

The Influence of Weather on Interest in a “Sun, Sea, and Sand” Tourist Destination: The Case of Majorca

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(Manuscript received 29 September 2015, in final form 15 January 2016)

ABSTRACT

Last-minute decisions to take vacations overseas have become popular in recent years. Because of the reduction of the time between the booking and the trip (lead time), and because climate conditions are acknowledged to be key factors in tourism decisions, this study aims to investigate whether weather anomalies are becoming a new key determinant in tourism destination interest. Using data from Google Trends, different time series models are estimated analyzing whether potential tourists' interest in Majorca, a popular Mediterranean “sun, sea, and sand” destination, is determined by previous and contemporaneous weather conditions both at the destination and in two main tourist countries of origin, Germany and the United Kingdom. Results show how favorable weather conditions at the destination but also adverse weather conditions at the origin are significantly related to a higher interest in Majorca.

1. Introduction

Many aspects of the tourist industry are climate dependent, especially for many warm destinations in the Northern Hemisphere that attract regular flows of tourists from northern to southern latitudes, above all during the summer months. Interest in climate change issues and, more particularly, in the economic consequences of climate change, has fueled a growing number of studies that evaluate the effects of climate change on tourism demand (Maddison 2001; Lise and Tol 2002; Amelung et al. 2007; Hamilton and Tol 2007; Hopkins and Maclean 2014; Ritty and Scott 2014; Priego et al. 2015), showing that traditional warm destinations face an expected drop in attractiveness and international tourist market share.

In contrast with long-term climate issues, the short-run relationship between weather and tourism has its own interest appeal. In the specific case of the airline industry, extreme wind speeds can prevent aircraft from landing at their designated airports, and in general adverse meteorological conditions cause delays, cancellations, and accidents entailing significant cost implications (Changnon 1996; Eads et al. 2000; Kulesa 2002; Koetse and Rietveld 2009; Coffel and Horton 2015). In fact, the air transport sector is usually highlighted as one of the highest users of climate information services (Changnon and Changnon 2010); it is possible to estimate the economic benefits of meteorological services in millions of U.S. dollars (USD) for some specific airports (von Gruenigen et al. 2014).

Within the tourist industry, not only airline companies are affected by weather anomalies and weather extremes. Rind (1996), using the case study of a casino hotel in Atlantic City, shows how that greater degrees of sunshine are associated with greater amounts of compliance and tipping. Chen and Lin (2014) study the effects of weather on room demand in the Taiwanese hotel

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industry evidencing how typhoon and rain are negatively associated with group visitors while temperature and sunshine hours lead to an increase of group visitors. Falk (2015) analyzes the impact of weather conditions on overnight tourists stays for nine provinces across German and Austria. Results show that sunshine hours and temperatures in a given month have a significant and positive impact on domestic overnight stays in the same month for most of the provinces except for the capital of Vienna. Furthermore, sunshine hours can affect overnight stays, mainly with a 1-yr lag. The largest weather effects could explain up to 47% of the variation in overnight stays for certain regions.

In this context, although weather conditions are widely seen as an important factor for tourism behavior, relatively little is known about the extent to which weather effects are present in the step of destination decision choice. It should be noted that the use of new distribution channels, the liberalization of the airline industry, and the elimination of border controls between Europe's main countries have reduced the booking lead times (time between booking and the date of travel), it being usual nowadays to book a trip just a few days in advance (Money and Crofts 2003; Malighetti et al. 2009). With this shorter booking lead times, new determinants of tourist trips could have emerged. Then, it can be reasonably assumed that tourism interest in specific destinations could be dependent on weather conditions in the country of origin, as a push factor, and/or weather conditions at the destination, as a pull factor.

In this paper, the relationship between the interest in Majorca, evaluated through Google searches, and the meteorological conditions both in the country of origin (United Kingdom and Germany) and at the destination is investigated. Majorca is a popular "sun, sea, and sand" destination in the Mediterranean, known for its warm climate conditions. Thus, this paper contributes to further knowledge of the interaction between weather and tourism by exploring the role of weather in determining interest in a popular European "sun, sea and sand" destination, showing how weather conditions can contribute to the level of searches of this destination.

2. Weather and tourist demand behavior

The effects of the weather on demand has been widely investigated for different locations and tourism related sectors such as transport, hotel industry, sky resorts, and so on [for recent surveys, see Gössling et al. (2012), Becken (2013), Becken and Wilson (2013), Pang et al. (2013), and Rosselló-Nadal (2014)]. In general terms, literature has identified temperatures, sunshine, and rainfall as important tourism behavior factors, especially

in the summer season. Good weather conditions in a destination lead frequently to increases in tourism demand while outbound tourism demand can also be related to weather conditions, especially if some lags are considered. In the context of time series analysis, the pioneering study of Subak et al. (2000) analyzes the impacts on different service sector activities of the anomalously hot summer of 1995 and warm period from November 1994 through to October 1995 in the United Kingdom. The Subak et al. study shows clear differences in the response to anomalous warm weather in winter and summer, with greater tourism demand sensitivity to winter anomalies.

