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The impacts of weather anomalies on international tourism demand

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Abstract
International tourism demand is sensitive to short-run weather, yet the high-frequency margin remains less studied than the long-run climate-change literature, a gap that matters for tourism-dependent economies. Using a monthly panel of overnight stays for 51 origin countries and five Portuguese NUTS II regions over 2007-2019, we estimate fixed-effects panel models exploiting within-pair variation in realised destination weather, controlling for relative prices and persistent demand dynamics. Weather acts primarily through lagged volatility rather than contemporaneous average anomalies. A one-unit increase in intra-month temperature variability is associated with a cumulative decline of approximately 5.7% in overnight stays over a seven-month window; compound temperature-precipitation volatility delivers a further cumulative decline of approximately 2.1%. Average anomalies, relative origin-destination weather, and origin-country anomalies provide weaker and less systematic evidence. The findings indicate that short-run tourism demand responds to the instability of destination weather rather than to average deviations, with implications for tourism forecasting and climate-risk management in tourism-dependent economies. (JEL: Z30, Z50, Q54, C23)

1. Introduction

Portugal's tourism sector is one of the most economically significant components of the national economy. In 2024, establishments recorded 88.3 million overnight stays generating roughly €6.7 billion in accommodation revenues (Instituto Nacional de Estatística 2025); the total direct and indirect contribution of tourism to GDP is estimated at €34 billion (about 11.9% of national output), and Portugal's tourism balance reached €18.8 billion in 2023, third in the European Union (INE 2024). Net exports of services, led by tourism, contributed positively to real Portuguese

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GDP growth in 2023 and 2024, supporting the recovery of the current account from the COVID-19 and energy-price shocks of the early 2020s (European Commission. Directorate General for Economic and Financial Affairs. 2024).

This dependence makes Portugal particularly exposed to inbound-demand shocks. The empirical literature identifies income in source markets, relative prices, exchange rates, transport costs, institutional quality, and political stability as the primary determinants of tourist flows, typically embedded in gravity-type frameworks (Lim 1999; Rosselló *et al.* 2020). A growing body of work also identifies climatic conditions as a distinct, quantitatively meaningful driver, operating both through structural destination attractiveness and through acute disruptions to travel.

The climate-tourism literature distinguishes two channels. In the short run, weather shocks (extreme precipitation, heatwaves, droughts, and storms), disrupt travel plans, infrastructure, and tourist satisfaction, with documented negative effects on arrivals and revenues (Dube *et al.* 2022; Rosselló *et al.* 2020). In the longer run, gradual climate change alters destination attractiveness, redistributes flows across latitudes and altitudes, and modifies seasonality (Amelung *et al.* 2007; García-León *et al.* 2025), with Mediterranean destinations particularly exposed as warming reduces sun-and-sea competitiveness and raises the frequency of extreme heat (Pintassilgo *et al.* 2016; Scott *et al.* 2019). Travellers alter timing, destination, or activity in response to climatic discomfort, with rain, humidity, and storm risk exerting stronger deterrent effects than moderate temperature increases alone (Gössling *et al.* 2012; Becken and Wilson 2013).

These mechanisms are made more salient by recent climate dynamics. Global temperature has risen by approximately 0.2°C per decade since 1980 (Pörtner *et al.* 2022); 2024 was the warmest year in the 176-year instrumental record, at 1.55 ± 0.13°C above pre-industrial, and the first individual calendar year in which warming is more likely than not to have exceeded 1.5°C (Sandford *et al.* 2025). Europe's 2024 summer exceeded the prior continental record by 0.2°C, an event characterised as impossible without anthropogenic forcing (Rantanen *et al.* 2025). The Portuguese context is acute: 2025 produced the country's driest summer since 1931, Mora reached 46.6°C on 27 June (a national June record), at least 264 excess deaths were attributed to heat, and over 670,000 hectares burned across Iberia, nearly four times the 2006-2024 average (World Meteorological Organization (WMO) 2026). Espinosa and Portela (2025) further document a contemporary intensification of exceptional daily-maximum temperature events in Portugal, especially in southern regions.

How weather variability and extreme events affect tourist demand in Portugal thus carries direct implications for economic forecasting, sectoral policy, and external-balance sustainability. Yet existing short-run climate-tourism work tends to focus on a narrow class of catastrophic events in isolation (Rosselló *et al.* 2020; Dube *et al.* 2022), rather than estimating the demand response to continuous weather variation across a range of conditions and across source markets.

The paper makes three contributions. First, it provides what is, to our knowledge, the first systematic short-run empirical analysis of the weather-tourism nexus for Portugal (and for Europe), a country whose tourism share of GDP exceeds the European average and whose external balance is materially exposed to inbound demand. Second, beyond conventional anomaly measures, the paper highlights temperature variability and compound weather volatility as distinct margins of weather risk; within-month temperature variability, and the joint realisation of temperature and precipitation variability, carry first-order explanatory content for overnight stays over subsequent months. Third, we extend to relative origin-destination conditions, origin-country anomalies, and Mediterranean-wide weather factors, finding weaker evidence for these external channels than for destination-side volatility. Together, the findings extend the short-run weather-tourism literature by showing that weather instability, rather than average deviations alone, is a relevant margin for tourism-dependent economies.

The remainder of the paper proceeds as follows. Section 2 describes the tourism, economic, and weather data. Section 3 sets out the baseline specification and the additional models for non-linearity, compound effects, and origin-side weather. Section 4 reports the main results, weather lag structure, compound-volatility specification, relative- and origin-weather analyses, and the Mediterranean substitution channel, with robustness checks summarised here and developed in full in the Appendix. Section 5 discusses the findings and their policy implications, and concludes.

2. Data

2.1. Economic and tourism data

This study primarily uses international tourism data from Statistics Portugal (INE). The dataset comprises monthly observations on overnight stays, the number of guests, and the average length of stay for each Portuguese NUTS II region[1], disaggregated by country of origin and type of establishment (a full list is provided in the Appendix). Owing to a substantial number of missing observations in some establishment categories, we aggregate the data across all accommodation types. All outcome variables are subsequently expressed in logarithms.

Our main dependent variable ($\log(y_{i,o,t})$) is the logarithm of total monthly overnight stays in destination region i by origin country o ($\log(nights)$). In additional specifications, we replace this baseline outcome with the logarithm of the number of guests ($\log(guests)$) and of the average length of stay ($\log(avg\_stay)$).

Empirical studies of tourism demand typically include a measure of relative prices. As Song *et al.* (2008) note, the relevant price for tourists depends on the cost of travel to the destination and the cost of living at the destination. In practice, researchers often use the destination consumer price index as a proxy for the latter, because an index based on the basket of goods purchased by tourists is rarely available. This proxy is imperfect because the consumption basket of tourists need not match that of local residents. For international tourism demand, the destination price index should also be adjusted for the exchange rate, since tourists evaluate destination costs in terms of their own currency.

1. Nomenclature of Territorial Units for Statistics.

Our measure follows this approach. We combine the monthly regional Consumer Price Index for each Portuguese NUTS II region, $cpi_{i,t}$, from INE; annual national Consumer Price Indices for origin countries, $cpi_{o,t}$, from the World Bank; and monthly period-average exchange rates, $fx_{o,t}$, from the International Monetary Fund (IMF).[2] Exchange rates are converted from domestic currency per US dollar to domestic currency per euro to make the components comparable.

Then, the index is defined as

$$lcp_{i,o,t} = \left(\frac{cpi_{i,t}}{cpi_{o,t}}\right) \times fx_{o,t}. \tag{1}$$

We include the logarithm of this index in the main specifications. The variable itself should be interpreted as a proxy for relative affordability, not as a direct measure of the full price of tourism.

Across Portuguese NUTS II regions over 2007–2019, Lisboa has the highest value for lcp, followed by the North, which is consistent with the higher general price levels associated with the two largest metropolitan areas. The Algarve, despite being a major tourism destination, has the lowest value of the index.

Figure 1 presents the average value of $\log(lcp)$ for each country of origin for the period 2007-2019. We can observe that the price index is relatively higher for Asian, African and South American countries, while countries in the Eurozone (that share the same currency) display a lower index.

