Is visitors' expenditure at destination influenced by weather conditions?

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Abstract:

Weather has been shown to affect consumption patterns by altering people's moods. This paper examines the impact of atmospheric conditions on destination expenditure considering cruise passengers' onshore expenditure as the case study. We exploit quasi-random variation in a set of hourly real-time weather indicators in a port of call, through the Tourism Climate Index (TCI) and the Physiologically Equivalent Temperature (PET), to draw inference about their effect on destination expenditure. Therefore, we capture the specific atmospheric conditions encountered by tourists, alleviating the usual aggregation bias in related studies. In particular, information about mean and maximum air temperature, wind speed, rainfall, sunshine duration and mean and minimum relative humidity is considered. We estimate a heteroskedastic Tobit model with an inverse hyperbolic sine transformation of the dependent variable that deals with problems of non-normality and extreme values. Controlling for several sociodemographic characteristics and cruise size, we find consistent evidence that pleasant weather (either using TCI or PET indexes) increases onshore expenditure. Our findings have important implications for destination management.

Keywords: weather conditions; tourism climate index; psychologically equivalent temperature; onshore expenditure; Tobit.

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1. INTRODUCTION

Weather conditions influence human behaviour and consumption patterns in different ways. Several studies in marketing, psychology and economics have shown that weather affects movie ticket purchase (Buchheim and Kolaska, 2017), retail sales (Sandqvist and Siliverstovs, 2021), car purchases (Busse et al., 2015), museum attendance (Cellini and Cuccia, 2015) and mobile promotion effectiveness (Li et al., 2017), to cite some. Using both experimental and field data, Murray et al. (2010) study the psychological causal mechanism that underlies this phenomenon and shows that bad weather conditions damage individuals' mood (affective state), which translates into lower consumer spending and willingness to pay. These findings, coupled with other works in psychology (Hsiang et al., 2013; Simonsohn, 2006), suggest that factors like sunshine, rainfall or temperature affect people's moods and their subsequent purchasing behaviours.

A large body of literature has shown that atmospheric conditions play a non-negligible role in tourism demand through different channels: (i) it is a travel motivator that affects tourism participation (Amelung et al., 2007; Boto-García, 2022); and (ii) it is a destination pull factor that determines destination choice (e.g., Bujosa and Rosselló, 2013) and the number of overnight stays (e.g., Muñoz et al., 2021). These decisions are typically made in advance, so individuals are supposed to consider the expected weather conditions for a given destination when making their ex-ante travelling decisions. This is the reason why most of the literature focuses on climate; that is, prevailing atmospheric conditions measured as a long-term average. However, once at the destination, tourists' behaviour and the type of activities to engage in will be conditioned by *actual* weather conditions (Becken and Wilson, 2013; Gómez-Martín, 2005; Matzarakis, 2006). In this regard, on-site unplanned tourism decisions like buying a souvenir or drinking a coffee at a bar are the most likely to be affected by the potential mood effects caused by weather variations because of their spontaneous *on-the-way* nature.

This paper investigates the effect of real-time weather conditions measured through two distinct weather indexes on tourists' expenditure at destination. Specifically, we analyse cruise passengers' onshore expenditure during different stopovers at the city of Gijón (Spain). Whereas tourists with long stays at a destination (several days) can postpone activities if faced with temporary unpleasant weather, the limited stay of cruise passengers at the port of call (some hours) makes their onshore expenditure to be heavily sensitive to the atmospheric conditions encountered when they land. As such, real-time weather is hypothesised to be a key factor for explaining their onshore expenditure, and, in turn, the contribution of cruise tourism to the local economy.

Since onshore expenditure for some cruise passengers is zero, we estimate a Tobit regression model with an inverse hyperbolic sine transformation (Brown et al., 2015) that deals with problems of non-normality. The censored least absolute deviation estimator (Powell, 1984) is also implemented as a robustness check. Controlling for cruise size and individuals' sociodemographic characteristics, we exploit quasi-random variation in a set of hourly weather conditions (mean and maximum air temperature, wind speed, rainfall, sunshine duration and mean and minimum relative humidity) to ascertain if weather *really matters* for explaining tourism expenditure. In particular, we implement the two well-known Tourism Climate Index (TCI) and Psychologically Equivalent Temperature index (PET) developed by Mieczkowski (1985) and Matzarakis (2006).