However, because tourism is not exclusively explained by climate variability, the use of statistical models and the consideration of other tourism determinants have dominated the study of the relationship between tourism and climatic and weather factors (Rosselló-Nadal 2014). It should be noted how some recent literature underscore the limitations of a statistical modeling approach for understanding behavior related to tourism and climate (Gómez-Martín 2005; Dubois and Ceron 2006; Gössling and Hall 2006; de Freitas et al. 2008; Moreno 2010; Denstadli et al. 2011; Scott et al. 2012; Ruddy and Scott 2013). These limitations include, among others, the validity and/or structure of statistical databases, the importance of other climatic variables beyond temperature, the unknown role of weather extremes and other information in tourist decision-making, and the uncertainty about future tourism determinants such as costs of transport, income, and availability of leisure time (Gössling and Hall 2006). These limitations remain unaddressed in the context of the evaluation of the effects of climate change on tourism demand; consequently, results have to be taken as average approximations. However, in the context of the direct quantification of the short-run relationship between weather and tourist behavior these limitations can be overcome.

In the context of time series analysis, Agnew and Palutikof (2006) analyze a set of climate indices, exploring current climate variability and its relationship with domestic and international tourism demand. They show that outbound tourist flows are more responsive to the preceding year's climatic variability, whereas domestic tourism is more responsive to variability within the year of the trip. Rosselló et al. (2011) focus on outbound flows from the United Kingdom. They estimate the sensitivity of this tourist time series to weather anomalies, showing that mean temperature, heat waves, frost, and sunshine days are the weather variables that can be significantly related to the dynamics of time series for outbound British flows.

Other case studies that explore the relations between weather and tourism demand have also been reported, based on the hypothesis that meteorological and climate conditions can act as both pull and push factors in determining tourist decisions. [Rosselló \(2011\)](#) studies the effects of the North Atlantic Oscillation on European air traffic, finding that the breakdown of the North Atlantic Oscillation index into positive and negative fluctuations can be related to changes in revenue passenger kilometers. [Otero-Giráldez et al. \(2012\)](#) also show there to be a significant positive connection between the North Atlantic Oscillation as a meteorological indicator and tourism demand in Galicia (Spain), using time series modeling. [Kulendran and Dwyer \(2012\)](#) identify the relationship between climate variables such as maximum temperatures, relative humidity, sunshine hours, and seasonal variations, defined as the repetitive and predictable movement around the trend line in holiday tourism demand, within the context of seasonal variations in holiday tourism demand to Australia.

[Álvarez and Rosselló \(2010\)](#) explore the possibility of improving a tourism demand model's predictive capacity by using meteorological explanatory variables, based on a case study of monthly tourist arrivals to the Balearic Islands. To do this, classic time series models and causal artificial neural networks are fitted and the results are compared with those obtained using noncausal methods. The study indicates that the inclusion of meteorological variables can boost the predictive power. However, these results are not conclusive because of the lack of statistical significance of the tests used to measure the increase in predictive power.

Finally, [Falk \(2014\)](#) investigates the impact of weather on overnight stays in Austria during the peak summer season employing static and dynamic tourism-demand models showing how first-difference regression models show that average sunshine duration and temperatures have a positive impact on domestic overnight stays, whereas precipitation had a negative effect. For foreign overnight stays, he finds that the positive impact of temperatures and sunshine duration occurs only after a 1-yr lag, with larger effects for visitors from neighboring countries.

Using Google Trends data on the interest on Majorca, this paper aims to contribute to the literature on the interaction between weather and tourism in two main ways. First, it centers attention on the purchasing time (approximated by the Google searches) rather than the trip time. Although searches on a tourism destination are not a direct indicator about purchasing behavior, previous research has found a strong correlation between both ([Peng et al. 2013](#); [Valek and Axelsson 2014](#)). Specifically, [Bangwayo-Skeete and Skeete \(2015\)](#) show

how Google searches on destination hotels and flights from source countries improve forecast results for tourism demand time series models, indicating that it is possible to use Google query search data to accurately project future monthly tourist arrivals in the Caribbean. This point is especially relevant for revenue managers to understand consumer behavior and to establish the efficient price. Second, because Google trends statistics show data at weekly periodicity, similar to [Bangwayo-Skeete and Skeete \(2015\)](#), it is possible to work with higher-frequency data than previous meteorological and tourism literature (which has used monthly, quarterly, and yearly data), a periodicity probably better suited to evaluate meteorological variability and its impacts.