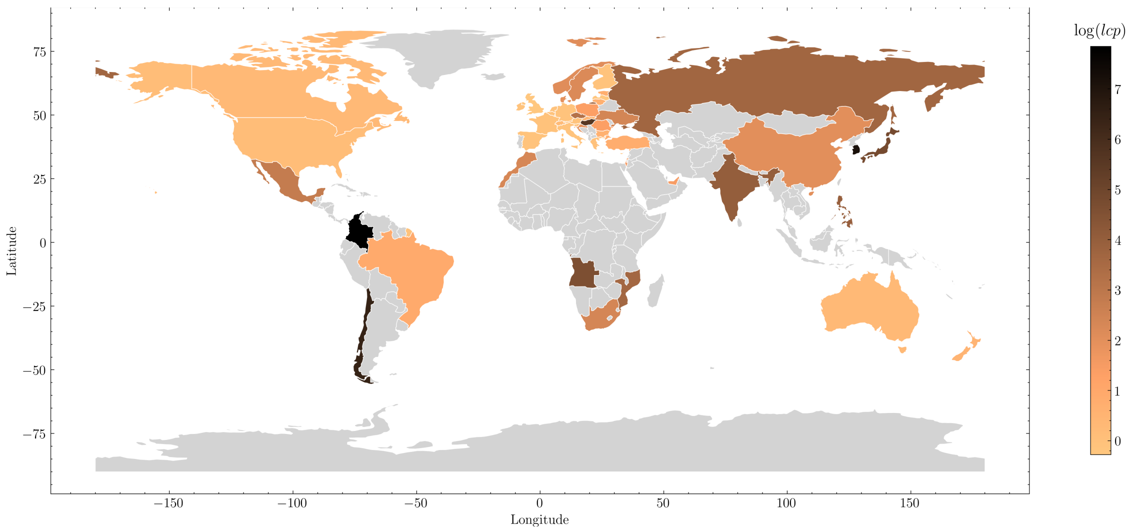


FIGURE 1: Relative price index, $\log(lcp)$, by country of origin, 2007–2019 average. Source: Author's calculations.

We also consider two additional controls in alternative specifications: accommodation supply in destination regions and macroeconomic conditions in origin countries.

2. Several countries joined the euro area during the sample period. For these countries, we use the exchange rate of the domestic currency before euro adoption and the euro exchange rate thereafter. The countries and joining years are Slovenia (2007), Cyprus (2008), Malta (2008), Slovakia (2009), Estonia (2011), Latvia (2014), and Lithuania (2015) (European Commission 2025).

We do not include these variables in the main specification because both are recorded annually, while the main analysis uses monthly variation. Including annual variables in the baseline would add little within-year variation and could obscure the interpretation of the monthly estimates. Instead, we use them to assess whether the baseline results are robust to broader supply-side and demand-side controls.

To account for destination-side accommodation supply, we use the annual number of establishments in each NUTS II region, by type of establishment, from INE. As with the tourism outcomes, we aggregate this variable across accommodation types and express it in logarithms, $\log(cap_{i,t})$. Because accommodation capacity may respond to tourism demand, we estimate alternative specifications using both contemporaneous and lagged capacity. The lagged measure treats capacity as predetermined relative to current tourism flows, while the contemporaneous measure provides a descriptive robustness check.

To capture macroeconomic conditions in origin countries, we use annual GDP per capita at constant 2015 US dollars, adjusted for purchasing power parity, from the World Bank. We express this variable in logarithms, $\log(gdp_{o,t})$. As with accommodation capacity, GDP per capita enters only in alternative specifications, both contemporaneous and lagged. These estimates show whether the main results are sensitive to controlling for annual variation in origin-country income.

2.2. *Weather data*

Weather variables are constructed using the ERA5-Land reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Muñoz-Sabater *et al.* 2021). This dataset has become widely used in the climate economics literature and has also been evaluated in the Portuguese context (Espinosa *et al.* 2024). ERA5-Land is available at an hourly temporal frequency and a spatial resolution of $0.1^\circ \times 0.1^\circ$ (approximately 9 km). From this, we extract the 2-metre air temperature and total precipitation. Temperature is converted from Kelvin to degrees Celsius, and precipitation is converted from metres to millimetres. All weather variables are first computed at the grid-cell level and then aggregated to Portuguese NUTS II regions using area weights, with the spatial aggregation implemented using the `xagg` Python package (Schwarzwald and Geil 2024).

Using the hourly series, we construct a set of destination-region weather variables designed to capture abnormal weather conditions in Portugal. In the baseline analysis, we use the monthly temperature anomaly ($\tilde{T}$), monthly precipitation anomaly ($\tilde{P}$), temperature volatility ($\breve{T}$), precipitation volatility ($\breve{P}$), and the monthly number of wet days (ω). These variables form the core weather vector in the main regressions. Briefly, $\tilde{T}_{i,t}$ and $\tilde{P}_{i,t}$ measure the deviation of monthly mean temperature and total precipitation in region i from their region-specific calendar-month climatology, capturing whether a given month was abnormally warm (cold) or wet (dry) relative to historical conditions; $\breve{T}_{i,t}$ and $\breve{P}_{i,t}$ are the intra-month standard deviations of daily mean temperature and daily precipitation, capturing the within-month variability of conditions; and $\omega_{i,t}$ is the count of days in month t with daily total precipitation exceeding $1\,\text{mm}$, providing a coarse but interpretable measure of how rainy the month was. Together these five variables span the conditioning of tourism demand on the level, the direction-of-deviation, and the volatility of destination-side weather. Full algebraic definitions are in the Online Appendix.

We also consider a number of alternative weather measures in additional specifications, including monthly heating degree days, two alternative measures of cooling degree days, and anomaly series constructed relative to alternative climatological baselines. To allow for non-linear responses, we estimate specifications that include squared temperature and precipitation anomalies. We also consider compound weather specifications that interact temperature and precipitation conditions. Full details on the construction of all weather measures, including sensitivity checks, are reported in the Online Appendix.

Weather conditions in external countries may also affect international travel decisions, particularly when tourists compare conditions at home with those in Portugal. To account for this possibility, we use population-weighted daily temperature and precipitation data from Gortan *et al.* (2024), provided at the country level and based on the ERA5 product variant. From this, we construct three sets of external-weather measures, each entering the empirical analysis in a separate specification. The first set (*relative origin-destination weather*) captures the difference between origin-country and destination-region conditions, on the rationale that tourists compare the weather at home with the weather they expect at the destination. We use monthly relative temperature, $\check{T}_{i,o,t}$, together with one of two relative rainfall measures: the relative number of wet days ($\check{\omega}_{i,o,t}$) or relative total monthly precipitation ($\check{P}_{i,o,t}$). In the main analysis we use concurrent population weights for the origin-country aggregation; specifications based on fixed 2015 population weights are reported as robustness checks.

The second set (origin-country anomalies) captures abnormal weather in the origin country itself, independently of conditions in Portugal. Temperature and precipitation anomalies $\tilde{T}_{o,t}$ and $\tilde{P}_{o,t}$ are constructed using the same baseline-deviation procedure as the destination-region anomalies but applied to population-weighted origin-country series. These measures isolate whether unusual weather at home alters outbound demand for Portugal, separately from any direct comparison with Portuguese conditions. The third set (Mediterranean common-weather factors) captures weather conditions across competing Mediterranean destinations, which may substitute for Portugal as warm-weather destinations. Following Pandit *et al.* (2025), we extract two factor variables from population-weighted weather data for the Mediterranean countries, a temperature anomaly factor η_t^T and a precipitation anomaly factor η_t^P. Detailed construction of all three sets of measures is described in the supplementary material.

3. Methodology

3.1. Baseline empirical specification

We estimate fixed-effects panel data models that exploit within-unit variation in realized weather over time to identify its effect on international tourism demand in Portugal (Dell *et al.* 2014; Hsiang 2016). The baseline panel is observed at the destination-region by country-of-origin level, with monthly observations from January 2007 to December 2019. Let $i \in \{1, \ldots, 5\}$ index Portuguese NUTS II destination regions, $o \in \{1, \ldots, 51\}$ index origin countries, and t denote the month-year observation. The model is,

$$\begin{aligned}\log(y_{i,o,t}) \quad = \quad & \sum_{p=1}^{P} \varphi_p \log(y_{i,o,t-p}) + \sum_{p=0}^{P} \gamma_p \log(lcp_{i,o,t-p}) + \sum_{k=0}^{K} \boldsymbol{\beta}_k' \mathbf{W}_{i,t-k} \\ & + \alpha_{i,o} + \lambda_{y(t)} + \theta_{o,m(t)} + \xi_{i,m(t)} + \psi_o t + \rho_i t + \varepsilon_{i,o,t}, \end{aligned} \tag{2}$$

where $\log(y_{i,o,t})$ is the natural logarithm of overnight stays in destination region i by visitors from origin country o in month t. The lagged dependent variable, $\log(y_{i,o,t-p})$, captures persistence in tourism demand, and the log price-of-tourism index, $\log(lcp_{i,o,t})$, controls for origin–destination price conditions. The vector $\mathbf{W}_{i,t} = \left(\tilde{T}_{i,t},\ \tilde{P}_{i,t},\ \breve{T}_{i,t},\ \breve{P}_{i,t},\ \omega_{i,t}\right)'$ contains the destination-weather variables of interest, where $\tilde{T}_{i,t}$ and $\tilde{P}_{i,t}$ denote temperature and precipitation anomalies, $\breve{T}_{i,t}$ and $\breve{P}_{i,t}$ denote temperature and precipitation volatility, and $\omega_{i,t}$ denotes the number of wet days.