To date, the literature on the effect of weather on tourists' expenditure is rather limited. Wilkins et al. (2018) and Lam-González et al. (2019) are among the few works that analyse how weather affects on-site expenditure. These authors agree to conclude that weather hardly impacts tourist expenditure at a destination but indicate there is a need for additional research. The present study aims to fill this gap by providing new evidence on how on-site weather conditions influence expenditure net of other confounding factors.

One archetypical problem of existing studies is the time aggregation of the weather information, which might average out the existing effects. Due to data availability limitations, most scholars rely on meteorological annual or monthly averages that cannot account for weather variations within periods. Even those who use daily data face the problem that a day might start out rainy and end up with brilliant sunshine. This sort of measurement error that ignores within-period variability might be quantitatively important. We, instead, use real-time hourly information of a set of weather indicators that directly match the weather conditions encountered by cruise passengers during their stopover. As a result, we provide finer estimates of the role of weather on tourist expenditure than previous attempts.

Our study has important implications for destination management. Although some studies show the direct contribution of cruise tourism to local economies is limited (Brida et al., 2015; 2018; Larsen et al., 2013), it constitutes a valuable opportunity for cities with a port of call to capture new visitors in the future because pleasant onshore visits translate into greater revisit intentions, positive word-of-mouth and improved destination image (Sanz-Blas and Carvajal-Trujillo, 2014; Ozturk and Gogtas, 2016; Sanz-Blas et al., 2019). Stakeholders at ports of call cities have been shown to positively value cruise traffic and advocate for promoting this sector (Castillo-Manzano et al., 2015) due to the monetary and non-monetary effects they generate to port communities (Chen et al., 2019). Therefore, our study further enhances the literature on cruise passenger expenditure (Douglas and Douglas, 2004; Brida et al., 2012, 2014, 2015; Baños and Tovar, 2019, 2021; Domènech and Gutiérrez, 2020; Casado-Díaz et al., 2021) by illustrating for the first time the impact of weather.

2. LITERATURE REVIEW

Weather has been conceptualized as an intangible asset for tourist destinations because it influences ex-ante destination selection (Bujosa and Rosselló, 2013) and ex-post satisfaction (Vojtko et al., 2022). In this vein, tourists' overall valuation of a tourist destination is determined by the weather conditions encountered during the stay (Stumpf et al., 2021).

Outdoor activities like visiting natural parks (Hewer et al., 2016), practising winter sports (Falk and Lin, 2018) or coastal tourism (Bujosa and Rosselló, 2013) are the most vulnerable to destination weather conditions. Broadly speaking, all forms of recreation and tourism-related activities associated with walkability in both natural environments and urban settings are strongly dependent on atmospheric conditions (Hall and Ram, 2021). A large body of research has empirically analysed the impact of weather on tourism demand and travel behaviour. In this review, we only focus on studies that examine the role of atmospheric conditions at any given time or place rather than the potential effects of climate change.

Several studies have evaluated how weather conditions affect visitation demand and the practice of outdoor activities. For the case of a well-known Nature Park in Northern Spain, Rasilla-Álvarez and Crespo-Barquín (2021) show that zoo visitation in winter is directly related to the frequency of dry, warm, calm and cloudless days; in the summer, attendance is found to be less sensitive to weather. Using data for two regions in New Zealand, Becken (2013) documents that visitor nights and scenic flights are positively associated with temperature and sunshine hours but unrelated to rainfall. This author discusses that the lack of a relationship between visitor nights and rainfall could be due to the use of monthly data, which could be too coarse as it ignores the daily variation. Furthermore, visits to a visitor centre are found to be sensitive to humidity and wind speed but not to temperature and rainfall. Relatedly, Becken and Wilson (2013) report that a non-negligible share of summer visitors to New Zealand change their travel plans when the weather is not as expected, and this translates into lower satisfaction. Similar results are presented in Hewer et al. (2017) for the case of campers in Ontario parks. Based on survey data, these authors find that engagement in sports activities is largely determined by ideal weather conditions, with weather preferences varying across seasons. Helbich et al. (2014) also document that temperature, wind speed and precipitation are key factors for explaining cycling trips for leisure purposes.

