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Climate change scenarios and the evolution of Spanish tourism

J.M. Barrutiabengoa, G. Carta, N. González,
D. Pérez, P. Más and G. Yücel

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J.M. Barrutiabengoa[a], G. Carta[a], N. González[a], D. Pérez[a], P. Más[a] and G. Yücel[a]

a BBVA Research

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Abstract

The tourism industry, a vital contributor to Spain's GDP, may face substantial challenges due to the worsening weather conditions as a result of climate change. This study investigates the potential effects of climate change on tourism demand across Spanish provinces up to the year 2100. By analyzing monthly data from the 50 Spanish provinces over a 22-year period (2002-2023), we assess the impact of the current climatic conditions -measured by the Tourism Climatic Index (TCI) and the Holiday Climate Index (HCI)- on tourism demand, according to various tourism typologies. Our findings indicate that climatic conditions significantly influence tourism demand, with eastern and southern coastal provinces being the most responsive. We then simulate the effects of future climate change on tourism demand under three emission concentration pathways (RCP 2.6, 4.5, and 8.5, which project mean temperature increases of 1.8°C, 2.8°C, and 4.8°C by 2100, respectively). Results reveal a clear north - south-east pattern in coastal tourism demand, where the northern coastal provinces benefit from increasing temperatures, while the southern and eastern regions experience notable declines in tourism, especially under higher warming scenarios. City tourism shows a less pronounced impact. Seasonal distribution of tourism demand is also expected to shift, with significant decreases in summer and increases in spring. Overall, the net effect on the Spanish tourism is negative according to the TCI specification, with mild impacts under RCP 2.6 and 4.5 (-0.3% and -0.6% in 2100 vs. 2024-2030), but a significant impact under RCP 8.5 (-7%). The study also highlights that the thresholds of climate Indexes, determine the results in a great extent, though selecting the most appropriate one remains challenging.

Keywords: Climate change, tourism demand, Spain, Tourism Climate Index, Holiday Climate Index, Emission Concentration Pathways, seasonal patterns.

JEL Classification: L83, Q54.

1. Introduction

Tourism, as a critical sector for many economies worldwide, is also one of the most vulnerable to the impacts of climate change. Variations in temperature, precipitation patterns and the frequency of extreme weather events can profoundly affect tourism demand and the attractiveness of destinations. This study investigates the intricate relationship between climate change and tourism demand in Spanish provinces, focusing on potential alterations in tourism patterns due to future climatic conditions. Building on the work of [Matei et al., 2023] for European regions, our work provides a more granular and extensive analysis for Spanish tourism.

The relevance of the climate-tourism relationship in Spain is twofold. Firstly, tourism is one of the main economic activities, contributing 11.6% of GDP and accounting for 9.3% of employment in 2022. In addition to the direct impact generated by tourism-related activities (such as industries, commodities, and spending) there are also significant indirect effects, including induced contributions through expenditures in other goods and services [Lemma, 2014]. Secondly, tourism in Spain is heavily dependent on weather, especially in beach destinations. Spain, with its rich cultural, historical and natural attractions, was the second most visited country globally in 2023. However, this weather-driven appeal, particularly crucial for coastal areas, is likely to be influenced by the impacts of climate change.

Extensive research has examined the effect of climate change on tourism demand. Notably, [Matei et al., 2023] conducted a regional panel analysis at European level using a climate index to explore the effects of climate change on tourism demand. Previous studies have highlighted that climate significantly influences tourists' decision-making processes, affecting the choice of destinations and travel timing [Gössling et al., 2023].

This study builds on the existing literature by utilizing a combination of econometric modeling and climate data analysis to estimate the relationship between tourism demand and climatic conditions. Specifically, it examines the influence of the Tourism Climate Index (TCI) and the Holiday Climate Index (HCI), controlling for economic variables such as GDP and prices (both in origin and destination), on tourism demand across different Spanish provinces using panel data models. The analysis also projects the potential impacts of future climate scenarios on tourism demand under varying global warming levels.

The results reveal a clear north - south-east pattern in coastal tourism demand changes, where northern coastal provinces benefit from climate change and southern and eastern regions experience notable declines in tourism demand, especially under higher warming scenarios, while city tourism shows a less pronounced impact. The seasonal distribution of tourism demand is also expected to shift, with significant decreases in summer and increases in spring. The net effect[1] on Spanish tourism demand is negative but depends on the climate index and the warming scenario considered. For instance, under the TCI specification, tourism demand may experience mild impacts under low to moderate projected temperature increases by the end of the century (-0.3% and -0.6% in 2091-2100 vs. 2024-2030, respectively) but could see a significant 7% decrease on tourism demand under a scenario of high temperature increase by 2100.

The analysis aims to contribute to the ongoing discourse on climate change and tourism by providing robust empirical evidence on the impact of climatic conditions on tourism demand as well as serving as a reference for policy strategies that mitigate and enhance the resilience of the tourism sector to climate change, thereby supporting the long-term viability of Spanish tourism destinations amid evolving climatic conditions.

The structure of this paper is as follows: Section 2 reviews the literature on the determinants of tourism demand, highlighting key findings and identifying research gaps. Section 3 delves into the data and the use of climate indexes, providing information about the sources and specifications used in the modeling. Section 4 outlines the modeling approach. Section 5 presents the empirical results, discussing the effects of TCI and HCI on tourism demand and providing projections under various climate scenarios. Finally, Section 6 summarizes the main findings of the work.

2. Determinants of tourism demand

The relationship between tourism demand and climate has been long debated due to the sensitivity of the tourism industry to climatic conditions. Early studies integrated climate variables as inherent characteristics of destinations, thereby improving tourism demand forecasting and evaluating policy outcomes. However, with the accelerating effects of global warming in recent decades, the literature has increasingly focused on analyzing the impact of climate change on the tourism sector. This shift presents challenges, particularly in selecting the appropriate indicators and accurately measuring the multifaceted impacts of climate change on tourism.

Temperature has been widely studied as a primary climate variable due to its direct and measurable influence on tourism decisions and behavior. [Bigano and Tol, 2005] examined the impact of temperature and precipitation on domestic tourism demand in

[1] By "net effect," we refer to the overall impact on tourism in Spain. While tourism may increase in certain provinces and/or seasons, the overall effect on the total number of tourists coming to Spain will be negative.

Italy, revealing that both variables significantly affect tourism flows, alongside climate expectations. Focusing on municipalities in Tuscany, [Cai and Leung, 2010] found that the average length of stay and tourist arrivals are responsive to local weather conditions, particularly benefiting the intermediate seasons. [Taylor and Ortiz, 2009] similarly explored the effects of temperature and sunshine on domestic tourism demand in the United Kingdom, predicting that tourism will likely increase with hotter summers. While these studies focused on the impact within individual countries, this relationship is also evident in studies using panel data, which, in addition to identifying a link between climate and tourism, reveal a divide between northern and southern regions. Higher temperatures enhance the attractiveness of a destination, particularly in northern regions, at the expense of traditionally warm destinations. Similarly, [Barrios and Ibañez, 2015] suggest that southern EU regions may lose tourism revenues, whereas northern EU regions could see modest gains, especially due to the adaptation in the timing and duration of holidays. Studies have also underscored the relevance of climate change in shaping tourism patterns in Spain, emphasizing the need for adaptive strategies to mitigate potential negative impacts ([Priego et al., 2015] or [Research, 2022]).

The use of individual climate variables as explanatory factors offer a direct measure of climate impact, however, they fall short in capturing interdependencies that shape tourism patterns. Recognizing this complexity, researchers have moved beyond isolated metrics, developing comprehensive climate indexes like the Tourism Climate Index (TCI) and the Holiday Climate Index (HCI) to provide a more complete understanding, by integrating a range of climate factors such as temperature, humidity, precipitation, sunshine and wind. The pioneer TCI [Mieczkowski, 1985] has become the most widely used measure for assessing how the climate change influences tourism. Recent studies have employed the TCI to assess both historical and future tourism patterns under different climate scenarios. Historically, temperature has had a positive correlation with tourism. Warmer countries, particularly for beach tourism, have generally attracted more tourists. However, the rising temperatures we are currently observing could alter this relationship. In some areas, once certain thresholds are reached, excessive heat may start to negatively impact tourism. Despite the possible declines in tourism levels, the duration of the tourism season could lengthen as a result of shifting climate patterns. This implies that there will be seasonal and spatial shifts in tourism demand driven by climate change, as shown by [Oğur and Baycan, 2023] in their study on tourism flows in 30 Turkish cities. In particular, coastal locations are expected to face the greatest impact from these changes, as [Matei et al., 2023] demonstrate in their comprehensive analysis of 269 European regions. The extent of this impact will depend not only on the future trajectory of climate change, but also on tourism's ability to adapt over time [Amelung and Moreno, 2012].

Given the differences in tourism attractiveness, the Holiday Climate Index (HCI) was developed as a more tailored indicator for assessing climatic comfort across different tourism segments. [Daniel Scott and Gössling, 2016] and [Rutty et al., 2020] designed the HCI to account for specific climatic preferences, creating distinct versions for beach and urban tourism, which make it an effective tool for forecasting tourism demand in specialized tourism markets. Their research suggests that the HCI: Urban offers a more favorable assessment of conditions in six major European cities compared to the Tourism Climate Index (TCI), especially during winter and under projected future scenarios [Daniel Scott and Gössling, 2016]. Similarly, the HCI: Beach seems to be a more accurate representation of tourist's preferences for beach destinations, as it shows a stronger correlation with actual tourist arrivals to Caribbean destinations [Rutty et al., 2020]. The underlying reason is that this indicator assigns higher values during hotter months, which aligns with peak tourism periods and makes tourism less senspitive to rising temperatures. Consequently, future projections using this index theoretically highlight the resilience of beach tourism, such as in mediterranean regions [Demiroglu et al., 2020].

Seasonal climate patterns significantly influence tourism demand fluctuations, particularly in regions where the tourism sector is highly sensitive to climatic variability. For instance, [Ridderstaat and Nijkamp, 2014] highlight how small island destinations, such as Aruba, are especially vulnerable to these fluctuations due to their reliance on a narrow tourism season. This vulnerability is further aggravated by the increasing severity and frequency of natural disasters and extreme events driven by climate change, which can severely disrupt tourism demand. Tourism demand is particularly affected to climate vulnerability, with higher levels of vulnerability correlating with more significant drops in tourism revenues [Cevik and Ghazanchyan, 2021]. While such events generally reduce tourism inflows, [Rosselló et al., 2020] found that extreme temperature events, like cold and heat waves, although significant, tend to have a more limited impact because they are not perceived as long-term or catastrophic threats. These findings underscore the urgent need for adaptation policies that enhance the resilience of the tourism sector to climate-related risks.