3. Methodology

According to the previous literature, the relationship between Google searches and weather data has been explored through regression analysis. However, given that the interest appeal of this study resides in the short-run relationship between weather and tourism searches, the direct consideration of multiple regression model linking the original tourism variable and its determinants would not be suitable. This is because it is expected that main part of total variation of a tourist variable during a year would be probably characterized by a high level of seasonality that is determined, among other factors, by school and working holidays, special events, and climatic factors (but not weather ones). Consequently, a regression analysis between the original variables, in the case that the spurious relationship could be controlled, would lead to establish, mainly, the relationship between tourism seasonality and climate.

If the attention has to be focused on the impact of weather factors, a detrending strategy has to be considered. With the use of high-frequency data the use of an autoregressive integrated moving average (ARIMA) model has been presented as suitable tool ([Díaz et al. 2005](#); [Hor et al. 2005](#); [Rosselló et al. 2011](#)). First described by [Box and Jenkins \(1970\)](#), ARIMA models have been widely used in tourism demand modeling and forecasting for many years ([Song and Li 2008](#)). The traditional formulation of an ARIMA model applied to Google searches can be specified as

$$\varphi_p(L)G_t = \theta_q(L)a_t, \quad (1)$$

where G_t are the Google searches for a given week t , a_t is the innovation or moving average term, and $\varphi_p(L)$ and $\theta_q(L)$ are the lag operator polynomials for both G_t and a_t respectively. For estimation purposes, Eq. (1) can be reformulated as

$$G_t = \sum_{i=1}^p \rho_i G_{t-i} + \sum_{j=1}^q \theta_j a_{t-j} + \varepsilon_t, \quad (2)$$

where ρ and θ are parameters to be estimated and ε_t is the error term distributed normally and independently. As is habitual in time series modeling, conventional steps must be followed to identify the most suitable orders for the ARIMA model (Brockwell and Davis 1991). Because of the tourism time series' strong seasonal behavior, different artificial variables can be considered in order to account for monthly effects. Thus M01, M02, M03, M04, M05, M06, M07, M08, M09, M10, M11, and M12 are artificial variables that account the number of days in each one on the different months. For instance, if a certain observation corresponds to a week where all the days belong to January, then M01 = 7 and the rest of dummy variables will be 0; if another one corresponds to a week with 3 days in July and 4 days in August, then M07 = 3, M08 = 4, and the rest of dummy variables will be 0. Once the long-run seasonal behaviors of the Google search time series have been captured, the information for the behavior of the weather variables can be included in the specification using the transfer function method (Box et al. 2013). From Eq. (1) we get

$$\varphi_p(L)G_t = \theta_q(L)a_t + \beta_s m_s + \phi_b^k(L)d(k)_t, \quad (3)$$

where m_s refers to the monthly dummy variables mentioned above and β_s are the estimated parameters of each dummy variable, while $d(k)$ is a vector of k weather variables that can potentially determine Google searches, and $\phi_b^k(L)$ are the lag operator polynomials (or transfer function) for each of the determining $d(k)$ variables. The parameterized version of the equation for estimation purposes can be written as

$$G_t = \sum_{i=1}^p \rho_i G_{t-i} + \sum_{j=1}^q \theta_j a_{t-j} + \sum_{s=1}^{12} \beta_s m_s + \sum_{w_1=1}^{r_1} \pi_{w_1} d1_{t-w_1} + \sum_{w_2=1}^{r_2} \pi_{w_2} d2_{t-w_2} + \dots + \sum_{w_k=1}^{r_k} \pi_{w_k} dk_{t-w_k} + \varepsilon_t, \quad (4)$$

where π are the weather parameters of the transfer function to be estimated. In this paper, initially, a maximum lag of 5 weeks is considered. In other words, it is hypothesized that the meteorological conditions, both in the origin and the destination, can determine Google searches from the same week to five weeks after. Afterward, because a high correlation between weather variables is expected, the general-to-specific strategy (Hoover and Perez 1999) is used to reduce the nonsignificant parameters and to get a reduced form of Eq. (4).

4. Data

The Google Trends site (<http://www.google.com/trends/>) provides the search intensity of any keyword for any specific geographical source market from January 2004 onward. A weekly reporting interval is shown and the results are updated every Sunday. Because of the special aim of this paper in analyzing the popularity of a "sun, sea, and sand" tourist destination, the interest in Majorca evaluated through Google searches is taken as reference.

Majorca is a popular destination in the Mediterranean, known for its warm climate conditions. According to official statistics, it had an annual volume of 9.6 million foreign tourists in 2014 (a figure that contrasts with the local population of 0.87 million inhabitants), with Germany (3.7 million tourists) and Britain (2.1 million) being the most popular markets of origin. Main differences between the two source markets include a more seasonal behavior for British tourists, who are more motivated by climate issues than German ones, who present a significant rate of second homes. Anyway, it is not surprising that, when the statistics from Google trends for "Mallorca" (for Germany) and "Majorca" (for the United Kingdom) are reported, the most related searches are referred to weather and accommodation services.