Caldeira and Kastenholz (2018) investigate the potential impact of climate change on tourists' time-space activity based on a post-visit survey of tourists visiting Lisbon in the summer period. They find that maximum air temperature negatively affects overall satisfaction while adverse meteorological conditions inhibit the performance of tourist activities. Jeuring (2017) evaluates how perceived personal significance of weather (i.e., sensitivity to weather conditions) determines satisfaction and domestic travelling engagement. This author presents evidence that weather salience is associated with a better attitude towards domestic travelling and with higher satisfaction. McKercher et al. (2015) examine if actual weather and perceptions about its comfort influence tourist movements in an urban destination. They show that neither actual nor perceived weather affect behaviour. However, they find evidence that weather influences their satisfaction. Tang et al. (2021) develop a theoretical framework to characterize how weather conditions affect tourists' decision-making process. They show that once at the destination, humidity, cloud cover and extreme weather affect tourists' decisions, particularly among females and young cohorts. More recently, Wang et al. (2021) model the effects of air quality and temperature on tourists' sentiments towards the destination, documenting an inverted U-shaped relationship between temperature on tourists' emotional experience.

To the best of our knowledge, there are only two studies that examine how weather conditions impact tourist expenditure at the micro level. Wilkins et al. (2018) investigate whether tourism-related spending at restaurants, lodgings and retail stores for ten years in three locations in Maine (U.S.) have been affected by weather. These authors consider several monthly measures of temperature and rainfall, finding that temperature is the most influential predictor of spending. In contrast, rainfall and snow depth are not significant. One important limitation of this study is that the use of monthly averages ignores the within-month variability in weather conditions. Indeed, the authors note that future studies might consider using weather variables on a daily scale to better understand how small fluctuations influence tourists' behaviour.

Lam-González et al. (2019) study how tourists' self-reported climatic sensations influence their demand for nautical activities and expenditure decisions during the visit. They show that satisfaction with weather conditions (perceived comfort) is the main determinant of the number of nautical activities consumed while expenditure is not directly affected by weather conditions. The main drawback of their approach is that they evaluate tourist satisfaction with atmospheric conditions rated on a Likert scale, which is subject to several problems of interpersonal comparability and likely to be affected by unobservable factors not directly related to the experienced weather.

Overall, this literature documents that weather exerts non-negligible effects on tourists' behaviour at destination, particularly on unplanned activities. The causal mechanism that underlies this pattern can be found in the work by Murray et al. (2010). These authors show that unpleasant weather conditions negatively affect people's moods (affective state), and this psychological mechanism is likely to explain why bad weather causes lower engagement into tourist activities and willingness to consume. As such, we hypothesize that unpleasant weather conditions translate into lower destination expenditure, *ceteris paribus.*

3. DATA

3.1. Cruise tourism as the case study

Ideally, in a quasi-experimental setting, we would like to observe the expenditure patterns of tourists with similar characteristics treated with distinct weather conditions to draw inference. Using observational data, the analysis of the impact of weather conditions on expenditure patterns considering the general population of tourists is problematic for at least two reasons. First, tourists who stay for several days at a destination can easily postpone their plans if faced with temporary unpleasant weather conditions. This is because, usually, they have the opportunity (time) to adapt their plans to circumstances, so that the impact of weather conditions is conflated with an intertemporal activity allocation change within the stay. Second, the general population of tourists typically exhibits large heterogeneity in trip motivations and unobservable characteristics.