3. Data

3.1. Historical economic variables

The choice of a tourism demand measure can be challenging, as the tourism activity is a multidimensional variable. Among the most common ones, there are tourist arrivals (total or bilateral), number of overnight stays, tourism expenditure or length of stay of tourists. In our study we have selected the number of bed nights provided by the Hotel Occupancy Survey from the Instituto Nacional de Estadística (INE)[2]. This survey covers the number of bed nights by Spanish provinces at the monthly frequency from 2002 to 2023. Additionally, it offers information on the origin of the tourists, allowing us to differentiate between domestic and foreign visitors. The bed nights variable is used in its raw or not seasonally adjusted value.

Regarding the economic factors driving the magnitude of touristic flows, we select the GDP and CPI, also sourced from INE. Monthly real GDP at the provincial level was derived by combining the annual provincial GDP ($GDP_{y,p}$) with the quarterly not seasonally adjusted autonomous community-level GDP ($GDP_{q,c}$), which is published by each regional statistical institute and it is not available for all regions (see Equation 1). In order to compute the provincial GDP, two assumptions are made. Firstly, the quarterly distribution of the Autonomous Community is assumed to be the same for all the provinces within that region. For those provinces in which the quarterly GDP data for its Autonomous Community is not available (either because the not seasonally adjusted variables are not published or the quarterly GDP is not available at all), the national quarterly GDP or that of another autonomous community with the highest correlation or similarity is used [3]. Secondly, the quarterly GDP for each province calculated as explained above is equally distributed across the three months. On the other hand, province-level monthly CPI was retrieved directly from INE (not seasonally adjusted also).

$$GDP_{q,p} = GDP_{q,c} \times \frac{GDP_{y,p}}{\sum_{p\in c} GDP_{y,p}} \tag{1}$$

Additionally, the ratio of real GDP per capita of the foreign tourists and real GDP per capita from the destination province is included to capture the realtive income

[2] Tourism demand in this study is measured by the number of bed nights spent at hotel accommodation establishments, as this variable is the most detailed and widely available at the province level from INE. The model's estimates and projections refer exclusively to overnight stays and do not account for same-day visitors.

[3] This was the case for 9 out of 17 autonomous communities.

differences, which is aimed to reflect the higher purchasing power of foreign visitors. [4] The steps to construct this variable were as follows:

1. Using information on the distribution of bed nights for foreign tourists provided by INE for 2019[5], the ten most relevant countries in terms of the number of bed nights for each province were selected.
2. The real quarterly GDP of each selected country was obtained and adjusted to a common base year (2015) to match that of Spain.
3. The real quarterly GDP per capita was calculated by dividing the GDP by the population of each country. The quarterly real GDP per capita was then converted to a monthly basis using the same method as for provincial GDP (equal distribution across the three months of the quarter).
4. A weighted average of the real monthly GDP per capita was computed, with the weights reflecting each country's share in the total number of bed nights provided by the ten selected countries for each province.

3.2. Climate variables

To assess the impact of climate conditions on tourism, composite indexes including various climatic variables are used. These indexes represent climate comfort on tourism by combining different scores. The most extensively used one of them is the *Tourism Climate Index* (TCI), developed by [Mieczkowski, 1985]. TCI methodology integrates the main climatic factors relevant to tourism into a single numerical value, thereby facilitating the understanding of climate conditions pertinent to tourism demand. This indicator combines temperature, humidity, precipitation, cloud cover and wind speed as depicted in Equation 2.

$$TCI = 5\,\text{Daily Comfort Index} + 2\,\text{Precipitation} + 2\,\text{Cloud Cover} + \text{Wind} \tag{2}$$

The Daily Comfort Index is built as a function of the mean daily air temperature and the mean daily dew point temperature (humidity) to represent the perceived temperature by tourists. This will imply that high temperatures combined with high relative humidity are perceived as warmer than those with lower humidity levels. The Humidex, contructed as in Equation 3, is the most commonly used index to describe how hot the

[4] A similar variable reflecting relative prices between origin and destination using CPI was used but it was found to be insignificant and did not alter any relevant conclusions of the study. Thus, it has not been included in the final model.

[5] We chose 2019 because it was the last available "normal" year, being the data unaffected by the pandemic or post-pandemic conditions.

weather feels to the average person.

$$H = T_{\text{air}} + 0.5555\left(6.11 \times \exp\left[5417.7530\left(\frac{1}{273.15} - \frac{1}{273.15 + T_{\text{dew}}}\right)\right] - 10\right) \quad (3)$$

All these components enter Equation 2 according to a classification that establishes the comfort levels (see Appendix A), where each variable ranges from 0 to 10, with 10 representing the ideal conditions. Once ranked, they are combined according to the formula described above with the corresponding weights. TCI values range from 0 to 100, where higher values indicate better comfort for tourist activities. Hence, 0 represents potentially dangerous conditions and 100 ideal for tourism. A value lower than 50 represents conditions that are considered unsuitable.

The Holiday Climate Index (HCI) is an alternative proxy for climatic comfort to the TCI. The TCI and HCI both use an additive methodology in which the weights of each sub-index indicate the relative impact of each climatic component. The HCI, however, was designed to be specified for major tourism segments and destination types by [Daniel Scott and Gössling, 2016] and [Rutty et al., 2020]. In particular, it distinguishes between "Beach" and "Urban" tourism. Since climatic conditions among different types of tourism vary, the optimal conditions should not be uniform among them. Another advantage of this indicator is that the thresholds have been selected according to tourists' preferences through empirical tests and surveys, whereas the TCI weights were determined by expert judgment and could be considered more subjective. In addition, this index assigns less weight to thermal comfort, which is the primary driving factor of the TCI.

$$HCI\ Beach = 2\,\text{Daily Comfort Index} + 4\,\text{Cloud Cover} + 3\,\text{Precipitation} + \text{Wind} \quad (4)$$

$$HCI\ Urban = 4\,\text{Daily Comfort Index} + 2\,\text{Cloud Cover} + 3\,\text{Precipitation} + \text{Wind} \quad (5)$$

Similar to the TCI, the HCI Beach and HCI Urban indexes include a daily comfort index, total daily precipitation, cloud cover and mean wind speed. However, the daily comfort index, which is the main component of the indexes driving different comfort levels, employs the average maximum daily air temperature instead of the mean. This creates some problems that are analyzed in following sections. Another interesting remark is that although the HCI Beach has the lowest weight for the daily comfort, it assigns the highest rating for higher temperature levels compared to the other indexes and penalizes values lower than a maximum temperature of 15 degrees (see Appendix A). This leads to a relatively lower score in the cold months (indicating that the conditions are not suitable for going to the beach), but remain elevated in the summer months despite very high temperatures.

The climate data required to build the historical series for both TCI and HCI was computed on a monthly basis at provincial level. The data was sourced from ERA5 hourly climate reanalysis data [Hersbach et al., 2023] and aggregated to match the granularity of the economic variables.

3.3. Descriptive statistics

Table 1 shows the descriptive statistics for the variables used in this study across the provinces and over time. The period ranges from January 2002 to December 2023 due to data availability. The sample (with 13,200 observations) does not suffer from missing data across provinces or time periods, resulting in a strongly balanced panel.

Table 1: *Descriptive Statistics*

	lnBN	lnGDP	lnGDPpcfor	lnCPI	lnTCI	lnHCI
Mean	11.93	13.90	0.81	4.50	4.10	4.17
SD	1.57	0.91	0.23	0.12	0.31	0.29
Min	0.00	11.97	0.02	4.19	3.14	1.61
Max	16.22	16.86	1.53	4.76	4.61	4.58
Median	11.70	13.86	0.83	4.53	4.08	4.19

Considerable variation is observed among most economic variables, with the exception of the Consumer Price Index (CPI), where price levels across provinces in Spain display an expected similarity. The relative GDP ratio (GDPpcfor) demonstrates less variability compared to other macroeconomic indicators, remaining consistently above 1 for all provinces and months (indicating that its natural logarithm is greater than 0). This is expected as the origin of tourist is similar in the majority of the provinces. Conversely, the number of bed nights (BN) and real GDP exhibit the highest variability, which could be attributed to significant differences in the sectoral mix and magnitude or development levels, as would be the case in interior provinces (excluding Madrid), which lag behind the leading provinces in terms of economic performance and sectoral mix.

Regarding the Tourism Climate Index (TCI), variability is lower compared to other variables, although noticeable regional differences exist especially between the northern and southern provinces. The distribution of the HCI is quite similar, but as the minimum of HCI indicates, it contains more values in the lower part of the distribution. This is because the HCI measures the maximum temperature, while the TCI assesses the average, as explained in the previous section. Consequently, higher temperatures are included in the HCI, resulting in rankings of 0 or close to 0. This has a significant impact, particularly on the forecasts. For more details on the differences between the HCI and TCI, please refer to Appendix A.