The fixed effects absorb several sources of unobserved heterogeneity. The pair fixed effects, $\alpha_{i,o}$, absorb all time-invariant differences across origin–destination pairs, including distance, cultural links, and persistent travel preferences. The year fixed effects, $\lambda_{y(t)}$, absorb common annual shocks. The origin-country-by-calendar-month fixed effects, $\theta_{o,m(t)}$, allow each origin market to have its own seasonal profile of outbound tourism. The destination-region-by-calendar-month fixed effects, $\xi_{i,m(t)}$, allow each Portuguese NUTS II region to have its own seasonal demand pattern. Finally, $\psi_o t$ and $\rho_i t$ denote origin-country-specific and destination-region-specific linear trends, which capture smooth long-run changes in outbound demand and destination attractiveness.

We set $P = 6$ for the lagged dependent variable and the monthly price controls, and $K = 6$ for the weather block. The six-month distributed-lag structure follows related evidence on the timing of international travel demand and allows weather shocks to affect tourism through immediate conditions as well as delayed booking, substitution, and cancellation responses (Gallego *et al.* 2022). This window is long enough to capture the main planning horizon relevant for short- and medium-haul European tourism, while avoiding the loss of precision from a more heavily parameterised dynamic specification. We therefore interpret the individual lag coefficients as a flexible reduced-form dynamic response and focus primarily on cumulative effects over the six-month window.

Identification comes from deviations in destination weather over time within an origin–destination pair, after accounting for time-invariant bilateral heterogeneity, common annual shocks, recurring origin- and destination-specific seasonality, and smooth origin- and destination-specific trends. The weather coefficients are therefore identified from months in which a destination region is unusually warm, wet, dry, or volatile relative to its expected seasonal pattern, conditional on lagged demand and price conditions. The identifying assumption is that, after these controls, remaining monthly weather variation is orthogonal to other unobserved shocks to origin–destination tourism demand.

We estimate (2) using the `fixest` package in `R` (Bergé *et al.* 2026). Standard errors are clustered two ways at the origin–destination-pair and month-year levels, allowing arbitrary serial correlation within panel units and arbitrary correlation across observations sharing the same time shock.

3.2. *Additional specifications*

We estimate several additional specifications to assess non-linearity, compound weather effects, external conditions, and sensitivity to modelling choices.

First, we allow weather effects to be non-linear and compound. To assess non-linearity, we augment (2) with squared temperature and precipitation anomaly terms, $\tilde{T}^2_{i,t}$ and $\tilde{P}^2_{i,t}$, including contemporaneous values and six monthly lags. These specifications allow the marginal effect of anomalous weather to vary over the distribution of temperature and precipitation shocks. We also estimate compound-weather specifications in which the weather vector is replaced by interactions between temperature and precipitation. Specifically, we consider the compound anomaly term, $\tilde{T}_{i,t} \times \tilde{P}_{i,t}$, and the compound volatility term, $\breve{T}_{i,t} \times \breve{P}_{i,t}$, again including contemporaneous values and six monthly lags. These models test whether tourism demand responds to the joint realization of temperature and precipitation conditions, rather than to each dimension separately.

Second, we examine whether tourism demand responds to external weather conditions. We consider three sets of external conditions. The first uses relative weather variables, defined as differences between weather in the origin country and weather in the Portuguese destination region. These specifications include relative temperature, $\check{T}_{i,o,t}$, and one relative rainfall measure at a time, i.e., relative wet days using concurrent population weights, $\check{\omega}_{i,o,t}$; relative wet days using 2015 population weights, $\check{\omega}_{2015,i,o,t}$; relative precipitation using concurrent population weights, $\check{P}_{i,o,t}$; and relative precipitation using 2015 population weights, $\check{P}_{2015,i,o,t}$. The second set replaces destination weather with anomalous weather in tourists' origin countries, to test whether unusual home-country conditions affect outbound demand for Portugal. The third set uses the Mediterranean common-weather factors, η^T_t and η^P_t, to assess whether abnormal weather in competing Mediterranean destinations is associated with tourism demand for Portugal. All external-weather specifications retain the six-month distributed-lag structure, economic controls, fixed effects, and trends used in the baseline model.

Third, we assess whether the estimates are sensitive to the definition of the outcome variable. We re-estimate the baseline model using the logarithm of the number of guests and, separately, the logarithm of average length of stay. These specifications distinguish whether weather affects the extensive margin of tourism demand, the duration of trips, or both.

Fourth, we account for additional annual controls in alternative specifications. We add regional accommodation capacity, $\log(cap_{i,t})$, to control for destination-side supply conditions, and origin-country GDP per capita, $\log(gdp_{o,t})$, to control for macroeconomic conditions in source markets. Because both variables are observed annually, we do not include them in the main monthly specification. Instead, we estimate alternative models with contemporaneous and lagged values. For accommodation capacity, the lagged specification also mitigates concerns that capacity responds endogenously to current tourism demand.

Fifth, we assess the sensitivity of inference to alternative variance–covariance estimators. We re-estimate the main equation using alternative clustering and robust standard-error assumptions. This exercise evaluates whether the statistical significance of the baseline estimates depends on the chosen inference procedure.

Finally, we examine sensitivity to weather measurement. We re-estimate (2) using alternative weather variables in place of the baseline anomaly measures, including heating degree days, alternative cooling degree day measures, and anomaly series constructed relative to alternative climatological baselines. All specifications retain the six-month distributed-lag structure. Details on variable construction and the corresponding estimates are reported in the supplementary materials.

3.3. *Identification assumptions and limitations*

The identifying assumption is that, conditional on the fixed effects, trends, lagged tourism demand, and lagged price controls in Equation (2), remaining variation in monthly destination weather is orthogonal to unobserved shocks to origin–destination tourism demand. The specification uses deviations in realised weather within an origin–destination pair over time, after accounting for time-invariant bilateral heterogeneity, common annual shocks, origin-specific and destination-specific seasonality, and smooth origin- and destination-specific trends. This source of variation is standard in climate-econometric applications, where short-run weather fluctuations are treated as plausibly exogenous conditional on location and time controls (Dell *et al.* 2014; Hsiang 2016).

The inclusion of lagged overnight stays changes the interpretation of the model. The coefficients on weather capture the effect of realised weather on tourism demand, holding fixed recent demand dynamics. This is useful because international tourism is persistent: past flows may reflect repeat visits, marketing, transport connections, and advance booking patterns. The dynamic terms therefore reduce the risk that weather coefficients capture serial persistence in tourism demand rather than weather effects. In dynamic fixed-effects panels, however, lagged dependent variables can generate Nickell bias when the time dimension is short (Nickell 1981). This concern is limited in our setting because our panel provides a relatively long time dimension of up to 156 months; the Nickell bias declines with T and is primarily a concern in short panels.

Several limitations remain. First, monthly weather is serially correlated. A single weather episode may affect several lags, so individual lag coefficients should not be interpreted as independent shocks. We therefore focus on cumulative effects over the six-month window and use Wald tests to assess the joint importance of the distributed-lag terms. Second, the six-month lag structure captures both immediate and delayed responses, including booking, cancellation, and substitution margins. The reduced-form model does not separately identify these mechanisms. Third, year fixed effects absorb common annual shocks, but not all origin- or destination-specific exposure to those shocks. The origin and destination trends, together with the interacted calendar-month fixed effects, reduce this concern but cannot rule it out completely.

The estimates should therefore be interpreted as short-run reduced-form responses of overnight stays to realised weather conditions, conditional on the dynamic demand process, relative price controls, fixed effects, and trends in Equation (2). The external-weather specifications impose an additional assumption: weather conditions in origin countries or competing Mediterranean destinations must be uncorrelated with other contemporaneous shocks that differentially affect demand for Portugal. We therefore interpret those estimates as complementary evidence on external weather channels rather than as the main source of identification.

4. Results

4.1. Data description

4.1.1. Tourism data

Before turning to the regression results, three stylised facts about the data motivate the empirical specification of Section 3 and frame the interpretation of the estimates that follow.

Figure 2 reports the 2007–2019 average length of stay across the five mainland NUTS II destination regions. Average stays vary substantially across regions, with the Algarve consistently showing the longest stays. The other regions generally display shorter and more similar stays. These persistent differences reflect regional tourism typologies and are absorbed by the origin–destination pair fixed effect $\alpha_{i,o}$ in (2). Identification therefore comes from within-pair variation in weather over time, not from cross-sectional differences in trip length.