Cruise tourists that stop for several hours at a port of call overcome these identification problems and are therefore an ideal tourist segment for testing the impact of weather on destination expenditure. On the one hand, their arrival at a destination is to some extent exogenous because it depends on when the cruise stops at the port. They have a limited time span to visit the city and therefore their onshore expenditure is heavily sensitive to the specific weather conditions encountered during that time. On the other hand, cruise tourists tend to be a homogeneous segment because they share similar travel motivations and personal characteristics (Jones, 2011). Therefore, by considering cruise tourists as the target population, we have several individuals with similar characteristics that are *treated* with plausibly exogenous weather conditions during a limited period during which we observe their expenditure patterns.

3.2. Data collection and descriptive statistics

The data used in this study come from a survey questionnaire developed by the authors. The target population were the cruise passengers who called at the Port of call of Gijón (Asturias, Spain) and disembarked during the period May-October 2013. This port of call represents an interesting case study for our research purpose because, contrary to other Spanish well-known ports of call like Valencia or those in the Canary Islands, Gijón is a Northern city with substantial weather variability within the same day and with large rainfall probabilities. [1] As a result, this port of call provides exogenous variation in weather circumstances that facilitates identification.

Table 1 presents a list of the cruise ships arriving at Gijón during 2013, indicating the specific date when they called at the port, the length of their stopover, their maximum capacity and the number of passengers. Although most cruise ships only stopped over the city once, *Seaborn Pride* and *Adventure of the Seas* did it twice. Table 1 also reports the total number of respondents for each cruise and the share they represent over total passengers. In total, 588 valid questionnaires were collected. This represents a maximum error of 3.76% at a 95% confidence level. Passengers were selected using simple random sampling in each stopover and the interviews were conducted on the dock while passengers reboarded after the visit. The sampling protocol mimics the procedures in Marksel et al. (2017) and Brida et al. (2012; 2013). As can be seen, there are notable differences in the share of passengers surveyed in each cruise ship, which likely reflects differences in the share of passengers that decided to disembark. Our sample is thus only representative of the cruise passengers that got off the ship, a choice decision that we cannot model and take as given.[2]

[1] Together with other ports located in the Atlantic arch, Gijón has become a popular port of call in the autumn season for routes that cover the North of Africa and for Northern European cruises. From 2006 onwards, the number of cruises calling at Gijón has seen a gradual increase, from 3 cruise ships and 1,391 passengers in 2006 to 11 cruise ships and 19,662 passengers in 2013 (Port Authority of Gijón, 2014).

[2] This is common assumption in related studies about cruise passengers' onshore expenditure, which only consider information about those who disembark (Henthorne, 2000; Marksel et al., 2017; Di Vaio et al., 2018; Baños and Tovar, 2019, 2021; Domènech and Gutiérrez, 2020; Casado-Díaz et al., 2021).

Cruise ship	Date	Stopover length	Max Capacity	Passengers	Sample size	% over passengers
Seabourn Soujourn	13/05/2013	8.00-18.00	780	428	20	4.67
Seabourn Pride	16/05/2013	8.00-18.00	368	207	34	16.42
Adventure of the Seas	27/05/2013	10.00-18.00	5,018	3,152	174	5.52
Silver Cloud	02/06/2013	8.00-18.00	504	252	55	21.82
Quest of Adventure	10/08/2013	7.00-18.00	702	202	49	24.25
Bremen	27/09/2013	8.00-19.00	264	117	12	10.25
Seabourn Pride	27/09/2013	8.00-19.00	368	195	20	10.25
Adventure of the Seas	01/10/2013	7.00-16.00	5,018	3,140	116	3.69
Infinity	27/10/2013	8.30-16.00	3,045	2,067	108	5.22
TOTAL				9,760	588	6.02

Table 1. Cruise ships arriving at the Port of Gijón in 2013 and sample sizes
Source: Own elaboration using data from Gijón Authority Port Annual Reports

The questionnaire was available in German, English and Spanish, and comprised a total of fifteen questions, lasting around ten minutes.[3] Respondents were asked the total *individual* expenditure made in the city during the stopover (in €). Because the survey is taken immediately after the visit, recall bias is minimized (Maksel et al., 2017). The composition of the travel party, the type of cruise company and standard sociodemographic characteristics like gender, age, income and nationality were also collected.