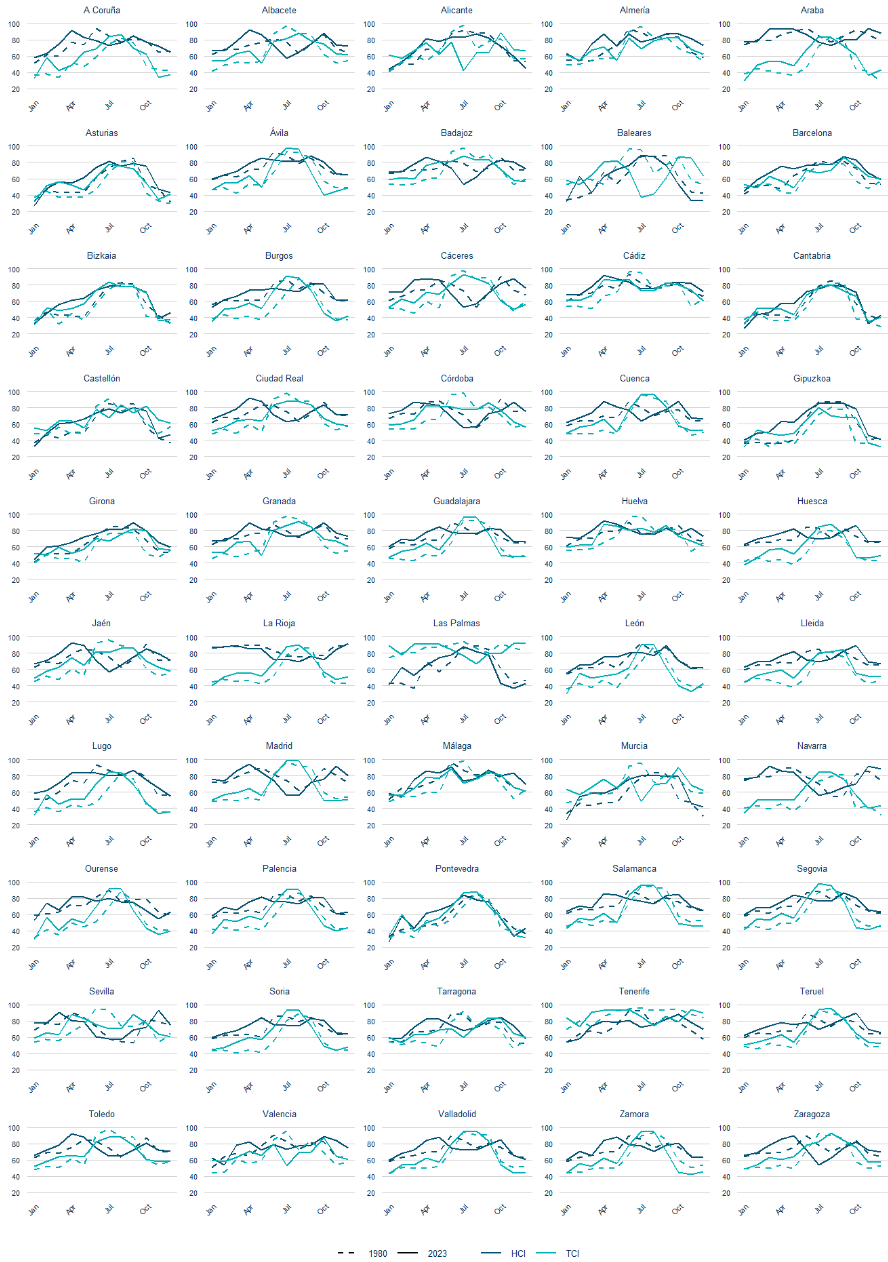

Figure 1: *TCI and HCI values in Spanish provinces (2023 vs 1980). Source: BBVA Research.*

Figure 1 illustrates the TCI and HCI monthly evolution for the 50 Spanish provinces for 1980 and 2023[6]. In general terms, there is a significant change in the indexes from 1980 to 2023. Both indexes indicate improved climate conditions for a considerable number of provinces, especially those that were originally colder. However, it is also evident that climate comfort has decreased in provinces that already had higher temperatures back in 1980, giving us an early indication of what the results of this study might reveal as we extend the trend further. Peaks in TCI are observed during the summer season (season during which higher temperatures are registered and higher tourism demand is reported), with moderate to high values in the shoulder seasons, and lower values typically in winter. The TCI profile of the Canary Islands on the other hand is more stable across seasons. Regarding the HCI, there is a clear divide between coastal (HCI Beach) and interior (HCI Urban) provinces. Overall, the HCI Beach displays a more defined bell shape, which assigns higher values in the months in which tourists prefer beach activities, while the HCI Urban displays more stable values since city sighteseeing is less sensible to climate conditions.

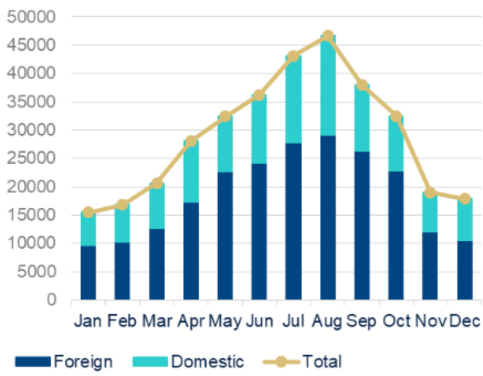

Figure 2: *Bed nights by month (foreign and domestic). 2023, thousands. Source: BBVA Research.*

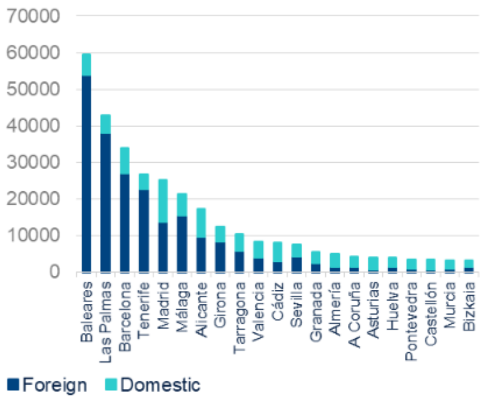

Figure 3: *Bed nights in Spanish provinces (foreign and domestic). 2023, thousands. Source: BBVA Research.*

Tourism behaviour also exhibits a seasonal pattern with a peak in the summer season (Figure 2). Foreign tourism accounts for a significant share of the total, especially in the most popular destinations, like Baleares, Las Palmas, Barcelona, Tenerife, Madrid and Malaga, which registered the highest numbers of bed nights in 2023 (Figure 3). In addition, the tourism demand has expanded significantly over the past two decades, increasing from approximately 222.66 million bed nights in 2002 to nearly 346.79 mil-

[6] Ceuta and Melilla are excluded from the analysis.

lion in 2023, with a substantial decline during the COVID-19 pandemic due to travel restrictions (92 million in 2020 and 172 in 2021).

3.4. Regional tourism typologies

Our approach also controls for the effect of different regional tourism typologies. We used a slightly modified (based on expert judgement) version of the [Batista et al., 2021] regional (NUTS 3) tourism typology for Europe, which is based on Geographical Information Systems (GIS) to integrate regional boundaries and geographical zoning with a detailed dataset of hotel locations and capacities. The modifications were aimed at enhancing the accuracy and relevance of the classification in reflecting the diverse tourism landscapes across the Spanish provinces. Regions were labeled according to four different tourism categories: "*Urban mix*", "*Coastal North*", "*Mediterranean & Islands*" and "*Mountains and Nature*". These categories represent the predominant tourism use in each province. The classification was modified as follows:

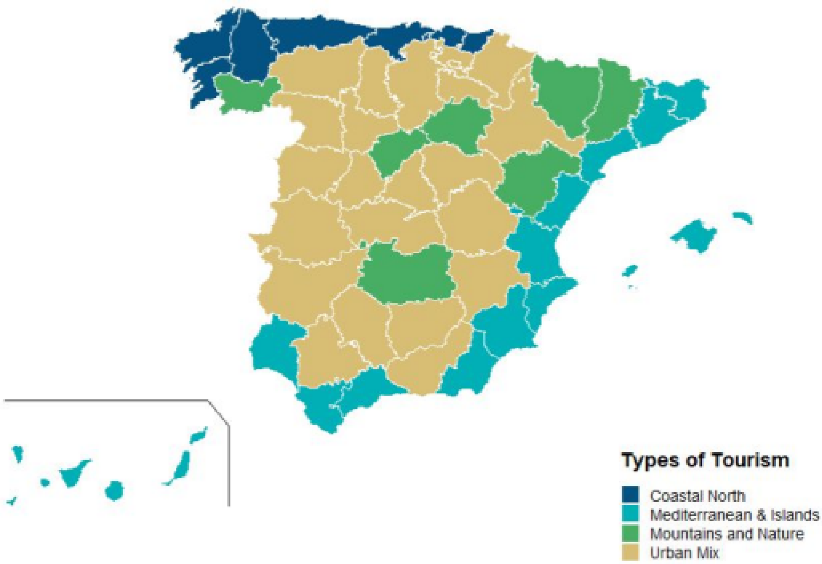

Figure 4: *Spanish provinces classified by type of tourism (Coastal North, Mediterranean & Islands, Mountains & Nature and Urban Mix. Source: BBVA Research adapted from [Batista et al., 2021].*

- *Splitting the coastal category* into North and Mediterranean & Islands, acknowledging the climatic and cultural differences that affect tourism patterns. Mediterranean & Island regions in Spain are more dependent on weather than northern regions, where tourism is less connected with beach tourism and relatively more related to other types of tourism, such as nature, gastronomic and sightseeing tourism. This historical difference is also related to the fact that northern regions have historically had worse weather.

- *Reclassifying cities* into Urban mix and Coastal, affecting only five cases based on their tourism behavior, to better reflect urban tourism dynamics. Cities with beaches were classified as Coastal, while inland cities were classified as Urban mix. These cities, although having more tourism than smaller cities, show similar dynamics in terms of seasonality and types of tourism. The change was made because the original group, called cities, included very different types of cities and excluded other ones like Seville or Granada, which exhibit similar behavior.
- *Merging Rural with Mountains and Nature*, combining these categories due to their similar tourism characteristics and to streamline the classification process. This change affects only Ourense and Ciudad Real, the only two regions originally classified as rural. For simplicity and because their behavior and type of tourism are very similar to Mountains and Nature, they were included in this group.

This refined classification was then used to assess the climatic preferences of tourists, providing valuable insights for regional tourism planning and development. The final classification can be seen in Figure 4 above, while the original classification can be found in [Batista et al., 2021].[7]

3.5. Future climate data

Evaluating the potential long-term impact of climate change on tourism demand involves calculating conditional forecasts while holding economic variables constant. Different scenarios, based on Representative Concentration Pathways (RCPs) quantify future greenhouse gas concentrations and radiance forcing due to increased pollution [Copernicus Climate Change Service, 2019]. The scenarios include RCP2.6, RCP4.5 and RCP8.5 (see Figure 5) .

[7] The overall workflow had already been tested and documented by [Batista e Silva et al., 2018], consisting of the following main steps:

- *Spatial delineation* of five distinct geographical areas within each NUTS 3 region.
- *Spatial intersection* between the 'accommodation layer' and the geographical zoning.
- *Classification* of each NUTS 3 region by typology using a rule-based approach applied to the relative presence of tourism accommodation capacity across the geographical zones.
- *Classification* of each NUTS region by typology based on a majority rule of nights spent across the respective region.

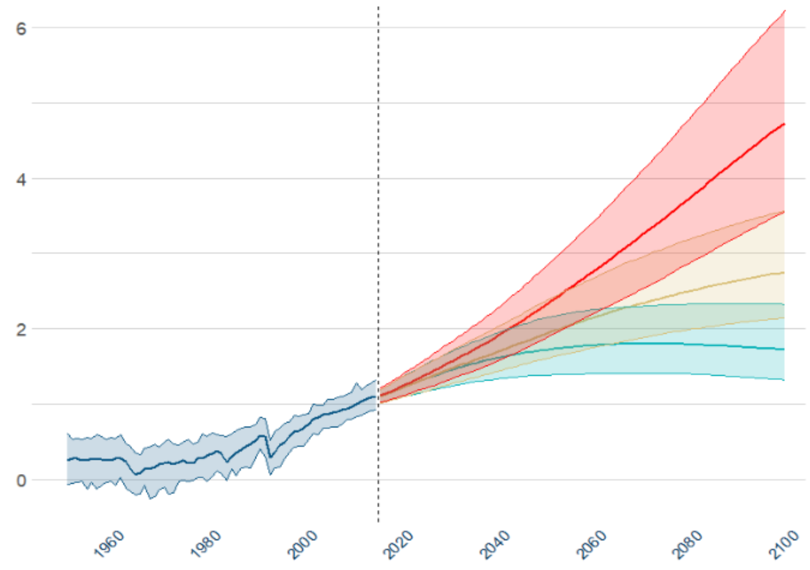

Figure 5: *Global surface temperature change (ºC), relative to 1850-1900. Source: BBVA Research from IPCC Sixth Assessment Report.*

The dark blue line and shaded area represent the historical observed changes. The lights blue, yellow and red solid line and shaded areas represent the estimated point estimate and 95% uncertainty bands for each of the RCP scenarios (8.5: red, 4.5: yellow and 2.6: blue).