Specifically, in this paper, records for each search for "Mallorca" and "Mallorca hotel" made in Germany and "Majorca" and "Majorca hotel" in the United Kingdom were gathered. Thus, searches made at national level were taken as a reference. In this point it is important to note how it is possible to get data from Google trends on searches for some specific regions for both countries, a point that would make it possible to take more accurate weather data on origin. However, it is assumed that the weather conditions remain more similar at national levels while differences in weather conditions between origin and destination can be more important. Consequently, this led to four time series, with an entry for each week, which can be seen in Fig. 1. As expected, a strong seasonal behavior pattern can be observed, highlighting the role of climate in the intensity of searches relating to Majorca.

It is important to note that Google reports both the raw search volume as well as search volumes that are normalized and scaled. Then, first interest is calculated as (number of queries for keyword)/(total Google search queries). Second, the combined interest data for the keywords is divided by the highest point of interest for that date range. This implies that if the overall search intensity for all the keywords is low in a given week because of a holiday period, the raw data are scaled appropriately to ensure meaningful intertemporal comparisons. Additionally it should be noted how, in some cases, it is possible to show a declining interest in

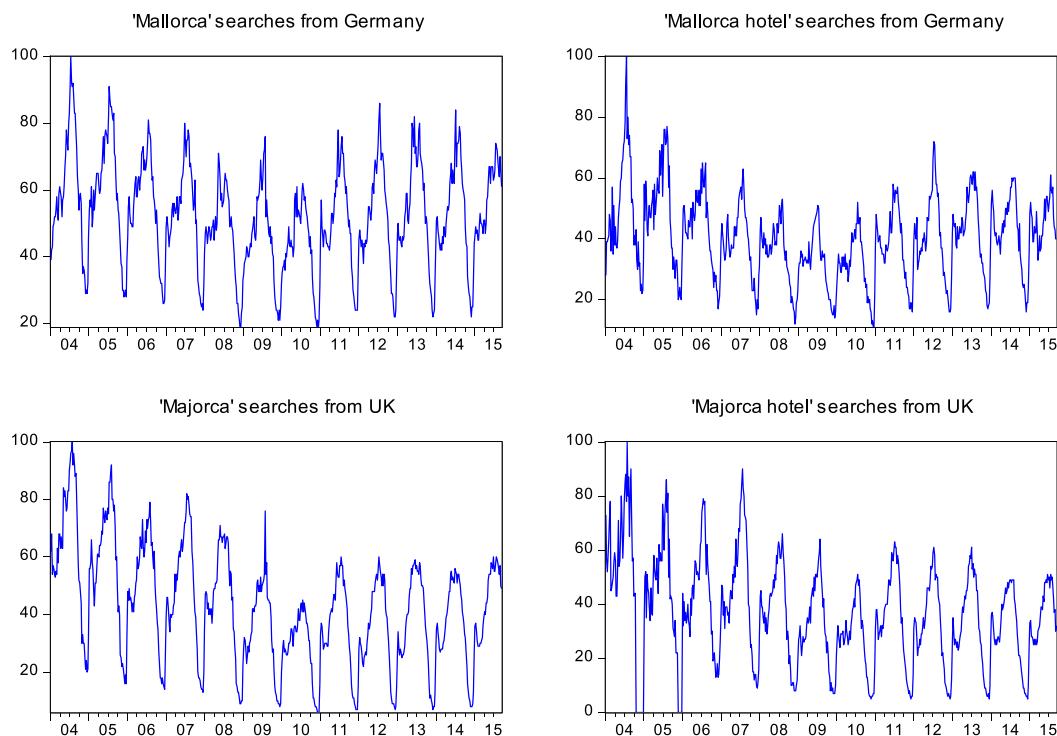


FIG. 1. Searches for “Mallorca,” “Mallorca hotel,” “Majorca,” and “Majorca hotel” in Google Trends from January 2004 to September 2015.

trends for a specific topic even if absolute query volume is increasing (that can happen if global searches have a higher growth rate than this specific topic). Anyway, it is assumed that this scaling system does not interfere with this research study, since a given level of search intensity should make more of an impact in a period of low overall search intensity than a high one.

The meteorological variables considered in this study take first daily average temperature, rainfall, and maximum wind speed during a day. The original data were obtained from the respective National Weather Services in Spain (<http://www.aemet.es/>), the United Kingdom (<http://www.metoffice.gov.uk/>), and Germany (<http://www.dwd.de/>). The stations used as reference were based in the airport station of Palma de Mallorca (PMI), London Heathrow Airport (LON), and main Frankfurt weather (FRAN). Weekly records for average temperatures (AT), rainfall (RAIN), and wind speed (W) were computed as averages within each week and can be observed in Fig. 2.

Because of the strong seasonal component shown by the average temperature and rainfall variables and the specific aim of the study the expected mean temperature and mean precipitation for each week of the year were estimated using the values for the whole sample. Second, each observation’s deviation from the expected meteorological conditions for each week was computed (Fig. 3). Thus, temperature and rainfall are not considered

directly but as the difference between the real temperature and the expected one. As shown in Fig. 3, as expected, the highest variability for the temperature is observed in Frankfurt, whereas the highest variability of rainfall is observed by the Palma de Mallorca station. Anyway, it is clear that by using these transformations the strong seasonal component is avoided.