Figure 3 shows the cumulative geographical distribution of guests over 2007-2019. The United Kingdom alone accounts for approximately 25% of total overnight stays, and the top five origin markets (the United Kingdom, Spain, Germany, France, and the Netherlands), collectively account for approximately 68% of the sample total. This high concentration in a small number of European source markets is relevant because the relative-weather and origin-anomaly specifications introduced in Section 3 are implicitly weighted by the realised distribution of bilateral flows.

Figure 4 combines two features. Panel 4a reports the aggregate seasonality index of inbound overnight stays where demand rises sharply from a trough in January (index

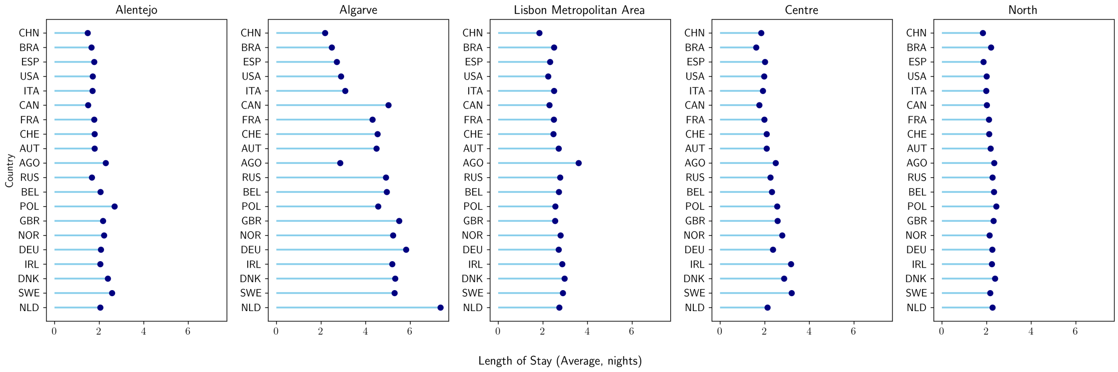


FIGURE 2: Average length of stay for top 20 countries of origin, by NUTS II region (2007–2019 average).

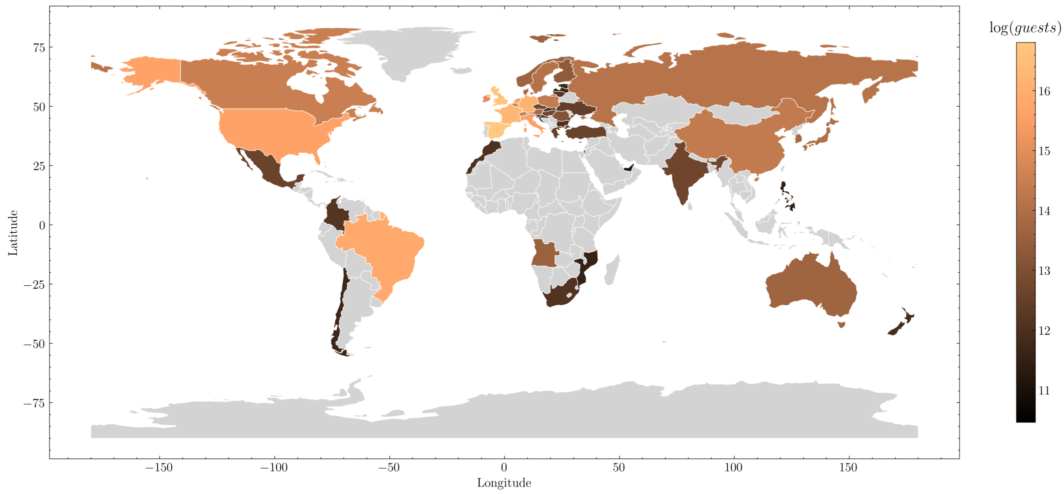
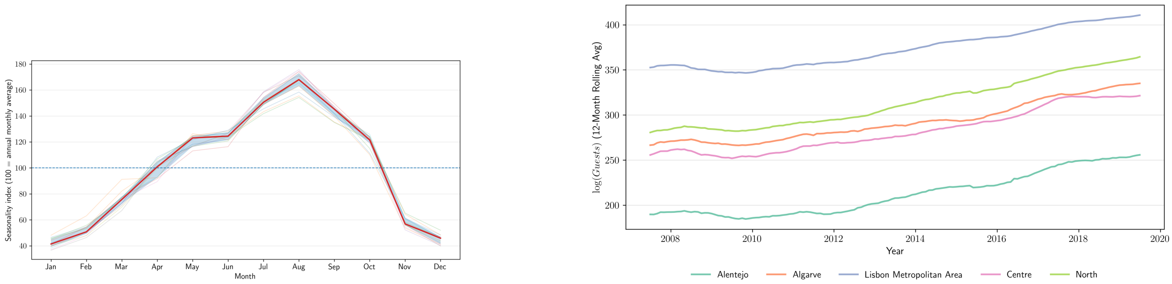


FIGURE 3: Cumulative number of guests by country of origin (2007–2019). Source: INE.

value of approximately 46) to a peak in August (approximately 154), with the shoulder months of April through October sustaining above-average volumes. Panel 4b displays the 12-month rolling average of $\log(\text{guests})$, summed across origin countries, for each NUTS II region. The series show a mild decline around 2009–2010, followed by steady growth over the rest of the sample. This upward trend becomes more pronounced after 2013 and is visible across all regions, with each region reaching its highest level near the end of the period. The figure also shows persistent level differences across regions, which motivate the inclusion of destination-region fixed effects in the empirical specification.

Figure 5 reports the monthly share of overnight stays for the ten largest origin markets over the 2007–2019 total, with each row normalised to sum to one. Two features stand out. First, all ten markets display clear seasonality, with visits concentrated between late spring and early autumn. The strongest summer peaks occur in August for Spain, Italy, and France, while Ireland concentrates a large share of stays in June–September. By contrast, Brazil, Germany, the United Kingdom, and the United States distribute stays more evenly across the year, with relatively elevated shares outside the core summer months. Second, the timing of peak demand differs across origins: some



(A) Seasonality index of inbound overnight stays (aggregate).

(B) Evolution of international tourism demand by each NUTS II region over 2007–2019.

FIGURE 4: Seasonality of inbound overnight stays in Portugal, and evolution of number of guests (2007–2019).

markets peak in July or August, while others reach their highest shares in September or October. This combination of strong seasonality and origin-specific travel calendars makes the distributed-lag structure on weather variables empirically informative, since abnormal weather conditions in a given month affect origin–destination pairs over different post-shock horizons depending on when their travel cycles peak.

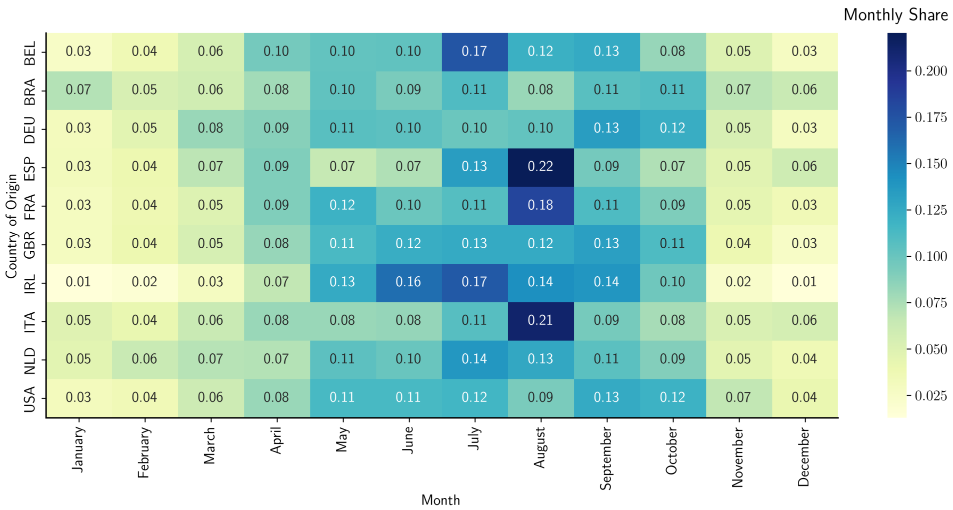


FIGURE 5: Monthly share of overnight stays in Portugal by country of origin for the ten largest source markets (2007-2019 average). Each row is normalised to sum to one, highlighting the seasonal concentration of inbound demand.