Table 2 presents descriptive statistics of the variables collected in the survey. The sample is mainly composed of middle-aged and elderly people; the average age is almost 61 years old, with around 42% between 46 and 65 years old and 43% over 65. About 52% are females, being the average number of people in the travel group three people.[4] Regarding income, 48% earn between €2,000 and €4,000 per month, with 35% gaining more than €4,000. Concerning nationality, most respondents are British (54%). Approximately 29% are North American, 6% are German and 7% are from other European countries (Austria, Ukraine, Belgium, Ireland, Italy or Switzerland). The remaining 10% are from Asia (Philippines, India or Indonesia), Africa (South Africa), Australia and Latin America (Jamaica or Honduras).

[3] Similar to related studies (Di Vaio et al., 2018; Casado-Díaz et al., 2021), the survey was pre-tested in a pilot study conducted on the 29th April in which cruise passengers from *Delphin* cruise ship were interviewed. The aim was to detect inconsistencies or the appropriate length that contributed to improve the wording of the final questionnaire. The data collected in this pre-test is not used in the analysis.
[4] Most respondents travel in couples (61%). Nonetheless, 19% of the sample travel in groups of four or more members. The distribution of the travel party variable is presented in Figure A1 in Supplementary Material.

Variable	Definition	Mean/ %	SD	Min	Max
Expenditure	Total expenditure per person at the city (€)	32.69	57.67	0	900
Female	=1 if female	51.53			
Age	Age in years	60.9	13.38	19	90
Low income	=1 if monthly income below €2,000	16.83			
Middle income	=1 if monthly income between €2,000-€4,000	47.78			
High income	=1 if monthly income over €4,000	35.37			
Travel party	Number of people in travel group	3.09	2.35	1	21
North American	=1 if North American (USA and Canada)	29.42			
British	=1 if British	54.59			
German	=1 if German	5.95			
Other European	=1 if Other European country	7.08			
Other nationality	=1 if Asian, African, Latin American or Australian	2.93			
Small-med ship	=1 if ship accommodates less than 2,000 passengers	32.31			
Large ship	=1 if ship accommodates between 2,000 and 3,500 passengers	18.36			
Super-sized ship	=1 if ship accommodates more than 3,500 passengers	49.35			
Stopover length	Hours the cruise stopped at Gijón	8.88	1.19	7.5	11

Table 2. Variable definition and descriptive statistics

Cruise passengers spent on average €32.7, ranging from zero (17.7% of the sample) to €900.[5] This money is mainly allocated to guided tours, generic purchases (food, clothes, souvenirs), restaurants/bars and transportation (bus, taxi). The share of zero expenditure is similar to Doménech and Gutiérrez (2020) using data for the port of Tarragona (15%) but lower than the figures reported in Brida et al. (2018) for the case of Uruguay (27%). Figure 1 presents a histogram of the expenditure variable. As can be seen, expenditure per person is rather low, in line with other studies collecting expenditure per person (Brida et al., 2018).[6] As discussed in Larssen et al. (2013), cruise tourists tend to spend less than other types of tourists, partially due to their reduced stay. Since the distribution is highly right-skewed, Figure 2 reports a histogram for those who spent less than €100.

[5] While 17.7€ of the sample declare not to have spent any money during the stopover, the share of cruise passengers that spent less than €2, €5 and €10 is 21.6%, 31.3% and 39.8€, respectively.

[6] Enumerators conducting the surveys were instructed about the importance of colleting individual expenditure. In this way, we make the expenditure variable directly comparable across cruise tourists travelling in travel groups of different sizes.