The first pathway, RCP2.6, corresponds to very low future emissions, where CO2 emissions start declining by 2020 and reach net zero by 2100. This scenario aligns with the Paris Agreement goal, and the temperature increase projected at the end of the century ranges from 0.9 to 2.4ºC degress above pre-industrial levels. RCP4.5 represents low to moderate future emissions, with a relatively small difference from RCP2.6 until the end of the century, where the objective is to limit warming to 3°C. Finally, RCP8.5 represents a scenario with very high future emissions, where CO2 emissions will be three times higher than current levels by the end of the century, leading to a temperature increase above 4ºC.

The projections of climate variables are derived from an ensemble of three regional climate models (RCMs) and global circulation models (GCMs) produced by the Coordinated Regional Climate Downscaling Experiment over Europe (CORDEX) project. The selected models are three (HIRHAM5 - ICHEC-EC-EARTH, RCA4 - ICHEC-EC-EARTH, and RCA4 - MOHC-HadGEM2-ES) due to the availability of the projected climate variables for the three scenarios (RCP2.6, RCP4.5 and RCP8.5). Each of the models employ different assumptions, leading to varying temperature increases. For instance, the RCA4 - MOHC-HadGEM2-ES model projects a 4ºC increase by 2071 under the RCP8.5 scenario, while the RCA4 - ICHEC-EC-EARTH model projects a 4ºC increase by 2090. Calculating the mean of several models reduces intrinsic uncertainty about future climate conditions. Projected climate variables were extracted from raster files at a resolution of 11º using geospatial analysis techniques, and then aggregated at the provincial level to match with the granularity of the economic variables.

Following the definition of climate variables for the different scenarios, the Tourism Climate Index (TCI) and Holiday Climate Index (HCI) are calculated as described in Sections 3.2 and 3.3. Both indexes indicate a worsening of climate comfort during the summer months, particularly notable in the RCP8.5 scenario at the end of the century.[8]

4. Methodology

This study's methodological approach builds on prior analyses, including [Matei et al., 2023] and those under the PESETA project by [Amelung and Moreno, 2012], which examined the influence of climatic conditions on regional tourist flows. While the former focused on EU NUTS 2 regions over a 12-month period, [Matei et al., 2023] extended the analysis to cover the years 2000-2019 with monthly data. Moreover, they employed panel data modeling that offers advantages such as increased degrees of freedom, mitigation of multicollinearity and reduction in omitted variable bias, as stated by [Hsiao, 2003]. This study follows a similar approach, enhancing regional granularity for Spain by analyzing 50 provinces from January 2002 to December 2023 and incorporating additional variables, such as the relative GDP per capita of foreign tourists compared to the GDP per capita in the province of origin.

Research exploring the relationship between climate and tourism demand has taken advantage of various methodologies, ranging from single equation specifications and time series analysis to gravity models and panel data techniques. Among these, panel data methods have been particularly prevalent in recent studies. For instance, [Bigano and Tol, 2005] and [Taylor and Ortiz, 2009] both utilized panel data models to examine the impact of temperature, precipitation, and other climate variables on domestic tourism demand in Italy and the United Kingdom, respectively. Similarly, [Cai and Leung, 2010] applied a panel dataset over eight years to investigate how local

[8] Using the projected TCI and HCI values, Spanish tourism demand is forecasted at provincial level for the different concentration pathways, while holding all other factors constant. Conditional forecasts on bednights up to 2100 are estimated based on several assumptions. First, the relationship between bednights and climate variables remains constant over time using the results obtained in the previous regression. Second, there is an absence of adaptation and non-linearities to changes in climate patterns. Finally, economic variables are held constant at their 2023 values.

weather conditions affect tourist arrivals and length of stay in Italian municipalities. In a more region-specific context, [Ridderstaat and Nijkamp, 2014] used panel data to analyze the influence of seasonal climate patterns on tourism demand and [Li et al., 2016] employed a dynamic panel data techniques to study the demand of tourists from Hong Kong visiting major cities in Mainland China.

In this study, we link the total number of tourists' bed nights to a set of economic determinants of tourism demand and two climate suitability indices: the Tourism Climate Index (TCI) and the Holiday Climate Index (HCI). This dual-index approach offers robustness checks and sensitivity analysis, providing a more comprehensive understanding than previous studies with this level of regional granularity. The economic determinants at the province level include real GDP, the consumer price index (CPI) in the destination regions and the relative real GDP per capita of foreign tourists divided by the real GDP per capita of the province of destination. Specifically, we estimate the following fixed effects monthly model for 50 Spanish provinces over the 2002-2023 period, including a dummy variable for the COVID-19 period:

$$\begin{aligned}\ln(BN_{it}) = \gamma + \alpha_i + \beta_1 \ln(TCI_{it} \times Tclass_i) + \beta_2 \ln(GDP_{it}) + \beta_3 \ln(CPI_{it}) \\ + \beta_4 \ln(GDPpcfor_{it}) + d_s M_s + d_c Covid + \epsilon_{it}\end{aligned} \tag{6}$$

where:

- γ represents the intercept.
- $\ln(BN_{it})$ is the natural logarithm of the number of bed nights in province i and month m.
- α_i represents regional fixed effects in province i.
- TCI_{it} is the monthly Tourism Climate Index in province i and month m. HCI is used when the specification changes to the Holiday Climate Index.
- $Tclass_i$ represents each province's (i) tourism typology.
- GDP_{it} is the real GDP in province i and month m.
- CPI_{it} is the consumer price index in province i and month m.
- $GDPpcfor_{it}$ is the relative real GDP per capita of the foreign tourist divided by the real GDP per capita of the province i of destination and month m.
- M_s are seasonal dummy variables capturing the influences of specific seasonal characteristics.
- $Covid$ is a time dummy variable capturing the effect of COVID-19 on tourism demand, covering the period from April 2020 to April 2021.
- ϵ_{it} is the error or residual term in province i and month t.

The residuals are modeled as an autoregressive process to account for potential autocorrelation in the error terms:

$$\epsilon_{it} = \rho\epsilon_{i,t-1} + \nu_{it} \tag{7}$$

where:

- ϵ_{it} is the error term in month t for province i.
- ρ is the autocorrelation coefficient.
- ν_{it} is the white noise error term in month t for province i.

5. Results

5.1. Results with TCI

5.1.1. Empirical results

The estimation of Equation 6 demostrates a significant relationship between the evolution of bed nights and the climate suitability index (TCI) across Spanish provinces. Table 2 presents the parameter estimates and significance levels derived from a panel analysis with entity fixed effects, including p-values and t-statistics. The model was estimated using feasible generalized least squares, which accommodates AR(1) autocorrelation in the residuals as well as cross-sectional correlation across panels.[9]

The analysis indicates that all the determinants considered significantly impact tourism demand. Higher climate comfort is associated with an increase in monthly tourism flow, with varying effects across different tourism segments. Specifically, the model confirms that coastal destinations in Spain, particularly those along the mediterranean coast and islands, are highly sensitive to climate-induced environmental changes. An increase or decrease of 1% in the TCI corresponds to a 0.5% change in bed nights for

[9] We conducted the Hausman test to differentiate between fixed and random effects, with a p-value of 0.00 indicating that the fixed effects model is appropriate. Post-estimation diagnostic tests for cross-sectional dependence, heteroskedasticity, and autocorrelation were also performed to ensure model robustness. The Breusch-Pagan LM test produced a statistic of 195,000 with a p-value of 0.00, indicating significant cross-sectional dependence. The Pesaran CD test also confirmed cross-sectional dependence with a statistic of 433.077 and a p-value of 0.00. The Durbin-Watson test yielded a value of 1.4350591, suggesting some autocorrelation in the model's residuals. These issues can bias standard errors and test statistics, potentially leading to unreliable inferences. To address these concerns, we employed the xtgls estimator, which accommodates heteroskedasticity and correlation across panels, yielding more efficient and consistent estimates. The xtgls command allows for specifying various error structures, including those accounting for cross-sectional correlation and autocorrelation in the residuals. We also performed unit root tests (Augmented Dickey-Fuller), all rejecting the null hypothesis, thereby confirming that all variables, including the dependent variable, are stationary.

Table 2: *Regression Results with TCI*

	lnBN_tot		
Coastal North × lnTCI	0.391	***	(25.05)
Mediterranean and Islands × lnTCI	0.501	***	(24.65)
Mountains and Nature × lnTCI	0.104	***	(8.89)
Urban Mix × lnTCI	0.060	***	(6.72)
lnGDP	4.470	***	(63.00)
lnCPI	−0.351	***	(-3.63)
lnGDPpcfor	3.638	***	(60.83)
Autumn	0		(.)
Spring	−0.067	**	(-1.96)
Summer	0.189	***	(5.70)
Winter	−0.284	***	(-8.63)
Covid	−1.598	***	(-25.82)
Constant	−55.360	***	(-53.21)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: BBVA Research.

these regions. Northern coastal regions demonstrate a lower elasticity of 0.39. Next is mountain tourism, with an elasticity of 0.10, reflecting the complex dynamics in these regions, where ski tourism and warm-weather activities may have offsetting effects. Urban areas present the lowest elasticity at 0.06, possibly due to a substitution effect between coastal and urban destinations.

Economic factor, such as real GDP, exhibit a positive and significant effect on bed nights, while the price elasticity is negative, confirming that higher prices reduce tourism demand. The relative foreign real GDP per capita also positively impacts tourism demand, suggesting that increased relative purchasing power of foreign tourists enhances external tourism demand in Spain. Seasonal patterns in tourism demand are also accounted for, revealing that summer has a substantial positive effect on bed nights, while winter has a negative impact. Summer shows the highest number of overnight stays, winter the lowest, with autumn and spring being relatively similar. [10] The seasonality of tourism, as well as the climate impact across tourism segments, is consistent with previous works ([Barrios and Ibañez, 2015]; [Matei et al., 2023]).