4.1.2. *Weather data*

The summary statistics for the five destination-region weather variables are provided in the supplementary materials. Two patterns are particularly relevant for the interpretation of the regression results that follow. First, mean temperature anomalies ($\tilde{T}$) are positive across all five NUTS II regions indicating that the sample period was systematically warmer than the 1971-2019 climatological baseline. Second, and notably, mean precipitation anomalies ($\tilde{P}$) are negative in every region; the median is also negative in all cases, confirming that the negative mean is not driven by outliers.

This indicates that Portugal was, on balance, drier than its historical norm throughout the estimation window, a pattern consistent with the broader Mediterranean drying trend documented in the climatological literature. The right-skew of the precipitation anomaly distribution, however, is also evident. While the 75th percentile remains close to zero or modestly positive in most regions, the maximum values exceed 0.23 in all cases, reflecting the episodic character of extreme rainfall events. With respect to spatial gradients, wet days (ω) and precipitation volatility ($\breve{P}$) both increase monotonically from south to north, the Algarve records the lowest mean wet-day count (9.7 days) and the Norte the highest (15.7 days), while temperature volatility ($\breve{T}$) is broadly similar across interior regions and somewhat lower along the coast.

4.2. Main results

Table A.1 in the appendix reports the baseline estimates for international tourism demand, with our preferred specification shown in column (8). This model includes origin–destination pair fixed effects, year fixed effects, destination-specific month fixed effects, origin-country-specific month fixed effects, as well as destination-specific and origin-country-specific linear time trends; six monthly lags of the dependent variable; six monthly lags of the price-of-tourism index $\log(lcp)$; and the five weather anomaly variables entering contemporaneously and with six monthly lags. We cluster standard errors at the origin–destination pair and time dimensions throughout.

The first lag of log overnight stays enters at 0.265 ($p < 0.01$), and lags two through four are also positive and statistically significant, confirming substantial month-to-month persistence in tourism demand. The fifth and sixth lags remain positive but are not statistically significant. The contemporaneous coefficient on $\log(lcp)$ is positive and close to zero (0.003), while the lagged price coefficients vary in sign and do not individually attain conventional significance. The cumulative price elasticity reported in Table 1 is negative, at approximately -0.047, but the pattern across lags provides little evidence of a stable dynamic price response. This suggests that the richer lag structure and the time-varying controls absorb most of the price variation that identified the static-model estimates.

The contemporaneous coefficients on the weather anomaly variables provide limited evidence that abnormal weather conditions affect tourism demand on impact. The coefficient on the temperature anomaly ($\tilde{T}$) is negative (-0.002) and not statistically significant; the contemporaneous precipitation anomaly ($\tilde{P}$) is positive (0.087) but also not statistically significant. Temperature volatility (σ_T), precipitation volatility (σ_P), and wet days (ω) are likewise not statistically significant contemporaneously. The lag structure, however, indicates that some weather effects unfold over subsequent months rather than immediately. For temperature anomalies, the first several lags are small and statistically insignificant, while the sixth lag is negative and statistically significant at the 5% level (-0.010; $p < 0.05$). Precipitation anomalies display no individually significant lags in the preferred specification. Temperature volatility is negative at all horizons, with statistically significant effects at lag one (-0.014; $p < 0.05$) and lag four (-0.018; $p < 0.05$). Precipitation volatility displays a negative and statistically significant coefficient at lag one (-0.013; $p < 0.01$), while the remaining lags are small and not statistically significant. Wet days are negative in the contemporaneous period and at most lag horizons, but no coefficient attains conventional significance in the preferred specification.

Variable	Cum. effect	s.e.	p	Wald p
$\log(lcp)$	-0.047	0.039	0.222	0.144
$\tilde{T}$	-0.015	0.011	0.173	0.015
$\tilde{P}$	0.022	0.225	0.921	0.890
$\breve{T}$	-0.057	0.022	0.012	0.076
$\breve{P}$	-0.013	0.014	0.349	0.151
ω	-0.002	0.002	0.239	0.634

Notes: The table reports the cumulative effect obtained by summing contemporaneous and lagged coefficients for each variable. The column p reports the test of whether the cumulative effect equals zero. The column Wald p reports the joint test that all lag coefficients for the corresponding variable are equal to zero.

TABLE 1. Cumulative lagged effects of price and weather variables on non-resident guests.

Table 1 reports cumulative effects, defined as the sum of the contemporaneous coefficient and six monthly lags, together with Wald tests for the joint significance of all seven coefficients. These estimates correspond to the preferred specification in column (8) of Table A.1. Over the seven-month horizon, the cumulative effect of temperature volatility is -0.057 and statistically significant at the 5% level ($p = 0.012$), with the Wald test rejecting joint insignificance at the 10% level ($p = 0.076$). A one-unit increase in intra-month temperature variability is therefore associated with a cumulative decline of approximately 5.7% in overnight stays. The difference between the cumulative-effect test and the Wald test suggests that the negative effect is spread across several lags, rather than being driven by a single precisely estimated coefficient.

For the remaining weather variables, the evidence is weaker. The cumulative effect of temperature anomalies is negative but not statistically significant (-0.015; $p = 0.173$), while the Wald test rejects joint insignificance at the 5% level ($p = 0.015$). This indicates that the individual lag coefficients are jointly meaningful, even though positive and negative effects partially offset over the full horizon. Precipitation anomalies display a cumulative effect close to zero (0.022; $p = 0.921$), and the Wald test does not reject joint insignificance ($p = 0.890$). Precipitation volatility is also negative but not statistically significant in cumulative terms (-0.013; $p = 0.349$), with no joint rejection at conventional levels ($p = 0.151$). Wet days likewise show a small negative cumulative effect (-0.002; $p = 0.239$), and the Wald test provides no evidence of joint significance ($p = 0.634$). The cumulative price effect is negative (-0.047), but it is not statistically significant ($p = 0.222$), and the corresponding Wald test does not reject joint insignificance ($p = 0.144$).

Two notes on inference are in order before drawing the broader pattern together. First, the distributed-lag specification estimates a large number of coefficients across price and weather variables, so individual point estimates should be read with appropriate caution. The paper's primary inference targets are the cumulative-effect and joint Wald-test summaries reported in Table 1, supplemented by the consistency of patterns across the alternative-outcome, alternative-weather-measure, and alternative-baseline specifications discussed in Section 4 and the supplementary materials. Second, the within-R^2 in the preferred specification is below 0.11, as is typical when the fixed-effects structure absorbs most of the systematic variation in a high-frequency panel. Weather anomaly variables explain only a modest share of the residual within-pair variation in monthly overnight stays, but the cumulative and joint significance tests indicate that this share is statistically meaningful for temperature volatility and for the dynamic profile of temperature anomalies.

Overall, international tourism demand in Portugal responds less to contemporaneous weather conditions than to their persistence and timing over subsequent months. Among the five weather measures, the clearest cumulative evidence points to a negative role for temperature volatility. Temperature anomalies display jointly significant lag dynamics that offset across horizons, yielding a small and statistically insignificant cumulative effect. By contrast, precipitation anomalies, precipitation volatility, and wet days provide little evidence of systematic effects in the preferred specification. This pattern is consistent with tourism demand adjusting gradually to realised weather conditions rather than instantaneously within the same month.

4.3. Non-linear and compound responses

We next allow the response to weather to be nonlinear and compound. We first add squared terms for temperature and precipitation anomalies, $\tilde{T}^2$ and $\tilde{P}^2$, and then replace the individual volatility measures with a temperature–precipitation anomaly interaction, $\tilde{T} \times \tilde{P}$, and a compound volatility index, $\breve{T} \times \breve{P}$. The fixed-effects structure, lag lengths, and clustering remain identical to the baseline. Since the full coefficient estimates and cumulative tests are reported in the supplementary materials, we focus here on the main patterns.

The squared anomaly terms provide little evidence of nonlinear responses. No individual lag of the squared temperature anomaly is statistically significant except at the sixth month, where the coefficient is negative and significant at the 10% level. The cumulative sum is small, at 0.003, and not statistically significant ($p = 0.407$). The joint test is marginally significant ($p = 0.094$), suggesting some joint relevance across lags, although this does not translate into a clear cumulative effect. The squared precipitation anomaly terms are also not cumulatively significant, with a cumulative effect of 0.038 and a p-value of 0.961. The Wald test does not reject joint insignificance ($p = 0.291$). Overall, the estimates provide limited support for U-shaped or inverted-U-shaped relationships between weather anomalies and overnight stays.