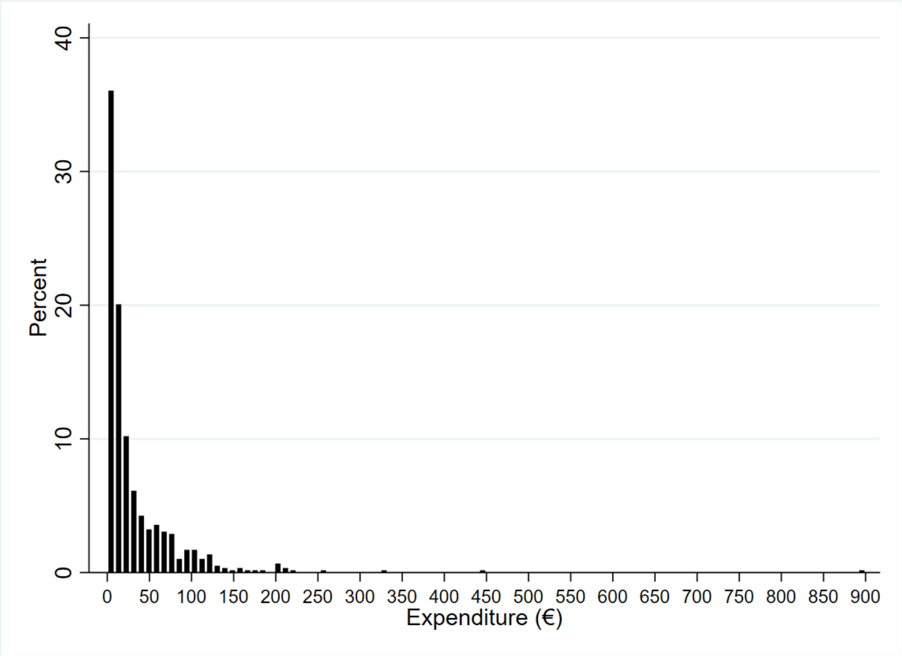

Figure 1.- Histogram of expenditure

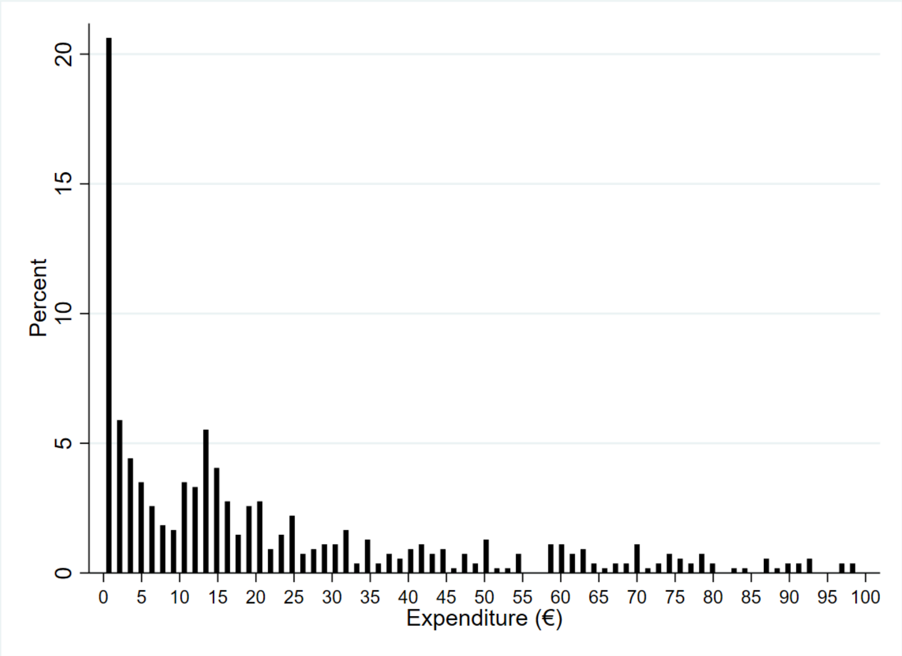

Figure 2.- Histogram of expenditure, restricted to values below €100

As regards the type of cruise ship, we group them into three categories: 'small-medium' (less than 2,000 passengers), 'large' (between 2,000 and 3,500 passengers) and 'super-sized' (more than 3,500 passengers). Approximately 49% of the sample travels in super-sized cruise ships, 19% do it in large ships and the remaining 32% come in a small-medium ship. This distinction follows Weaver (2005) and Di Vaio et al. (2018), who indicate that cruise capacity matters for explaining cruise passengers' behaviour.[7]