Given the relevance of foreign tourism flows, the previous regression was sub-

[10] September is classified in autumn, which significantly affects the results.

sequently re-estimated by considering the number of foreign overnight stays as the dependent variable, all other variables remaining equal (see Appendix B). The main findings are confirmed, although the results show higher elasticities. Consequently, foreign tourism is more elastic to climatic changes than domestic tourism since it is considered a luxury good, whereas for the domestic tourism there are other variables despite climate, such as distance, that play a relevant role [Priego et al., 2015]. This higher elasticity is particularly pertinent since foreign tourism predominates in mediterranean coastal areas, which is the type of tourism mostly affected by climatic conditions, and a worsening of these conditions could significantly impact both arrivals and revenue of the sector.

5.1.2. Tourism demand projections

This section presents a summary of the effects of future climate change scenarios on tourism demand in Spain, summarizing a conditional scenario exercise based on the values of the Tourism Climate Index (TCI) across different Representative Concentration Pathways (RCPs). Three scenarios -RCP 2.6, RCP 4.5, and RCP 8.5- are analyzed, corresponding to projected mean global temperature increases of 1.8°C, 2.8°C, and 4.8°C by 2100, respectively. The analysis compares tourism demand for the 2090s decade, defined as the period 2091–2100, against a baseline from 2024–2030.[11] The model assumes that the influence of climatic variables on tourism demand (the elasticity) remains stable throughout the projection period (2024–2100), with economic determinants held constant at 2023 levels. The model does not account for adaptation and non-linearities to changes in climate patterns.

Figures 6, 7, and 8 illustrate the projected changes in provincial tourism demand across Spanish provinces under the three global warming scenarios. The impact of climate change on tourism demand is highly heterogeneous, revealing a pronounced north-south divide. Specifically, while mediterranean and southern regions are anticipated to experience significant reductions in total bed nights, northern regions are projected to witness an overall increase in tourism demand. These regional differences align with the findings of [Matei et al., 2023], who documented similar patterns across Europe.

Under the RCP 2.6 scenario, the national net effect on tourism demand is projected

[11] Decades are defined throughout the document by taking the first year as the starting year (e.g. 2091-2100 for 2090s). The comparison of the percentage effect across decades reduces the variability and uncertainty of projections of a particular year. Moreover, the baseline current decade is restricted to 2024-2030 to avoid some jumps in the data that could arise from the covid, its recuperation or the anomaly high temperatures experienced in 2023.

to be a marginal decline of approximately -0.3% by 2100. Despite this overall modest impact, regional variations emerge, where coastal regions in the north may see slight increases in demand, while mediterranean regions are likely to experience marginal declines.

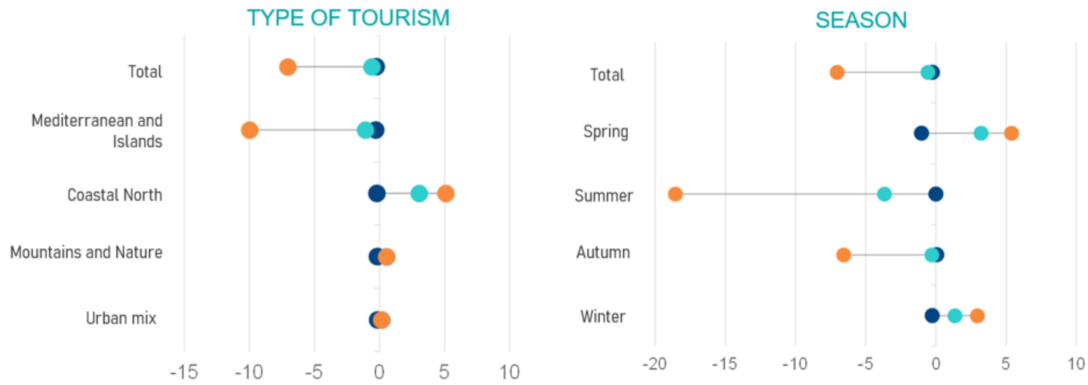

Figure 6: *Change in tourism demand (TCI) by type of tourism and season. Net effect under RCP 8.5, 4.5 and 2.6 for 2091-2100 (%, using 2024-2030 as the base). Orange represents the RCP 8.5 scenario, light blue indicates the RCP 4.5, and dark blue corresponds to the RCP 2.6. Source: BBVA Research.*

Under a moderate emissions and consequently moderate temperature increase scenario (RCP 4.5), which is the most likely scenario under current policies, the projected national net effect on tourism demand shows a more pronounced decrease of about 0.6% and a greater spatial and seasonal effect. Northern coastal regions are expected to experience moderate increases in demand, particularly during spring. In contrast, mediterranean and island regions are likely to face substantial declines, especially in summer. At the national level, the summer tourism demand is projected to decline by around 4%, partially offset by an increase in spring tourism, particularly in beach-reliant provinces (see Figure 7).

The RCP 8.5 scenario, representing the most severe warming scenario, projects the most substantial changes, with a national net effect of approximately -7% (see Figure 8), highlighting the urgent need for mitigation and adaptation strategies. The northern coastal provinces exhibit the largest projected increase in tourism demand, with an average of 5.8% for the 2090s relative to the 2024-2030 baseline, ranging from a 6.9% increase in Asturias to 3.2% in Pontevedra. Supply should satisfy this rise in demand while preventing the overcrowding present in the mediterranean coastlines at the moment. Precisely, mediterranean and island provinces are anticipated to suffer severe declines. For example, the Balearic Islands could experience a dramatic 60% reduction in summer tourism demand, partially offset by a 10% recovery in autumn.

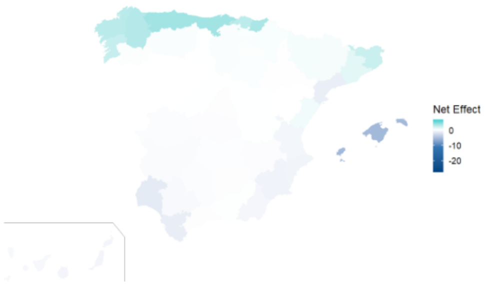

Figure 7: *Change in tourism demand (TCI). Net effect by province under RCP 4.5 for 2091-2100 (%, using 2024-2030 as the base). Source: BBVA Research.*

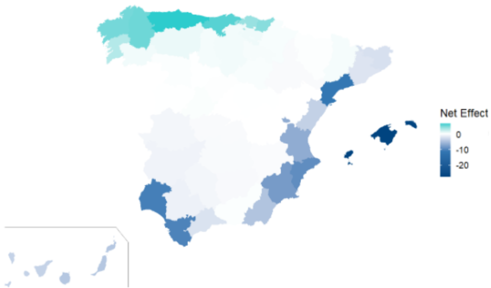

Figure 8: *Change in tourism demand (TCI). Net effect by province under RCP 8.5 for 2091-2100 (%, using 2024-2030 as the base). Source: BBVA Research.*

Similarly, the Canary Islands are projected to face declines in tourism during both summer and autumn, resulting in a net contraction of approximately −3.2% in Santa Cruz de Tenerife and −4% in Las Palmas. Barcelona, with an approximate decline of 2%, is expected to be the least affected province in this category. These projections align with [Amelung and Moreno, 2012], who highlighted the vulnerability of southern European regions under severe warming scenarios.

Mountain and nature tourism is projected to slightly increase during Spring and Autumn, although no significant changes are observed during the winter months. The absence of a decline in winter demand, despite expected higher temperatures and reduced snowfall, may be due to an inability to adequately distinguish between warm-weather mountain tourism and the ski season, which may offset each other's effects. On average, the net effect remains positive at around 0.6% in the 2090s. Provinces in the north with tourism oriented to urban activities are projected to see improvements throughout the year, particularly in spring and autumn, resulting in a net positive impact of 0.48%. In contrast, southern urban provinces may recover in spring and autumn but face declines in summer, leading to a marginal net positive effect of 0.11%.

As short:[12]

- **Northern Coastal Regions:** These regions are projected to benefit the most under all scenarios, with demand peaking in spring and autumn. Summer demand shows a general increase, although this trend is less consistent across all northern

[12] The results have also been differentiated between foreign and domestic tourism. Foreign tourism demand exhibits similar trends, albeit with greater sensitivity to climate change. The elasticity of foreign demand is higher, particularly in coastal regions. Notably, foreign tourists tend to perceive northern and mediterranean coastal regions similarly, leading to a more uniform impact across coastal tourism (see Appendix B for more details).

coastal areas.

- **Mediterranean and Island Regions:** These regions are expected to suffer under higher warming scenarios (RCP 8.5), particularly during the summer, where demand is projected to drop sharply.
- **Mountain and Nature Tourism:** While winter tourism remains relatively stable, spring and autumn are expected to see increases in demand due to more favorable weather conditions. However, this increase is modest, averaging around 0.6% under RCP 8.5.
- **Urban Tourism:** Urban areas in the north are projected to experience an increase in demand, particularly in spring and autumn, leading to a slight overall positive impact. In contrast, southern urban areas are expected to show significant drops in summer demand, resulting in a minimal net positive effect.

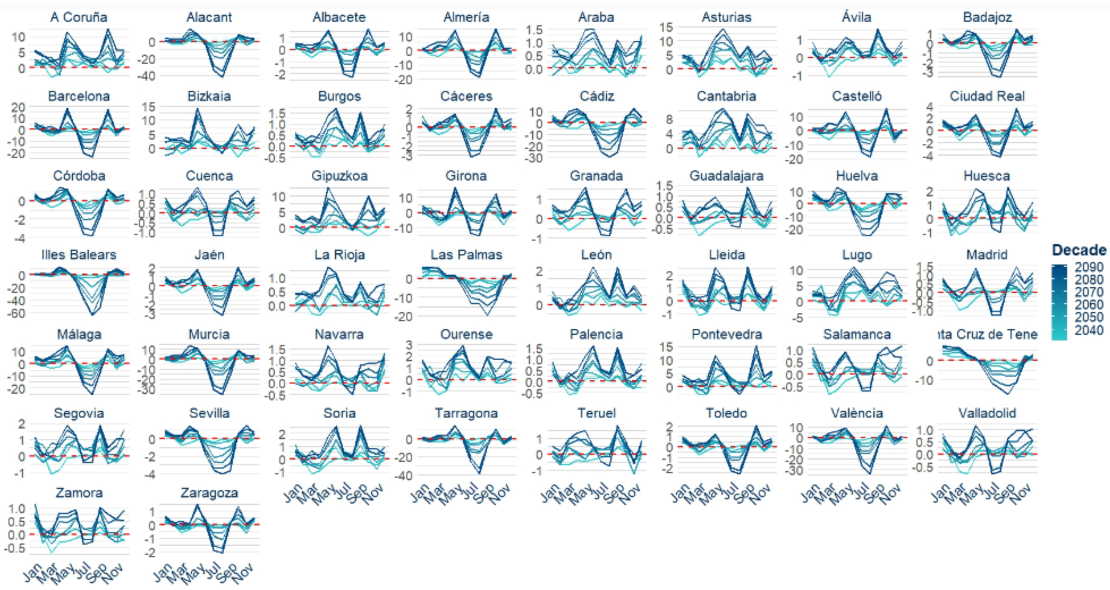

Figure 9: *Change in tourism demand (TCI) through decades and by province. Net effect under RCP 8.5 for 2091-2100 (%, using 2024-2030 as the base). Source: BBVA Research.*

Overall, the effects of climate change on tourism demand in Spain vary by region and season, with a general trend toward increasing demand in northern and coastal regions as new competitors to the traditional tourist provinces located in the Mediterranean and island regions, particularly under more severe climate scenarios (RCP 8.5). (see Figure 9). It is also important to note that changes in tourism demand are generally non-linear in relation to warming levels. For instance, moving from a 1.8°C warming scenario to a 4.8°C warming scenario (2.66 times greater) results in a disproportionately larger reduction in relative demand in Spain (from −0.6% in the 1.8°C scenario to −7% under the 4.8°C scenario, approximately 11.66 times more). Similar non-linear effects are observed at the provincial level, even in regions where the impacts are positive, such as the northern coastal areas. Additionally, it is noteworthy that our estimated impacts are higher than those reported by [Batista et al., 2021], particularly under the highest warming scenario, where the impact is nearly double, underscoring the importance of conducting analyses with greater spatial granularity in such estimations. Finally, these results do not account for any type of adaptability (neither school nor work), which will be key for limiting the negative impacts.