The interaction and compound specifications yield stronger evidence. The temperature–precipitation anomaly interaction, $\tilde{T} \times \tilde{P}$, is not statistically significant at shorter lags, but the sixth lag is negative and significant at the 5% level, with a coefficient of -0.009. The cumulative interaction is also negative, at -0.013, but is not statistically significant ($p = 0.192$). The joint test rejects insignificance at the 1% level ($p = 0.010$), indicating that the lag profile is jointly meaningful even though effects partly offset across months. This pattern is consistent with joint temperature–precipitation anomalies being associated with weaker tourism demand at longer horizons, although the cumulative response remains imprecisely estimated.

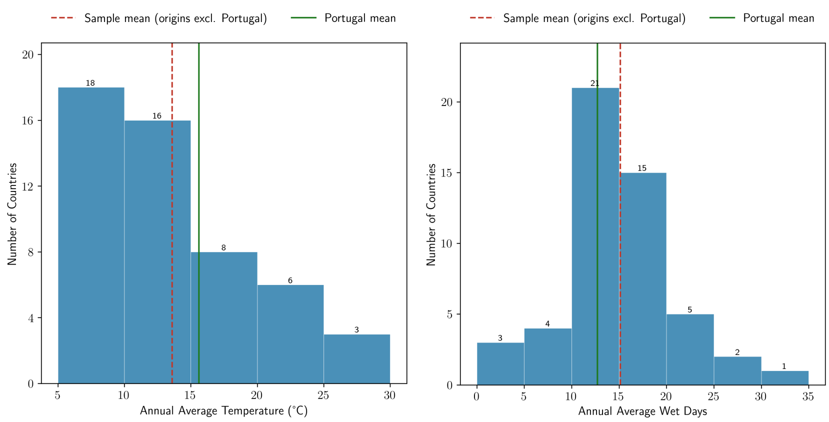
Compound volatility provides the clearest evidence of weather-related demand reductions. The first lag is negative and significant at the 1% level, with a coefficient of -0.010, while the remaining lags are mostly negative but not individually significant. The cumulative effect equals -0.021 and is statistically significant at the 1% level ($p = 0.003$); the joint test also rejects insignificance at the 1% level ($p = 0.010$). A one-unit increase in the compound volatility index is therefore associated with an approximate 2.1% cumulative decline in overnight stays over the seven-month window. This result complements the baseline evidence on temperature volatility and suggests that months in which temperature and precipitation are both unusually volatile are associated with larger reductions in tourism demand than either dimension alone would imply.

4.4. *Impacts from weather conditions in external countries*

The origin-weather specifications are estimated on a reduced sample of 50 origin countries, as Russia is excluded owing to inconsistencies in the precipitation data. The full coefficient tables, together with the cumulative effects and Wald tests for the three- and six-lag horizons, are reported in the Appendix.

4.4.1. *Relative weather conditions*

We augment the preferred specification with measures of weather conditions in origin countries expressed as deviations from destination-level conditions, thereby capturing the relative attractiveness of Portugal vis-à-vis the tourist's home climate. Figure 6 provides context for this exercise. The majority of origin countries in the sample are cooler than Portugal, with a mean annual temperature of approximately 14° C compared to Portugal's 16° C (Panel 6a), while the distribution of wet days is broadly centred around 12-15 days per month, with Portugal's mean sitting at the lower end (Panel 6b). These distributional features imply that most origin–destination pairs exhibit a positive temperature gap and a small negative wet-day gap, creating scope for relative weather conditions to operate as a push factor in tourism demand.



(A) Temperature conditions in origin countries. (B) Precipitation conditions in origin countries.

FIGURE 6: Distribution of weather conditions in origin countries (2007–2019).

We estimate four specifications that pair relative temperature ($\check{T}$) with alternative measures of relative precipitation: relative wet days computed against the 2015 baseline ($\check{\omega}_{2015}$), relative wet days computed against the full-sample climatology ($\check{\omega}$), and the analogous pair for relative total precipitation ($\check{P}_{2015}$; $\check{P}$). Across all four specifications, relative temperature is negative at shorter horizons and positive only at longer horizons. The sixth lag is positive and statistically significant in each specification, but the cumulative effect is essentially zero and never statistically significant. The Wald tests also do not reject joint insignificance, with p-values ranging from 0.202 to 0.259. The relative precipitation measures provide similarly limited evidence. For relative wet days, the third lag is positive and marginally significant when computed against the 2015 baseline, but the cumulative effects are small and not statistically significant ($p = 0.115$ and $p = 0.134$). For relative total precipitation, the first lag is positive and statistically significant at the 5% level in both baseline definitions, but the cumulative effect remains small and statistically insignificant ($p = 0.158$), and the Wald tests do not reject joint insignificance. Overall, we find little robust evidence that the relative weather gap between origin and destination is systematically associated with international tourism demand to Portugal. The signs are directionally consistent with worse home-country conditions being associated with higher demand for a comparatively drier destination, but the cumulative and joint tests do not support a strong or stable relationship.

4.4.2. Weather anomalies in origin countries

We replace the relative measures with anomalies computed at the origin-country level, that is, deviations of origin-country weather from its own historical climatology, to test whether abnormal conditions at home are associated with outbound tourism flows to Portugal. We estimate four specifications that pair origin-country temperature anomalies ($\tilde{T}_o$) with alternative origin-country precipitation measures: origin wet days ($\check{\omega}_{2015}$; $\check{\omega}$) and origin precipitation anomalies ($\tilde{P}_{o,2015}$; $\tilde{P}_o$).

The results are largely null. Origin-country temperature anomalies are negative at most horizons, but the coefficients are generally small and not statistically significant. The only exception is the contemporaneous coefficient in the specifications that include origin precipitation anomalies, where the estimate is negative and marginally significant. The cumulative temperature-anomaly effect is approximately -0.004 across specifications and is not statistically significant ($p > 0.34$); the Wald tests likewise do not reject joint insignificance ($p > 0.69$). Origin-country wet days display a similar pattern to the relative-weather specifications. The third lag is positive and marginally significant when computed against the 2015 baseline, but the cumulative effects are small and not statistically significant ($p = 0.118$ and $p = 0.135$), and the Wald tests do not reject joint insignificance. Origin-country precipitation anomalies are also not statistically significant, with cumulative effects close to zero and Wald p-values around 0.90. Overall, origin-country weather anomalies do not display a robust association with international overnight stays in Portugal.

4.4.3. Mediterranean-wide anomalies

We introduce Mediterranean-wide weather factors (η^T, η^P) to test whether region-level anomalies, which capture conditions across competing Mediterranean destinations, are associated with tourism demand to Portugal. We estimate two specifications that pair the Mediterranean temperature factor with alternative precipitation measures (η^P_{2015}; η^P_{conc}).

The Mediterranean temperature factor displays the strongest individual-lag evidence among the external weather measures considered in this section. The contemporaneous coefficient is negative and statistically significant at the 5% level, at approximately -0.011, and the second lag is also negative and statistically significant at the 5% level. The pattern is stable across both precipitation specifications. The cumulative effect is negative, at approximately -0.011, but it is not statistically significant ($p = 0.308$ and $p = 0.309$). The Wald tests also do not reject joint insignificance ($p = 0.309$ and $p = 0.322$). This negative association is consistent with warmer-than-usual conditions across the broader Mediterranean reducing Portugal's relative appeal as a warm-weather destination, although the cumulative and joint tests do not support a robust dynamic effect.

The Mediterranean precipitation factors display mixed lag patterns and weak cumulative evidence. The contemporaneous coefficient is positive and statistically significant at the 5% level in both specifications, while the second lag is negative and statistically significant at the 5% level. These offsetting effects leave the cumulative effect close to zero, at approximately -0.002, and statistically insignificant ($p > 0.80$). The Wald tests do not reject joint insignificance at conventional levels. Overall, the Mediterranean-factor specifications provide suggestive evidence that warmer external conditions are associated with lower demand for Portugal at specific horizons, but the cumulative evidence remains limited. For precipitation, the signs vary across lags and do not indicate a stable relationship.

Taken together, these results suggest that external weather conditions matter less robustly than Portugal's own realised weather conditions. The Mediterranean temperature result is directionally consistent with Portugal's climatic advantage being diminished when competing destinations experience warmer-than-usual conditions, but the evidence is concentrated in individual lags rather than in the cumulative or joint tests. These estimates should therefore be interpreted as reduced-form associations, while remaining agnostic as to whether tourists stay home or reallocate towards alternative destinations. By contrast, the evidence for rainfall is weaker and less consistent across specifications. Relative and origin-country precipitation measures generate small and statistically insignificant cumulative effects, while Mediterranean precipitation factors display offsetting positive and negative lag coefficients. This pattern suggests that rainfall-related external conditions do not have a stable association with tourism demand to Portugal in these specifications.