5. Empirical results and discussion

- Based on the above considerations, Tables 1 and 2 present regression models that explain German and British interest in web searches relating to “Mallorca” and “Mallorca hotel” (“Majorca” and “Majorca hotel” in the case of the United Kingdom). The estimation results can be rated as satisfactory in terms of the significance of the parameters, the R^2 values, and the Lagrange Multiplier (LM) tests (used to validate the nonexistence of residual autocorrelation). As expected, dummy variables for the different months explain most of the variation of the dependent variable in the four time series analyzed. Thus, the highest coefficients are obtained for the summer months and the lowest for the winter months. ARIMA terms show how no moving average terms remain significant after the model reduction process while different autoregressive terms (AR) are kept.

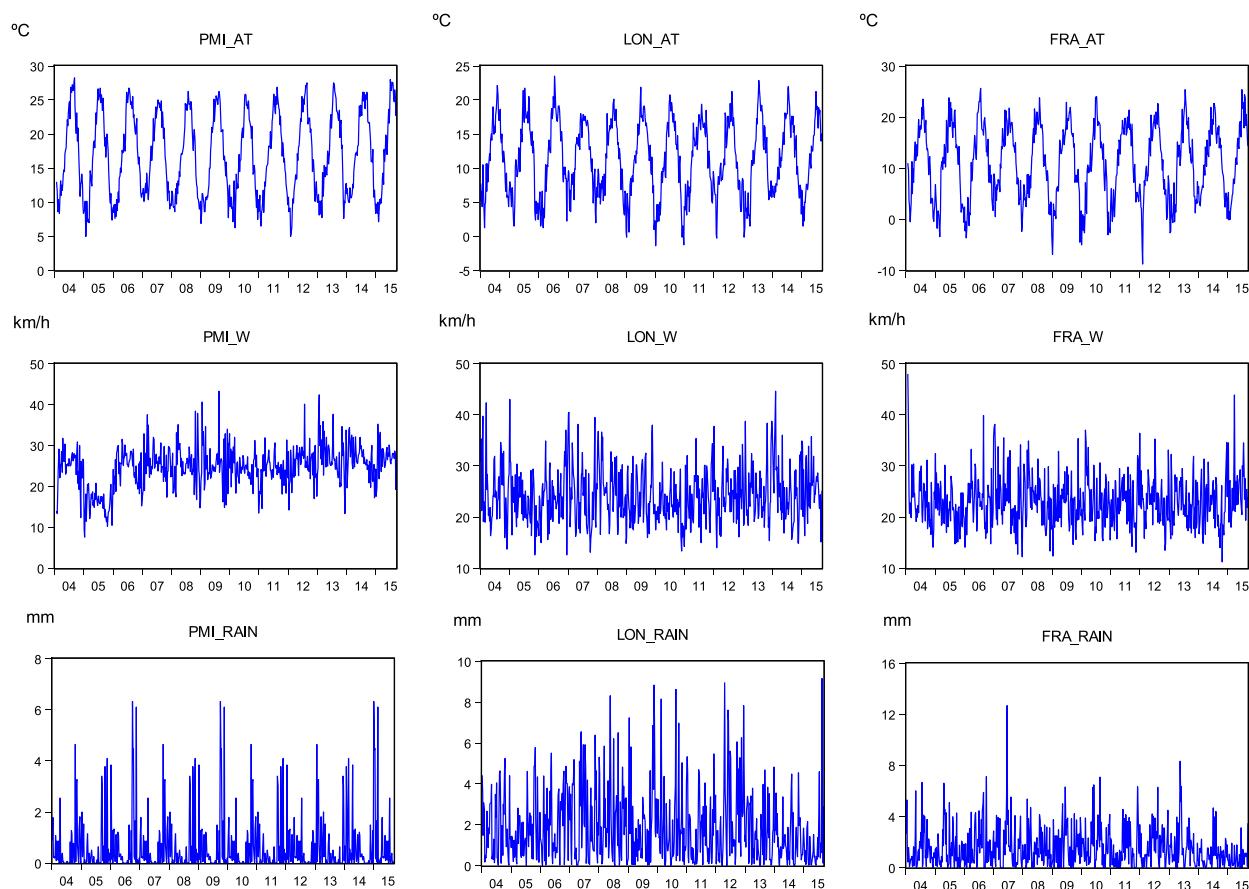


FIG. 2. Weekly meteorological conditions in Palma de Mallorca, London, and Frankfurt from January 2004 to September 2015.