5.2. Results with HCI

5.2.1. Empirical results

Table 3: *Regression Results with HCI*

	lnBN_tot		
Coastal North × lnHCI	0.374	***	(29.92)
Mediterranean and Islands × lnHCI	0.390	***	(24.22)
Mountains and Nature × lnHCI	0.054	***	(2.97
Urban Mix × lnHCI	0.229	***	(21.46)
lnGDP	4.535	***	(62.44)
lnCPI	−0.389	***	(-4.37)
lnGDPpcfor	3.630	***	(60.33)
Autumn	0		(.)
Spring	−0.091	**	(-2.56)
Summer	0.287	***	(8.44)
Winter	−0.301	***	(-8.89)
Covid	−1.620	***	(-25.45)
Constant	−56.180	***	(-52.65)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: BBVA Research.

As detailed in Table 3, the HCI[13] slightly reduces the climate impact on beach tourism,

[13] The Holiday Climate Index (HCI), developed by [Daniel Scott and Gössling, 2016] and [Rutty et al., 2020], serves as an alternative to the Tourism Climate Index for assessing climatic comfort, tailored for major tourism segments and destination types. Unlike the TCI, which can be somewhat subjective, the HCI is based on surveys, making it a more objective measure. However, the thresholds of the HCI, and its respective rankings, could create problems in the upper-side of the distribution, as it will be analyzed in the

particularly in mediterranean and island provinces, while it increases the sensitivity of urban tourism to climate conditions. This shift is attributed to the different thresholds and weighting systems used in the HCI for both segments of tourism - beach and urban-, whereas the TCI assigns uniform rating regardless of the tourism type[14].

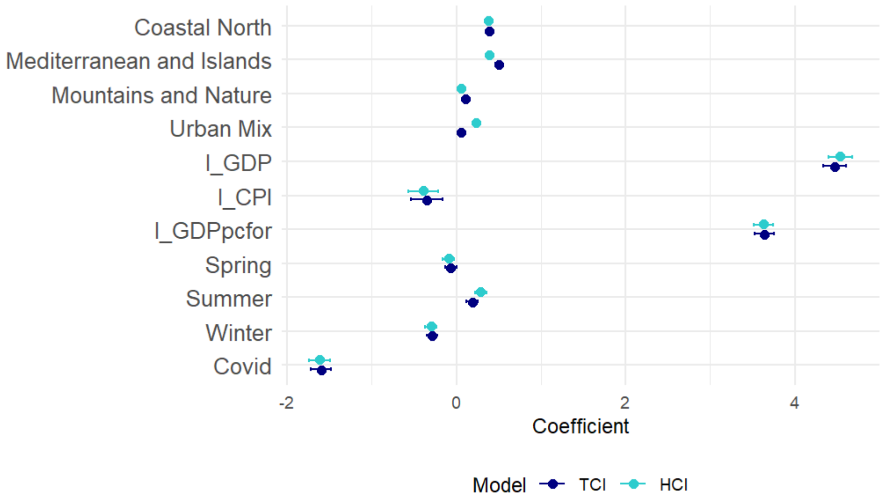

Figure 10: *Comparison of TCI and HCI model specifications. Coefficients with 95% confidence intervals. Source: BBVA Research.*

However, as illustrated in Figure 10, the overall model and conclusions remain consistent between the two indices, with most variables displaying similar coefficients. The statistical comparison between the two models reveals no significant difference in most coefficients, except for the Urban Mix category. This finding suggests that the sensitivity of different tourism types to climate conditions is statistically equivalent when using historical data, thus adding robustness to the analysis.

The primary differences between the TCI and HCI projections, as discussed in Section 3.2., arise from how each index translates future climate scenarios (RCPs) into their respective climate proxies over the forecast period (2024–2100). These variations stem from the distinct classification and threshold systems used by the TCI and HCI, which influence the ranking of climate variables and, consequently, the projected impacts on tourism demand.

next section of the work.

[14] HCI: Beach tourism assigns less weight to temperature extremes and places greater emphasis on other variables, such as precipitation and cloud cover, which can moderate the overall climatic impact on these regions. Conversely, urban tourism shows increased sensitivity to climate change when evaluated using the HCI.

5.2.2. Tourism demand projections

As discussed in the previous section, the results derived from the HCI offer several important insights. However, as previously demonstrated, statistically, there is no significant difference between the coefficients of the two models. Therefore, the differences in the projections are mainly attributable to the different HCI and TCI values observed under future RCP scenarios.

The HCI projects a national net effect on tourism demand of approximatly -0.12% under the RCP 2.6 scenario, which is less severe than the -0.3% projected by the TCI. Similarly, under the RCP 8.5 scenario, the HCI forecasts a national net effect of around -0.42%, compared to the more substantial -7% decline indicated by the TCI. This discrepancy underscores the importance of the selected climate proxy, as the different weights and ranking criteria of the HCI and TCI significantly affect the projections of tourism demand (see Figures 11 and 12).

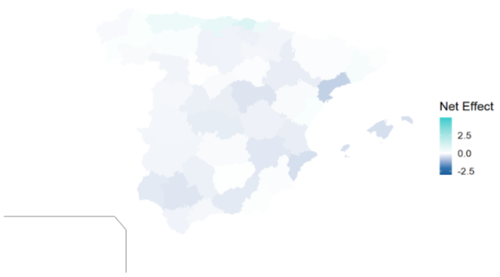

Figure 11: *Change in tourism demand (HCI). Net effect by province under RCP 2.6 for 2091-2100 (%, using 2024-2030 as the base). Source: BBVA Research.*

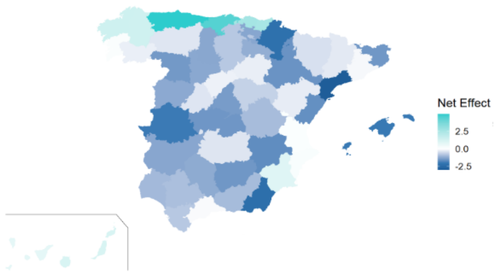

Figure 12: *Change in tourism demand (HCI). Net effect by province under RCP 8.5 for 2091-2100 (%, using 2024-2030 as the base). Source: BBVA Research.*

It is crucial to emphasize that the differences between the HCI and TCI results primarily stem from how the reference climate scenarios (RCPs) are translated into the respective proxy —whether TCI or HCI— over the forecasted period. The key difference does not lie in the model coefficients themselves, but rather in the future scenarios. The HCI applies a different ranking system, particularly regarding thermal comfort, where a considerable part of the maximum temperatures in Spain are already in the upper end of the distribution, translating into low or even zero values (see Appendix A). This reflects a limitation in the HCI's ability to adequately penalize temperature increases once maximum temperatures reach very high levels, as already seen in many Spanish provinces. As a consequence, there is a reduced overall effect and a less pronounced north-south differentiation.

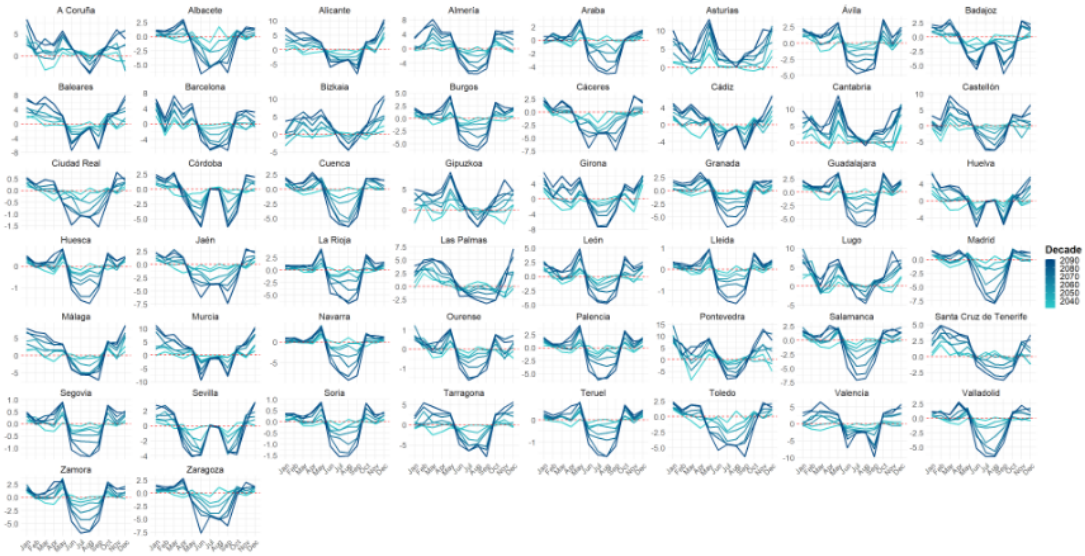

Figure 13: *Change in tourism demand (HCI). Net effect by province under RCP 8.5 for 2091-2100 (%, using 2024-2030 as the base). Source: BBVA Research.*

The results derived from the HCI also indicate a clear trend towards deseasonalization of tourism demand, consistent with the findings using the TCI. This trend involves a shift in tourism demand across seasons, with increased emphasis on spring and autumn rather than summer. However, the extent of this shift may be contingent on the implementation of more flexible school and work holidays, as well as the adoption of remote working schemes, which could enhance this flexibility. Such adaptability is crucial for mitigating significant negative impacts on tourism demand, particularly in southeastern Spain, where beach tourism is vital. This conclusion is robust across both indices (see Figure 13).