4.5. *Alternative specifications for robustness checks*

We first vary the dependent variable. For overnight stays and guests, results align with the baseline: temperature volatility is negative and statistically significant cumulatively ($-0.052, p = 0.032$ for nights; $-0.061, p = 0.017$ for guests), while temperature anomalies and wet days are not. The price coefficient is negative and significant for guests but not for nights. The average-stay specification (estimated on a reduced sample with Malta and Cyprus dropped owing to missing values in the $avg_s tay$ series) produces a different pattern: weather measures are mostly insignificant cumulatively, except wet days ($-0.003, p = 0.020$), but the Wald test does not reject joint insignificance, so the effect is not supported by a stable lag profile. The alternative-outcome exercise reinforces that $\breve{T}$ is most consistently associated with lower demand at the nights and guests margin, while the average-stay margin provides weaker and less systematic evidence.

We next assess robustness to additional controls for destination accommodation capacity and origin-country GDP per capita. Adding contemporaneous $\log(cap)$ leaves the temperature-volatility coefficient essentially unchanged (-0.057, $p = 0.012$). With 12-, 24-, and 36-month lags of capacity, the sample shrinks and $\breve{T}$ attenuates but remains marginally significant (-0.041, $p = 0.058$); $\breve{P}$ also becomes marginal (-0.031, $p = 0.086$). Adding contemporaneous origin GDP yields $\breve{T}$ at -0.057 ($p = 0.012$); the lagged-GDP specification preserves the negative effect (-0.044, $p = 0.040$) while indicating a positive contemporaneous and 12-month GDP effect and a negative 36-month effect on overnight stays. The $\breve{T}$ result is robust to these controls.

Re-estimating the cumulative effects under five variance estimators, IID, HC1, two-way clustered, Newey-West and Driscoll-Kraay (both with six lags), the cumulative point estimates are identical by construction and only inference changes. $\breve{T}$ remains significant across all five, with p-values from 0.006 (Newey-West) to 0.017 (Driscoll-Kraay), and 0.012 under the preferred clustered estimator. $\tilde{T}$ is marginally significant under IID, HC1, and Newey-West but insignificant under clustering and Driscoll-Kraay; the Wald test rejects joint insignificance throughout. Precipitation measures and wet days remain insignificant under all five estimators.

Replacing the temperature and precipitation anomalies with degree-day variables, we examine cold-day exposure (HDD_0, below 0°C) and two cooling thresholds (CDD_{30} above 30°C; CDD_{35} above 35°C). HDD_0 has significant individual lags of offsetting sign and an insignificant cumulative effect (-0.028, $p = 0.436$; -0.032, $p = 0.386$ across the two specifications), with the Wald rejecting joint insignificance. CDD_{30} shows no cumulative effect (0.001, $p = 0.910$). CDD_{35}, by contrast, delivers a large cumulative decline (-0.434, $p = 0.001$). Extreme heat above 35°C is therefore associated with a sizeable reduction in overnight stays over the seven-month window, consistent with the baseline finding that extreme and volatile temperature conditions matter more than average anomalies.

Finally, we vary the climatological reference period used to construct the anomalies (the 1971–2019 baseline replaced by 1961-1990, 1981-2010, and 1991-2020 in turn). The cumulative weather coefficients are stable across baselines: $\breve{T}$ ranges from -0.055 to -0.061 with $p \leq 0.013$ throughout; $\tilde{T}$ remains in $[-0.015, -0.013]$ with the Wald test rejecting joint insignificance at conventional levels. Precipitation measures and wet days remain insignificant. The baseline $\breve{T}$ result is not an artefact of the chosen climatology.

5. Conclusion

This paper examines the short-run effects of weather shocks on international tourism demand in Portugal, using a monthly panel of overnight stays for 51 origin countries across five NUTS II destination regions over 2007-2019, with fixed effects on origin-destination pairs, year, calendar-month, and origin- and destination-specific linear trends.

Two findings stand out. First, tourism demand responds to temperature variability more clearly than to average temperature anomalies. A one-unit increase in intra-month temperature variability is associated with a cumulative decline of approximately 5.7% in overnight stays over the seven-month window. The effect is statistically significant in the baseline and stable across alternative outcomes, additional controls, alternative standard errors, and alternative climatological baselines. Average temperature anomalies show jointly significant lag dynamics but no clear cumulative effect, as positive and negative coefficients offset across horizons. The relevant margin is not whether a month is warmer or cooler than usual, but whether conditions become less stable and less predictable. Second, compound volatility amplifies this pattern. The interaction of $\breve{T}$ and $\breve{P}$ is statistically significant and delivers a cumulative effect of approximately -2.1%. Periods in which both dimensions are unusually variable appear to reduce the reliability of the destination experience, particularly for trips whose value depends on outdoor amenities and advance planning. The degree-day specifications reinforce this reading: moderate heat above 30°C lacks a robust cumulative effect, while extreme heat above $35°$C is associated with a large decline. Weather instability and sharp within-month temperature swings, rather than average conditions, emerge as the main weather-related margins shaping international tourism demand.

Three potential policy implications follow. First, tourism forecasting could benefit from incorporating short-run volatility indicators alongside seasonal averages, providing leading information for accommodation providers, regional tourism boards, and external-balance forecasting. Second, adaptation measures that preserve the reliability of the visitor experience under unstable weather, e.g. shaded public space, heat-resilient transport, and flexible visitor management, have higher leverage than measures targeting average conditions. Third, exposure differs by region and tourism type, so adaptation needs to be spatially targeted: beach-oriented destinations are more exposed to temperature swings, while urban and cultural destinations can buffer instability through diversified activities.

Four limitations frame the natural extensions of this work. The 2007-2019 sample avoids the COVID-19 break but leaves open whether the post-2021 tourism boom, record arrivals despite repeated weather extremes, has shifted the weather sensitivity; explicitly modelling the 2020 break and re-estimating is the most direct extension. Monthly frequency partially aggregates away within-month adjustments in bookings and trip timing; weekly or daily data would sharpen identification of short-run adjustment dynamics. NUTS II aggregation may mask heterogeneity across coastal, urban, and inland destinations; disaggregation to NUTS III or municipal level would improve weather-exposure measurement and tests of heterogeneous adaptation. Finally, the Mediterranean-factor specifications provide only reduced-form evidence on external conditions; bilateral arrivals data for competing destinations, combined with a structural gravity framework, would identify the substitution elasticity and quantify how weather volatility redistributes demand across the Mediterranean basin.

As climate change continues to reshape weather patterns across Europe and the Mediterranean basin, the channels documented here are likely to grow in salience. The key risk is not gradual warming alone, but increasingly volatile temperatures, sharper within-month swings, and less predictable destination conditions, with material implications for short-run forecasting, regional adaptation planning, and the management of economies whose external accounts depend on inbound visitor demand.

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Appendix: Main results table