In reference to the causal effects of the meteorological conditions, the general-to-specific strategy was applied using the backward stepwise technique, trying to obtain the best Akaike information criterion. With this procedure, although all lags in all the explanatory variables were initially included, only those significant at the 10% level were kept. Then, less significant lags were discarded from the model in each round and new transfer functions were estimated without the discarded variables. The process was repeated until a model was found where all the variables were statistically significant at a 10% level at least.

In the four analyzed cases of Tables 1 and 2, the statistical significance of different of the weather variables evidences the relevance of weather conditions both in the country of origin and at the destination in determining Google searches on “Mallorca” and “Mallorca hotel.” Signs of parameters show how, on the one hand, adverse meteorological conditions in the country of origin were found to be a determinant of a stronger interest in Majorca. On the other hand, good meteorological conditions at the destination boost Google

searches for data relating to Majorca, especially in the case of the United Kingdom. Thus, statistically, weather conditions in the country of origin were found to act as a push factor, while weather conditions at the destination are a pull factor.

In the case of Germany (Table 1), it seems clear that contemporary weather conditions in the origin, captured by wind conditions (FRA_W) and abnormal levels of temperatures (D_FRA_AT) and rainfalls (D_FRA_RAIN), but also with the weather conditions in the destinations captured by the abnormal level of temperature in the previous week [D_PMI_AT(-1)], determines the interest in “Mallorca.” In other words, it seems that colder, windy, and wetter conditions in Germany but also hotter conditions in Majorca are related to a stronger interest in Majorca for Germans. Specifically, 1°C above the mean temperature in Frankfurt is related to a decrease of 0.15 points in the Google Search Index; 1 additional liter of precipitation by squared meter above the expected rainfall is linked to an increase of 0.273 points; 1 additional km s^{-1} in the maximum wind speed in Frankfurt is related to 0.085 increase in the

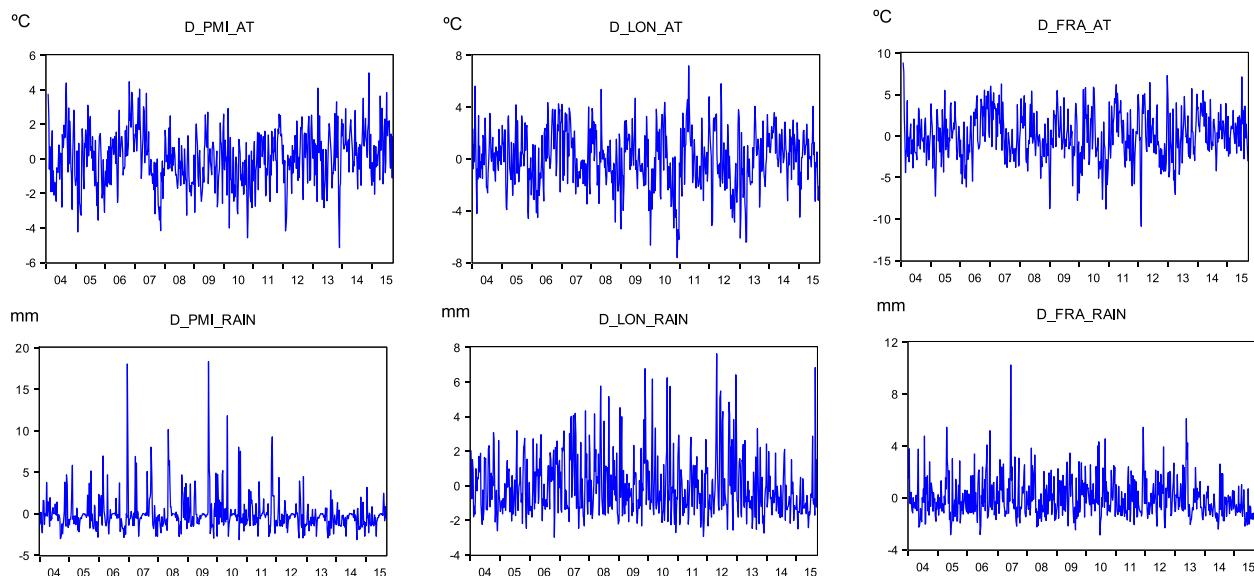


FIG. 3. Weekly deviation of temperatures and rainfall in Palma de Mallorca, London, and Frankfurt from January 2004 to September 2015.

index; and 1°C above the mean temperature in Palma is related to an increase of 0.15 points.

The results for “Mallorca hotel” searches go in line with these but with some differences. Thus, it has been found a higher dependence on the meteorological conditions during the last two weeks though the wind variable [FRA_W(-1) and FRA_W(-2)] although the rest of meteorological conditions in the origin are not significant. Additionally, local conditions seem not to play a significant role in “Mallorca hotel” searches.

The results for the British equation (Table 2) also confirm the main hypothesis. In the case of searches made in the United Kingdom (Table 2), rain and wind within the same week and during previous weeks shows statistical significance with “Majorca” and “Majorca hotel” searches. In this case, additionally, it seems clearer that these weather conditions at the destination play a significant role in determining Google Trend searches, since the higher the wind, the fewer searches that were recorded.