In summary, this comparison highlights the need for careful consideration in the selection of climate indices,[15] based on the specific characteristics of the tourism sector and the regions being studied. Both TCI and HCI show advantages and drawbacks, but the differences in projections emphasize that the index selection can significantly influence the anticipated impacts of climate change on tourism demand.

[15] Findings from research papers such as those of [Daniel Scott and Gössling, 2016] and [Rutty et al., 2020] already mentioned that indices reflecting the distinct climatic preferences of various tourist sectors are necessary.

6. Conclusion

This study provides a comprehensive analysis of the implications of climate change on tourism demand within Spanish provinces, focusing on the Tourism Climate Index (TCI) and the Holiday Climate Index (HCI) as key indicators of climatic conditions. By assessing the projected shifts in climatic conditions across various provinces, the research provides nuanced insights into how temperature, precipitation and other climate variables are likely to influence the spatial and temporal distribution of tourism activities.

The findings indicate a complex interplay between climate change and tourism patterns, with significant regional variations. As global temperatures continue to rise, the traditionally favored southern and mediterranean coastal provinces of Spain, particularly those that thrive during the peak summer months, are projected to experience a decline in their appeal due to increasingly uncomfortable heat levels. This could lead to a redistribution of tourism flows, with northern provinces potentially benefiting from warmer conditions that become increasingly attractive during the summer period.

Additionally, the study highlights a critical aspect of tourism demand: the process of deseasonalization. Our results suggest that climate change may extend the tourist season into the spring and autumn, as these periods become more climatically favorable compared to the increasingly extreme summer months. This shift could have substantial economic implications, potentially reducing the negative net-effect and alleviating the traditional seasonal concentration of tourism demand and leading to more stable revenue streams throughout the year. However, such changes also pose challenges for tourism-dependent regions that must adapt to these new patterns, requiring investment in infrastructure, marketing, and services tailored to off-peak visitors.

A key methodological insight of this study is the difference in outcomes produced by the TCI and HCI indices. While both indices are designed to assess the suitability of a destination's climate for tourism, they have different weights and rankings for climatic factors, leading to variations in the magnitude of projected impacts. The HCI, which incorporates maximum temperatures more heavily, provides a different perspective, particularly under scenarios of extreme heat. This divergence in results underscores the importance of selecting the appropriate climatic index depending on the specific characteristics of the province under study and the nature of tourism activities being analyzed.

The economic implications of these findings are substantial. Provinces that have historically relied on predictable patterns of high-season tourism must now prepare for a future where these patterns are less certain. This necessitates a strategic shift in tourism planning and policy-making, focusing on enhancing the resilience of the tourism sector to climate-induced changes. Overall, the net effect on the Spanish tourism is negative according to the TCI specification, with mild impacts under RCP 2.6 and 4.5 (-0.3% and -0.6% in 2091-2100 vs. 2024-2030), but a significant impact under RCP 8.5 (-7%). Investments in infrastructure that can mitigate the effects of extreme heat, such as shaded areas, water management systems and climate-controlled facilities, will be crucial. Additionally, marketing strategies and labour flexibility may need to be adjusted to promote the attractiveness of off-peak seasons, thereby smoothing the demand curve and ensuring more consistent economic returns throughout the year. If this is not the case, the estimated impact, which assumes that provinces will have the infrastructure and capacity to manage the movement of demand between months and regions, will be bigger, even under the most probable scenario under actual conditions, which is RCP 4.5.

In conclusion, while climate change poses significant challenges to the traditional tourism model in Spain, it also presents opportunities for innovation and adaptation. By proactively addressing the anticipated shifts in climate and their effects on tourism demand, Spain can not only mitigate potential negative impacts but also harness new opportunities for sustainable tourism growth. Future research should continue to explore the dynamic relationship between climate change and tourism, particularly with a focus on the economic strategies that can support the resilience and adaptability of the tourism sector in the face of ongoing environmental changes.

A Appendix. Comparison of rating schemes by climate index

The tables of this Annex present for all climate indexes the rating schemes, as well as the graphical comparison of the thermal confort rating as these thresholds account for most of the variability.

A.1 TCI

Table A.1.1: *TCI: Rating Temperature (°C)*

Rating	Temperature (°C)
0	≥ 36
1	35-36
2	34 - 35
3	33 - 34
4	32 - 33
5	31 - 32
6	30 - 31
7	29 - 30
8	28 - 29
9	27 - 28
10	20 - 27
9	19 - 20
8	18 - 19
7	17 - 18)
6	16 - 17
5	10 - 16
4	5 - 10
3	0 - 5
2	-6 - 0
0	-11 - -6
-1	-16 - -11
-2	-21 - -16
-6	≤ -21

Table A.1.2: *TCI: Rating Cloud Cover (%)*

Rating	CC (%)
10	0.0 - 16.6
9	16.7 - 24.9
8	25.0 - 33.2
7	33.3 - 41.6
6	41.7 - 49.9
5	50.0 - 58.2
4	58.3 - 66.6
3	66.7 - 74.9
2	75.0 - 83.2
1	83.3 - 91.6
0	≥ 91.7

Table A.1.3: *TCI: Rating Precipitation (mm)*

Rating	Precipitation (mm)
10	0.0 - 0.5
9	0.5 - 1.0
8	1.0 - 1.5
7	1.5 - 2.0
6	2.0 - 2.5
5	2.5 - 3.0
4	3.0 - 3.5
3	3.5 - 4.0
2	4.0 - 4.5
1	4.5 - 5.0
0	≥ 5

Table A.1.4: *TCI: Rating Wind Speed (m/s)*

Rating ($\leq$ 23.9ºC)	Rating ($24 - 32.9$C)	Rating ($\geq$ 32.9C)	Wind (km/h)
10	4	4	≤ 2.88
9	5	3	2.89 - 5.75
8	6	2	5.76 - 9.03
7	8	1	9.04 - 12.23
6	10	0	12.24 - 19.79
5	8	0	19.80 - 24.29
4	6	0	24.30 - 28.79
3	4	0	28.80 - 38.51
0	0	0	≥ 38.52

A.2 HCI Beach

Table A.2.1: *HCI BEACH: Rating Temperature (°C)*

Rating	Temperature (°C)
-10	<10
-5	10 - 15
0	15 - 17
1	17 - 18
2	18 - 19
3	19 - 20
4	20 - 21
5	21 - 22
6	22 - 23
7	23 - 26
9	26 - 28
10	28 - 31
9	31 - 33
8	33 - 34
7	34 - 35
6	35 - 36
5	36 - 37
4	37 - 38
2	38 - 39
0	≥ 39

Table A.2.2: *HCI BEACH: Rating Cloud Cover (%)*

Rating	Cloud Cover (%)
8	<1
9	1 - 15
10	15 - 26
9	26 - 36
8	36 - 46
7	46 - 56
6	56 - 66
5	66 - 76
4	76 - 86
3	86 - 96
2	≥ 96

Table A.2.3: *HCI BEACH: Rating Precipitation (mm)*

Rating	Precipitation (mm)
10	<0.01
9	0.01 - 3
8	3 - 6
6	6 - 9
4	9 - 12
0	12 - 25
-1	≥ 25

Table A.2.4: *HCI BEACH: Rating Wind Speed (m/s)*

Rating	Wind Speed (m/s)
8	<0.6
10	0.6 - 10
9	10 - 20
8	20 - 30
6	30 - 40
3	40 - 50
0	50 - 70
-10	≥ 70

A.3 HCI Urban

Table A.3.1: *HCI URBAN: Rating Temperature (°C)*

Rating	Temperature (°C)
0	≥ 39
2	37 - 39
4	35 - 37
5	33 - 35
6	31 - 33
7	29 - 31
8	27 - 29
9	26 - 27
10	23 - 26
9	20 - 23
7	18 - 20
6	15 - 18
5	11 - 15
4	7 - 11
3	0 - 7
2	-6 - 0
1	≤ -6

Table A.3.2: *HCI URBAN: Rating Cloud Cover (%)*

Rating	Cloud Cover (%)
8	<1
9	1 - 11
10	11 - 21
9	21 - 31
8	31 - 41
7	41 - 51
6	51 - 61
5	61 - 71
4	71 - 81
3	81 - 91
2	91 - 100
1	

Table A.3.3: *HCI URBAN: Rating Precipitation (mm)*

Rating	Precipitation (mm)
10	<0.01
9	0.01 - 3
8	3 - 6
5	6 - 9
2	9 - 12
0	12 - 25
-1	≥ 25

Table A.3.4: *HCI URBAN: Rating Wind Speed (m/s)*

Rating	Wind Speed (m/s)
8	<0.02
10	0.02 - 10
9	10 - 20
8	20 - 30
6	30 - 40
3	40 - 50
0	50 - 70
-10	≥ 70

A.4 Comparing Thermal Comfort

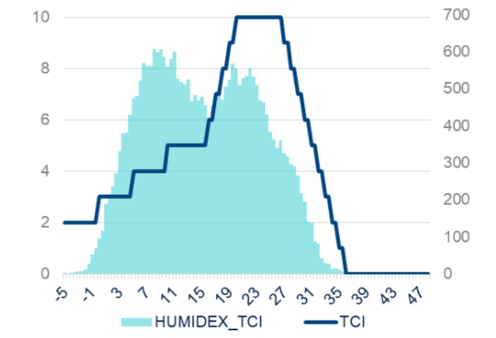

Figure A.1: *Humidex historical distribution 1980-2023 (right-axis) and TCI rating (left-axis). Source: BBVA Research. Calculated using monthly mean temperature. The right-hand side axis represents the number of times a temperature was registered.*

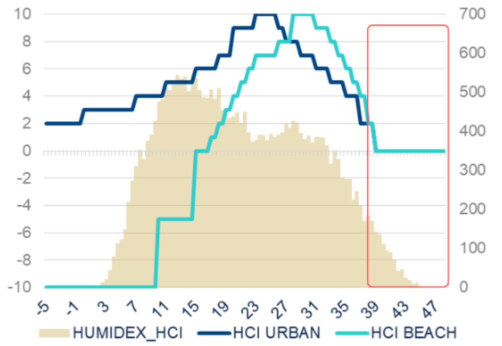

Figure A.2: *Humidex historical distribution 1980-2023 (right-axis) and HCI rating (left-axis). Source: BBVA Research. Calculated using monthly maximum temperature. The right-hand side axis represents the number of times a temperature was registered.*

B Appendix. Foreign tourism demand

Given the significance of foreign tourism flows, the initial regression was re-estimated using the number of foreign overnight stays as the dependent variable, while keeping all other variables unaltered. The primary findings are consistent with the initial analysis, but the results indicate higher elasticities. This suggests that foreign tourism is more sensitive to climatic changes. This finding is particularly important since foreign tourism is concentrated in coastal areas, where climatic conditions play a crucial role. A deterioration in these conditions could lead to a decrease in foreign tourist arrivals, thereby reducing the overall revenue of the tourism sector.

