jtr.2344

Artus, J. R. (1972). An Econometric Analysis of International Travel. *International Monetary Fund Staff Papers*, 579-614.

Betancor, O., & Llobet, G. (2015). Contabilidad Financiera y Social de la Alta Velocidad en España. *Fundación de Estudios de Economía Aplicada, FEDEA*. doi:10.13140/RG.2.2.27483.46886

Boto-García, D., & Pérez, L. (2023). Te effect of high-speed rail connectivity and accessibility on tourism seasonality. *Journal of Transport Geography*.

Bujosa, A., & Rosselló, J. (2013). Climate change and summer mass tourism: the case of Spanish domestic tourism. *Climate Change*, 363-375.

Bujosa, A., Riera, A., & Torres, C. M. (2015). Valuing tourism demand attributes to guide climate change adaptation measures efficiently: The case of the Spanish domestic travel Market. *Tourism Management*, 233-239.

Cafiso, G., Cellini, R., & Cuccia, T. (2016). Do economic crises lead tourists to closer destinations? Italy at the time of the Great Recession. *Papers in Regional Science*, 369-386.

Crouch, G. I. (1992). Effect of income and price on international tourism. *Annals of Torusim Research*, 643-664.

de la Mata, T., & Llano-Verduras, C. (2012). Spatial pattern and domestic tourism: An econometric analysis using inter-regional monetary flows by type of journey. *Papers in Regional Science*, 437-471.

Garín-Muñoz, T. (2006). Inbound international tourism to Canary Islands: a dynamic panel data model. *Tourism Management*, 281-291.

Garín-Muñoz, T. (2007). German demand for tourism in Spain. *Tourism management*, 12-22.

Garín-Muñoz, T., & Pérez, T. (2000). An econometric model for international tourism flows to Spain. *Applied Econometric Letters*, 525-529.

Goh, C. (2012). Exploring impact of climate on tourism demand. *Annals of Tourism Research*, 1859-1883.

Gray, H. P. (1966). The Demand for International Travel by the United States and Canada. *International Economic Review*, 83-92.

Jena, S. K., & Dash, A. K. (2020). Does exchange rate volatility affect tourist arrival in India: a quantile regression approach. *Regional and Sectoral Economic Studies*, 65-84.

Keum, K. (2010). Tourism flows and trade theory: a panel data anlysis with the gravity model. *The Annals of Regional Science*, 541-557.

Martin, C. A., & Witt, S. P. (1987). Tourism Demand Forecasting Models: Choice of Appropiate Variable to Represent Tourists' Cost of Living. *Tourism Management*, 223-245.

Massidda, C., & Etzo, I. (2012). The determinants of Italian domestic tourism: A panel data analysis. *Tourism Management*, 603-610.

Mendez, J. (2020). Not niggas. *Transports*, 12.

Muñoz, C., Álvarez, A., & Baños, J. F. (2021). Modelling the effect of weather on tourism: does it vary across seasons? *Tourism Geographies*. doi:10.1080/14616688.2020.1868019

National Aeronautics and Space Administration (NASA). (2005, Feb 1). *NASA - What's the Difference Between Weather and Climate?* Retrieved from NASA Web Site: https://www.nasa.gov/mission_pages/noaa-n/climate/climate_weather.html

Patuelli, R., Mussoni, M., & Candela, G. (2013). The effects of World Heritage Sites on domestic tourism: a spatial interaction model for Italy. *J Geogr Sys*, 369-402. doi: https://doi.org/10.1007/s10109-013-0184-5

Pompili, T., Pisati, M., & Lorenzini, E. (2019). Determinants of international touristic choices in Italian provinces: A joint demand-supply approach with spatial effects. *Papers in Regional Science*, 2251-2273.

Priego, F. J., Rosselló, J., & Santana-Gallego, M. (2015). The impact of climate change on domestic tourism: a gravity model for Spain. *Regional Environmental Change*, 291-300.

Song, H., & Li, G. (2008). Tourism demand modelling and forecasting - A review of recent research. *Tourism Management*, 203-220.

Song, H., Li, G., Witt, S. F., & Fei, B. (2010). Tourism demand modelling and forecasting: how should demand be measured? *Tourism economics*, 63-81.

UNWTO, World Tourism Organization. (2020). *Yearbook of Tourism Statistics.*

Xu, L., Wang, S., Li, J., Tang, L., & Shao, Y. (2019). Modelling international tourism flows to China: A panel data analysis with the gravity model. *Tourism Economics*, 1047-1069.

Appendix 1

Table A.1.1. Classification of World Heritage Sites (WHS)

Importance 2 (WHS_2)	*Importance 1 (WHS_1)*
• Alhambra, Generalife and Albayzín, Granada • Historic Centre of Cordoba • Cathedral, Alcázar and Archivo de Indias in Seville • Old City of Salamanca • Old Town of Segovia and its Aqueduct • Burgos Cathedral • Works of Antonio Gaudí • Santiago de Compostela (Old Town) • Historic City of Toledo	• Caliphate City of Medina Azahara • Teide National Park • Antequera Dolmens Site • Renaissance Monumental Ensembles of Úbeda and Baeza • Mudejar Architecture of Aragon • Monuments of Oviedo and the Kingdom of the Asturias • Cultural Landscape of the Serra de Tramuntana • Ibiza, Biodiversity and Culture • Old Town of Ávila with its Extra-Muros Churches • Historic Walled Town of Cuenca • Archaeological Ensemble of Mérida • Old Town of Cáceres • Tower of Hércules • Roman Walls of Lugo • Monastery and Site of the Escorial, Madrid • Routes of Santiago de Compostela • Rock Art of the Mediterranean Basin on the Iberian Peninsula • Cave of Altamira and Paleolithic Cave Art of Northern Spain • Risco Caido and the Sacred Mountains of Gran Canaria Cultural Landscape • San Cristóbal de La Laguna • Garajonay National Park • Prehistoric Rock Art Sites in the Côa Valley and Siega Verde • Las Médulas • Archaeological Ensemble of Tarraco • Catalan Romanesque Churches of the Vall de Boí • Palau de la Música Catalana and Hospital de Sant Pau • Poblet Monastery • Palmeral of Elche • La Loja de la Seda • Doñana National Park

	• Archaeological Site of Atapuerca • Pyrénées - Mont Perdu • Royal Monastery of Santa María de Guadalupe • Aranjuez Cultural Landscape • University and Historic Precinct of Alcalá de Henares • Vizcaya Bridge • San Millán Yuso and Suso Monasteries