TABLE A.1. Main results with different fixed effects specifications

Dep. Var.:	$\log(nights)$							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$\log(nights)_{t-1}$	0.455***	0.387***	0.381***	0.299***	0.323***	0.232***	0.303***	0.265***
	(0.021)	(0.020)	(0.021)	(0.019)	(0.018)	(0.016)	(0.017)	(0.016)
$\log(nights)_{t-2}$	0.085***	0.045***	0.043***	0.002	0.099***	0.052***	0.103***	0.074***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)
$\log(nights)_{t-3}$	0.046***	0.009	0.015	-0.019	0.051***	0.018	0.064***	0.037***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.012)	(0.013)	(0.012)
$\log(nights)_{t-4}$	0.057***	0.022*	0.035***	0.002	0.034***	0.004	0.048***	0.021**
	(0.013)	(0.012)	(0.013)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)
$\log(nights)_{t-5}$	0.034***	-0.002	0.010	-0.021*	0.030***	-2.81×10^{-5}	0.044***	0.017
	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
$\log(nights)_{t-6}$	0.065***	0.003	0.007	-0.041***	0.027**	-0.017	0.039***	0.003
	(0.013)	(0.014)	(0.014)	(0.014)	(0.011)	(0.012)	(0.011)	(0.011)
$\log(lcp)$	-0.007	-7.26×10^{-5}	-0.026	-0.168	-0.012	-0.144*	-0.024	0.003
	(0.073)	(0.066)	(0.072)	(0.152)	(0.025)	(0.085)	(0.024)	(0.026)
$\log(lcp_{t-1})$	0.080	0.087	0.056	0.065	0.027	0.038	0.026	0.030
	(0.122)	(0.109)	(0.112)	(0.106)	(0.043)	(0.044)	(0.049)	(0.044)
$\log(lcp_{t-2})$	-0.109	-0.099	-0.013	-0.009	0.022	0.027	0.032	0.030
	(0.143)	(0.128)	(0.126)	(0.127)	(0.092)	(0.088)	(0.093)	(0.091)
$\log(lcp_{t-3})$	-0.053	-0.041	-0.012	0.0004	-0.094	-0.079	-0.092	-0.088
	(0.142)	(0.117)	(0.112)	(0.105)	(0.092)	(0.085)	(0.091)	(0.087)
$\log(lcp_{t-4})$	0.054	0.060	0.040	0.042	0.074	0.070	0.072	0.069
	(0.104)	(0.095)	(0.089)	(0.093)	(0.080)	(0.076)	(0.076)	(0.076)
$\log(lcp_{t-5})$	-0.094	-0.116	-0.138*	-0.131	-0.076	-0.069	-0.068	-0.070
	(0.099)	(0.089)	(0.077)	(0.080)	(0.063)	(0.064)	(0.060)	(0.063)
$\log(lcp_{t-6})$	0.032	0.054	0.043	0.041	0.013	0.008	0.011	-0.018
	(0.070)	(0.069)	(0.057)	(0.072)	(0.056)	(0.084)	(0.055)	(0.064)
$\tilde{T}$	0.019*	0.006	0.0007	0.0007	-0.0005	-0.002	0.0001	-0.002
	(0.011)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\tilde{T}_{t-1}$	0.020*	0.007	0.012***	0.009**	0.009**	0.004	0.007**	0.005
	(0.011)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
$\tilde{T}_{t-2}$	0.021**	0.008	-0.001	-0.002	-0.003	-0.005	-0.003	-0.005
	(0.010)	(0.009)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
$\tilde{T}_{t-3}$	0.002	-0.013	-0.003	-0.001	-0.004	-0.004	-0.002	-0.004
	(0.013)	(0.009)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\tilde{T}_{t-4}$	0.035***	0.020**	0.008**	0.008**	0.006	0.004	0.006	0.004
	(0.013)	(0.009)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
$\tilde{T}_{t-5}$	0.018	0.002	0.0006	-0.0003	-0.001	-0.004	-0.002	-0.004
	(0.014)	(0.009)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
$\tilde{T}_{t-6}$	0.023*	-0.001	-0.008**	-0.008**	-0.010**	-0.011***	-0.007*	-0.010**
	(0.012)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\tilde{P}$	-0.193	0.104	0.0006	0.049	0.049	0.116	0.051	0.087
	(0.320)	(0.200)	(0.138)	(0.121)	(0.139)	(0.107)	(0.122)	(0.114)
$\tilde{P}_{t-1}$	0.426	0.780***	0.088	0.078	0.120	0.121	0.026	0.069
	(0.258)	(0.189)	(0.100)	(0.074)	(0.116)	(0.083)	(0.083)	(0.081)
$\tilde{P}_{t-2}$	0.209	0.563***	0.140	-0.052	0.178	-0.015	-0.108	-0.062
	(0.268)	(0.142)	(0.127)	(0.105)	(0.133)	(0.107)	(0.112)	(0.108)
$\tilde{P}_{t-3}$	-0.649**	-0.245	0.052	0.065	0.077	0.081	0.054	0.064
	(0.283)	(0.198)	(0.114)	(0.106)	(0.120)	(0.098)	(0.102)	(0.095)
$\tilde{P}_{t-4}$	-1.30***	-0.877***	-0.169	-0.007	-0.172	0.0009	-0.005	0.0003
	(0.356)	(0.230)	(0.142)	(0.104)	(0.150)	(0.113)	(0.109)	(0.106)
$\tilde{P}_{t-5}$	-1.88***	-1.59***	-0.139	-0.029	-0.159	-0.058	-0.045	-0.057
	(0.320)	(0.211)	(0.121)	(0.092)	(0.129)	(0.089)	(0.094)	(0.088)
$\tilde{P}_{t-6}$	-0.899***	-0.803***	0.064	0.023	0.067	0.005	0.028	0.008
	(0.250)	(0.192)	(0.120)	(0.084)	(0.125)	(0.096)	(0.084)	(0.082)
σ_T	0.033	0.025	-9.34×10^{-5}	-0.012*	0.002	-0.007	-0.012*	-0.008
	(0.022)	(0.016)	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)	(0.006)
$\sigma_{T,t-1}$	0.031	0.022	-0.013	-0.018***	-0.012	-0.013*	-0.018***	-0.014**
	(0.022)	(0.016)	(0.008)	(0.006)	(0.009)	(0.007)	(0.007)	(0.007)
$\sigma_{T,t-2}$	-0.003	-0.006	-0.003	-0.005	-0.003	0.0006	-0.005	-0.0009
	(0.021)	(0.015)	(0.008)	(0.006)	(0.009)	(0.007)	(0.007)	(0.006)
$\sigma_{T,t-3}$	0.002	0.008	-0.006	-0.007	-0.004	0.0009	-0.007	-0.002
	(0.021)	(0.016)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)
$\sigma_{T,t-4}$	-0.024	-0.011	-0.030***	-0.025***	-0.028***	-0.017**	-0.022**	-0.018**
	(0.020)	(0.015)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
$\sigma_{T,t-5}$	-0.053**	-0.041**	-0.034***	-0.021**	-0.034***	-0.012	-0.016*	-0.012
	(0.021)	(0.016)	(0.011)	(0.008)	(0.010)	(0.008)	(0.009)	(0.008)
$\sigma_{T,t-6}$	-0.069***	-0.058***	-0.036***	-0.019**	-0.034***	-0.010	-0.013	-0.010
	(0.021)	(0.016)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
σ_P	0.003	0.006	0.008	0.005	0.004	-0.002	0.002	-0.0002
	(0.015)	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
$\sigma_{P,t-1}$	-0.045***	-0.045***	-0.011	-0.009*	-0.016*	-0.016***	-0.010**	-0.013***
	(0.015)	(0.010)	(0.007)	(0.005)	(0.008)	(0.005)	(0.005)	(0.005)
$\sigma_{P,t-2}$	-0.034***	-0.041***	-0.010	0.004	-0.016**	-0.004	0.004	0.0002
	(0.013)	(0.010)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)	(0.006)

$\sigma_{P,t-3}$	0.026*	0.013	-0.002	-0.002	-0.006	-0.008	-0.003	-0.005
	(0.014)	(0.011)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
$\sigma_{P,t-4}$	0.062***	0.044***	0.015**	0.005	0.012	-0.0004	0.004	0.002
	(0.015)	(0.011)	(0.007)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)
$\sigma_{P,t-5}$	0.108***	0.092***	0.012*	0.005	0.010	0.0009	0.006	0.004
	(0.017)	(0.011)	(0.007)	(0.005)	(0.008)	(0.006)	(0.006)	(0.006)
$\sigma_{P,t-6}$	0.047***	0.042***	-0.002	0.002	-0.005	-0.003	0.001	-0.0002
	(0.015)	(0.010)	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)
ω	0.003	-0.001	-0.001	-0.002	-0.002	-0.002	-0.001	-0.002
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ω_{t-1}	-0.002	-0.007***	-0.001	-0.0008	-0.001	-0.0010	-2.29×10^{-5}	-0.0006
	(0.003)	(0.002)	(0.001)	(0.0009)	(0.001)	(0.001)	(0.0010)	(0.0010)
ω_{t-2}	0.001	-0.003	-0.001	6.18×10^{-5}	-0.001	0.0002	0.0009	0.0004
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ω_{t-3}	0.006*	0.002	-0.0007	-0.001	-0.0009	-0.001	-0.0009	-0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ω_{t-4}	0.013***	0.008***	0.0003	-0.001	0.0003	-0.001	-0.001	-0.002
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ω_{t-5}	0.014***	0.012***	0.002*	0.0009	0.003**	0.001	0.0009	0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ω_{t-6}	0.008**	0.008***	-0.001	-0.0010	-0.0007	-0.0005	-0.0008	-0.0007
	(0.003)	(0.002)	(0.001)	(0.0009)	(0.001)	(0.001)	(0.0010)	(0.0010)
Fixed-effects								
country-NUTSII	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year		Yes	Yes	Yes			Yes	Yes
month			Yes					
NUTSII-month				Yes		Yes	Yes	Yes
country-year				Yes		Yes		
NUTSII-year					Yes	Yes		
country-month					Yes	Yes	Yes	Yes
NUTSII								Yes
country								Yes
Varying Slopes								
t (NUTSII)								Yes
t (country)								Yes
Fit statistics								
Observations	38,250	38,250	38,250	38,250	38,250	38,250	38,250	38,250
R^2	0.93514	0.93948	0.94137	0.94674	0.95303	0.95790	0.95471	0.95638
Within R^2	0.58241	0.47407	0.17725	0.09558	0.18321	0.06839	0.19014	0.10248

Clustered (country-NUTSII & time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*