Table B.1: *Regression Results of Foreign Bednights with TCI*

	lnBN_for		
Coastal North × lnTCI	0.462	***	(20.05)
Mediterranean and Islands × lnTCI	0.503	***	(20.96)
Mountains and Nature × lnTCI	0.152	***	(5.55)
Urban Mix × lnTCI	0.169	***	(10.30)
lnGDP	5.121	***	(40.34)
lnCPI	−0.0395		(-0.36)
lnGDP_pcfor	4.006	***	(43.58)
Autumn	0		(.)
Spring	−0.127	***	(-3.30)
Summer	0.000801		(0.02)
Winter	−0.478	***	(-12.67)
Covid	−1.846	***	(-28.08)
Constant	−68.170	***	(-35.35)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: BBVA Research.

The results also reveal that the disparity between Spain's two coasts diminishes for foreigners, with the northern coast becoming more sensitive to climate. Meanwhile, the elasticity for the mediterranean coast remains largely unchanged. That is, weather plays a more significant role in their decision-making. In contrast, domestic tourists may place greater value on other aspects of the northern coast beyond the weather, such as the cuisine or the landscapes. A similar trend is observed in urban tourism, where the elasticity coefficient nearly triples. Results indicate that foreign tourists place a higher value on favorable weather when visiting cities compared to domestic tourists. This difference could be attributed to the fact that domestic tourists often engage in activities less influenced by weather, such as business travel, musicals, or other cultural activities conducted in Spanish.

Figure B.1 illustrates the overall impact on tourism demand under the RCP 8.5 scenario (TCI specification), by decomposing the total impact into foreign and domestic tourism (with the latter serving as the residual). As shown, the role of foreign tourists is highly significant.

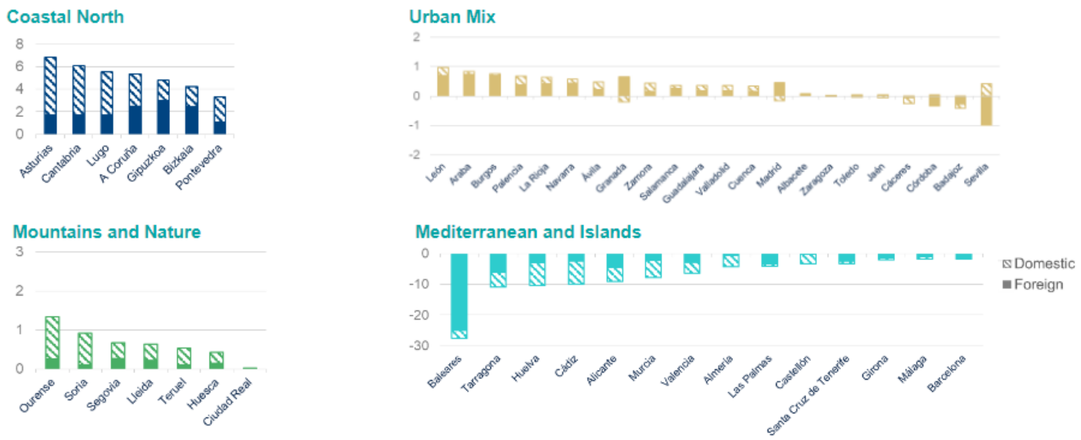

Figure B.1: *Bed nights change decomposition. RCP 8.5. 2091-2100 (% using as base 2024-30). Source: BBVA Research.*

C Appendix. Modeling approach with Humidex

An alternative modeling approach involves estimating the impact of warming levels by directly employing the humidex, an integrated index combining temperature and humidity, as the independent variable. [16] Using the humidex directly as an independent variable, instead of composite indices like TCI ir HCI, reduces the complexity of the analysis and it makes it less reliant on externally calibrated thresholds and rankings, allowing for a more data-driven approach. The sample data determines whether temperature changes positively or negatively affect tourism demand in Spanish provinces, rather than relying on predefined climate index rankings.

To account for the nonlinear effects of temperature, the squared term of the humidex is included in the model. This approach allows us to capture the hypothesized relationship between temperature and tourism demand: positive and increasing at lower temperatures, but detrimental and increasingly intense once certain temperature thresholds are exceeded. [17]

The model was estimated with a single temperature threshold and its squared term, but also interacting with the different types of tourism, i.e., with a single threshold and with different thresholds for different types of tourism activities. The latter allow us to reflect varied tolerance to temperature changes depending on the type of tourism activity. For instance, one might tolerate higher temperatures when planning a beach vacation compared to engaging in mountain tourism or physical activities.

Overall, the results demonstrate significant outcomes for both the linear and quadratic terms of the humidex across both model specifications, indicating a non-linear relationship between climate conditions and tourism demand (see Table C.1). The linear term has a positive coefficient, while the quadratic term is negative, suggesting an inverted U-shaped relationship between the humidex and tourism demand, consistent with expectations.

Figure C.1 illustrates this relationship for both specifications, with and without interactions with tourism types. It is particularly interesting to observe that the relationship varies significantly by tourism type, with beach tourism being more tolerant of high temperatures (especially in southern and mediterranean regions), whereas urban tourism appears nearly inelastic until quite high temperatures are reached. It is impor-

[16] See [Canadian Centre for Occupational Health and Safety, nd] for more information.

[17] The analysis was also conducted independently for other climatic variables, but since the results were not statistically significant, only the analysis using the humidex is presented here. From a theoretical perspective, it is logical that perceived temperature would be the most significant factor in determining tourism demand and, consequently, the most statistically significant variable in the model.

Table C.1: *Humidex Coefficients and p-values*

	lnBN_tot	
Single threshold specification		
HUM	0.0285155***	(34.89)
HUM2	-0.0007885***	(-37.08)
Multiple threshold specification		
Coastal North × HUM	0.03991***	(28.08)
Mediterranean and Islands × HUM	0.0508615***	(34.99)
Mountains and Nature × HUM	0.0160776***	(34.99)
Urban Mix × HUM	0.0034634***	(4.10)
Coastal North × HUM2	-0.0011152***	(-23.29)
Mediterranean and Islands × HUM2	-0.0010248***	(-25.07)
Mountains and Nature × HUM2	-0.0006259***	(-16.91)
Urban Mix × HUM2	-0.0002203***	(-10.21)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: BBVA Research.

tant to note that the relationship depicted in the figure is based on observed data, and therefore, the actual relationship may differ for higher values or under different model specifications. These results are presented to highlight the potential and interest in this type of data-driven analysis for future research.

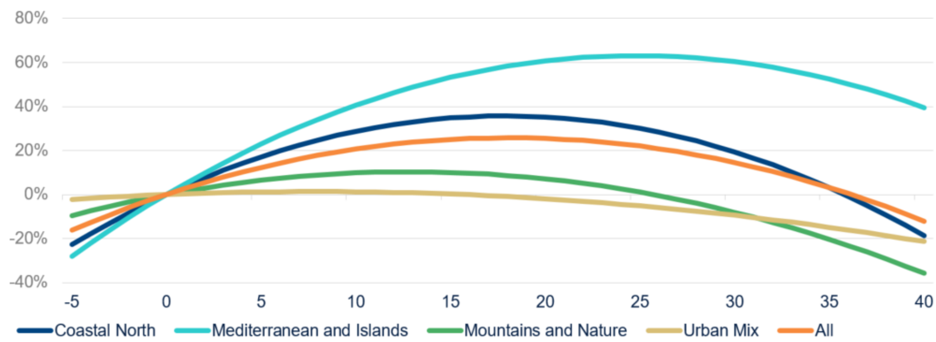

Figure C.1: *Percentage effect of Humidex, °C (x-axis) on Bed Nights, % (y-axis). Source: BBVA Research.*

Interestingly, the results obtained using the humidex differ significantly from those derived using traditional comfort indices like TCI or HCI, not so much in their net effect but in their geographical distribution. This is particularly evident when the humidex is interacted with the type of tourism. By assuming different tolerance levels, which are generally higher in regions with hotter climates, the impacts become more homogeneous. This discrepancy could stem from limited data in the upper tail of the humidex distribution or from the humidex capturing broader factors beyond climate, such as socio-economic or infrastructural variables. However, the coefficients of control variables in the humidex-based models are nearly identical to those obtained using TCI and HCI, suggesting that the overall structure of the models remains consistent. The net effect under the RCP scenario, as shown in Figures C.2 and C.3) , is also negative and significant, aligning with the results obtained in previous sections. Furthermore, when the model is restricted to a single threshold, the results appear more consistent with those obtained using comfort indices. This makes sense, as TCI and HCI include only one and two thresholds respectively, whereas in the interaction model, we introduce four different thresholds.

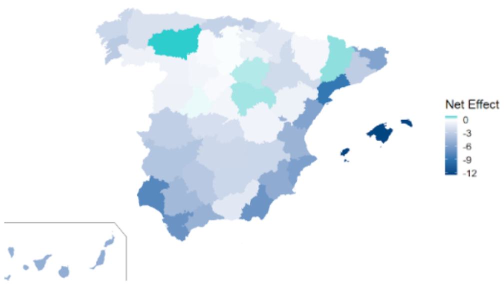

Figure C.2: *Change in tourism demand (Humidex). Net effect by province under RCP 8.5 for 2091-2100 (%, using 2024-2030 as the base). Single threshold. Source: BBVA Research.*

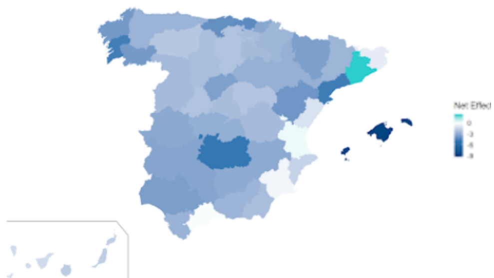

Figure C.3: *Change in tourism demand (Humidex). Net effect by province under RCP 8.5 for 2091-2100 (%, using 2024-2030 as the base). Multiple thresholds. Source: BBVA Research.*

In conclusion, while the humidex-based model presents a promising alternative for capturing the impact of climatic factors on tourism, further research is warranted. A more detailed analysis could be valuable in determining whether an exhaustive examination of climatic variables, possibly through a multi-threshold approach, might offer a more comprehensive understanding of climate's role in tourism demand.

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BBVA Research: Azul Street. 4. La Vela Building – 4th and 5th floor. 28050 Madrid (Spain).
Tel.:+34 91 374 60 00 y +34 91 537 70 00 / Fax:+34 91 374 30 25
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