Finally, because it has been assumed that the meteorological conditions have emerged as new determinants of tourist interest jointly with the trend in the reduction of booking lead times, two subsamples for “Mallorca” and “Majorca” searches for both Germans and British are considered. The first subsample takes data from the first week of 2004 to week 52 of 2009 (w1/2004–w52/2009), and the second subsample considers data from the first week of 2010 to week 37 of 2015, the last available in our sample (w1/2010–w37/2015). Results are presented in Table 3.

Again, the estimation results are satisfactory in terms of the significance of the parameters and the regression

statistics. Focusing on the meteorological variables, signs of parameters show again how favorable meteorological conditions at the destination boost Google searches for Majorca, although only one variable, the deviation of the average temperature, was found significant at 10% for the first subsample in the German case. On the other hand, adverse meteorological conditions in the country of origin were also found to be a determinant of a stronger interest in Majorca. Again, in view of the significance of parameters it seems that better results are obtained for the second subsample, the newest one, for both case studies. In line with this idea, both R^2 values and the Akaike information criterion show better values for the second period of analysis, providing evidence that the models with meteorological data work better for more recent data.

6. Conclusions

The uses of the Internet, the liberalization of the airspace, and fewer border restrictions have caused an increase in last-minute bookings and the reduction of the lead booking time. In the case of the “sun, sea, and sand” tourist market, for many years the industry was dominated by tour operators that created holiday/travel packages conceived to be sold to end customers some months prior to the trip. Nowadays, the market has changed and a great majority of international tourists use the Internet to plan their trip and book some kind of tourism services (IET 2013).

In this context, this paper has explored meteorological conditions as new short-run factors determining tourist

TABLE 1. Estimation results from Germany weekly models. Estimation period January 2004–September 2015 [*** and ** stand for statistical significance at 1% and 5% respectively; AR(t) refers to the autoregressive terms with t lags].

	“Mallorca” searches		“Mallorca hotel” searches	
M01	7.118	***	5.620	***
M02	6.948	***	4.826	***
M03	7.358	***	4.958	***
M04	7.467	***	4.840	***
M05	8.173	***	5.729	***
M06	8.095	***	6.281	***
M07	8.469	***	7.029	***
M08	7.831	***	6.512	***
M09	7.145	***	4.832	***
M10	6.810	***	3.705	***
M11	5.795	***	3.060	***
M12	5.390	***	2.546	***
AR(1)	0.890	***	0.478	***
AR(2)	—		0.203	***
AR(4)	—		0.218	***
D_FRA_AT	-0.150	**	—	
D_FRA_RAIN	0.273	***	—	
FRA_W	0.085	**	0.213	**
FRA_W(-1)	—		0.214	**
FRA_W(-2)	—		0.069	**
D_PMI_AT(-1)	0.320	***	—	
Equation statistics				
Observations	606		602	
R^2	0.931		0.895	
Adjusted R^2	0.929		0.892	
Log likelihood	-1723		-1754	
Durbin–Watson statistic	2.038		2.020	
Mean dependent variable	52.472		40.475	
S.D. dependent variable	15.803		13.805	
Akaike info criterion	5.745		5.888	
LM(7)	0.480		0.83	

travel choices, investigating the role of weather variables in explaining short-term variability in Google searches relating to Majorca from its two main tourist markets: Germany and the United Kingdom. The estimated statistical models provide evidence that the weather conditions in both the country of origin and at the destination are related to data recorded by Google Trends. Bearing in mind the limitations of this kind of model, which can only capture average tourist behaviors, results show clearly that as weather conditions improve at the destination or as they worsen in the country of origin, more searches relating to Majorca are reported by Google Trends. Additionally, results show how the effect seems more evident for the most recent data.

This research extended previous research by showing that beliefs about weather, in addition to actual weather, can affect travel behavior. Models that incorporate meteorological information, such as those developed in this paper, could be essential for national and regional

TABLE 2. Estimation results from British weekly models. Estimation period January 2004–September 2015 [***, ** and * stand for statistical significance at 1%, 5%, and 10% respectively; AR(t) refers to the autoregressive terms with t lags].

	“Majorca” searches		“Majorca hotel” searches	
M01	6.102	***	5.745	***
M02	5.487	***	5.377	***
M03	6.192	***	5.490	***
M04	7.134	***	6.496	***
M05	8.382	***	7.461	***
M06	8.653	***	8.287	***
M07	9.381	***	9.344	***
M08	8.907	***	8.407	***
M09	7.223	***	6.044	***
M10	4.691	***	3.796	***
M11	2.952	***	2.429	***
M12	2.842	***	2.196	***
AR(1)	0.479	***	0.587	***
AR(4)	0.232	***	0.290	***
AR(5)	0.149	***	—	
D_LON_RAIN	0.178	*	—	
D_LON_RAIN(-1)	0.182	**	—	
LON_W(-1)	—		0.095	**
LON_W(-2)	0.081	***	0.067	*
LON_W(-4)	0.063	**	—	
D_PMI_AT	—		0.270	*
PMI_W	-0.106	***	-0.141	***
PMI_W(-1)	-0.111	***	-0.130	**
PMI_W(-2)	-0.133	***	-0.134	**
Equation statistics				
Observations	601		602	
R^2	0.931		0.895	
Adjusted R^2	0.929		0.892	
Log likelihood	-1723		-1754	
Durbin–Watson statistic	2.038		2.020	
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tourism organizations in assessing the effect of new weather conditions on tourism in a context of global warming. This knowledge is needed by public and private tourism organizations so that they can provide better strategic information to clients on how to manage weather impacts more effectively. However, the meteorological effects in origins have been considered at national levels. The importance of differing regional climates (or even microclimates) for tourism decision-making and behavior could also have relevance, as has been evidenced in [Hartz et al. \(2006\)](#), [Wilson and Becken \(2011\)](#), and [Rutty and Scott \(2014\)](#). Consequently, future research could try to consider the regionalization of the tourism data.

Although the statistical results found in this paper are enough to confirm the hypothesis on the relationship

TABLE 3. Estimation results for Mallorca/Majorca searches from Germany and the United Kingdom [***, **, and * stand for statistical significance at 1%, 5% and 10% respectively; AR(*t*) refers to the autoregressive terms with *t* lags].

	Germany				United Kingdom			
	Sample: w1/2004–w52/2009		Sample: w1/2010–w37/2015		Sample: w1/2004–w52/2009		Sample: w1/2010–w37/2015	
M01	7.414	***	6.899	***	7.772	***	5.753	***
M02	7.197	***	6.667	***	6.906	***	5.243	***
M03	7.860	***	6.860	***	7.965	***	5.012	***
M04	7.741	***	7.222	***	8.919	***	5.129	***
M05	8.408	***	8.100	***	10.481	***	5.226	***
M06	8.645	***	7.712	***	10.546	***	5.209	***
M07	9.048	***	8.113	***	11.895	***	5.567	***
M08	8.242	***	7.624	***	11.477	***	5.538	***
M09	7.325	***	7.139	***	9.015	***	5.363	***
M10	7.221	***	6.483	***	5.870	***	4.778	***
M11	6.211	***	5.505	***	3.879	***	4.135	***
M12	5.781	***	5.059	***	3.783	***	3.661	***
AR(1)	0.891	***	0.91	***	0.785	***	0.602	***
AR(2)	—	—	—	—	−0.203	***	0.451	***
AR(4)	—	—	—	—	0.295	***	−0.208	***
MA(1)	—	—	—	—	−0.493	***	0.505	***
D_FRA_AT	—	—	−0.154	**	—	—	—	—
D_FRA_AT(−1)	−0.162	*	—	—	—	—	—	—
D_FRA_RAIN	0.232	*	0.417	***	—	—	—	—
FRA_W	—	—	0.122	***	—	—	—	—
D_LON_RAIN	—	—	—	—	0.363	*	—	—
D_LON_RAIN(−1)	—	—	—	—	—	—	0.306	***
D_LON_RAIN(−2)	—	—	—	—	—	—	0.159	**
D_LON_RAIN(−3)	—	—	—	—	0.385	**	—	—
LON_W(−2)	—	—	—	—	—	—	0.053	*
LON_W(−4)	—	—	—	—	—	—	0.070	***
D_PMI_AT(−1)	0.368	*	0.480	***	—	—	—	—
PMI_W	—	—	—	—	−0.143	**	−0.171	***
PMI_W(−1)	—	—	—	—	−0.175	***	—	—
PMI_W(−2)	—	—	—	—	−0.132	**	—	—
Equation statistics								
Observations	308		298		304		298	
R ²	0.929		0.934		0.957		0.968	
Adjusted R ²	0.925		0.931		0.954		0.965	
Log likelihood	−882.259		−833.770		−887.121		−721.652	
Durbin–Watson statistic	2.072		1.951		2.003		2.021	
Mean dependent variable	53.705		51.198		5.981		35.668	
S.D. dependent variable	16.575		14.884		6.250		15.215	
Akaike info criterion	5.833		5.710		6.089		4.984	
LM(7)	1.37		1.04		1.33		1.45	

between weather and the interest in Majorca, it should be noted how the use of autoregressive terms has two main effects on the empirical application carried out. On the one hand, this ensures no spurious regression and that the captured effect is related to weather and not to climate. However, it also reduces the statistical significance of weather effects longer than a week. Thus, if a heat or a cold wave persists during some weeks, and precisely this persistence motivates the interest in a tourist destination, the relationship between weather variables and tourism will be covered by the autoregressive terms. Future research would try to solve this dilemma.

Acknowledgments. This paper has benefit from financial support of the ECO2013-44823-R project.

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