3.3.Weather data

Air temperature stands as the most relevant factor for the climatic comfort perceived by individuals (Matzarakis, 2006). Nevertheless, some studies have shown that other factors like humidity, cloud coverage, wind speed and rainfall cannot be neglected (Ridderstaat et al., 2014; Wang et al., 2021). Since using temperature alone might provide an incomplete picture of weather conditions and most meteorological variables are highly correlated (Auffhammer et al., 2013), the literature has typically relied on weather indexes. Possibly the Tourism Climatic Index (TCI) developed by Mieczkoswski (1985) is the most popular, having been used in several studies concerned about the effect of climate on tourism demand (Amelung et al., 2007; Perch-Nielsen et al. 2010). The TCI uses a combination of five subindexes as follows:

$$TCI = 8 * CID + 2 * CIA + 4 * R + 4 * S + 2 * W \quad (1)$$

where *CID* is the daytime comfort index, constructed based on the mean maximum air temperature and the mean minimum relative humidity; *CIA* is the daily comfort index, calculated as the mean air temperature and the mean relative humidity; *R* denotes the rainfall (mm); *S* stands for the daily sunshine duration (in hours) and *W* indicates the mean wind speed (in metres per second). Each factor can reach a maximum of 5 points, being the maximum value of TCI equal to 100. In general, when TCI is above 80, it indicates that the weather conditions are 'very good'; values between 60 and 79 are considered as 'good' to 'very good'; values between 40 and 59 are deemed as 'acceptable'; finally, when TCI is lower than 40 it means weather conditions are 'bad' or 'uncomfortable'.

The TCI has some weaknesses. The weights of the different facets are based on biometeorological literature and expert opinion but are, to some extent, arbitrary. Most importantly, the TCI is typically constructed on a monthly frequency; however, some scholars indicate that monthly averages might not be appropriate for modelling tourism decisions (de Freitas et al., 2008). Perch-Nielsen et al. (2010) propose to adjust the TCI to a daily scale. We follow their approach and construct it on a daily basis.

As discussed in Matzarakis (2006), another weakness of the TCI is that it does not include the effects of short- and long-wave radiation fluxes; that is, it does not consider human thermal sensitivity or thermal stress caused to individuals. Since consumers' affective state appears to be the channel by which weather affects consumption patterns (Murray et al., 2010), we need an indicator that captures how weather alters humans physiologically. The Physiologically

[7] As opposed to small-medium ships, large and super-sized ships can be understood as 'vacation destinations' themselves. Since they offer many different services and leisure opportunities, cruise passengers could be motivated to spend more money and time on board than at stopover destinations.

Equivalent Temperature (PET) index (Matzarakis and Mayer, 1997) expands the TCI index by considering the effect of the thermal environment on humans (i.e., the human energy balance for the assessment of the thermal ambient conditions). This index is computed using the same atmospheric input variables as the TCI and is measured in degrees Celsius (ºC). Assuming internal heat production equals 80 W and heat transfer resistance of clothing is 0.9 clo, PET values between 18ºC-23ºC are deemed 'comfortable' (no thermal stress). A PET index between 23ºC-35ºC is labelled as 'warm' (slight to moderate thermal stress) while values over 35ºC are considered as 'hot' or 'very hot' (strong to extreme heat stress). In contrast, PET values between 4ºC-º18ºC are considered 'cold' (strong to slight cold stress) whereas values lower than 4ºC are taken as 'very cold' (extreme cold stress). The reader is referred to Matzarakis and Mayer (1997) and Matzarakis et al. (1999) for further details.

We collected hourly data for a wide set of meteorological variables for the specific days and periods during which the cruise ships stopped at Gijón. Specifically, the following weather variables were drawn from the Spanish State Meteorology Agency (AEMET): mean and maximum air temperature, mean and minimum relative humidity, rainfall, sunshine duration, wind speed and cloud cover. With this information, we constructed daily TCI and PET weather indexes. Since the computation of the PET index is not straightforward, it was calculated using RayMan 1.2 software package (https://www.urbanclimate.net/rayman/). By specifying the date and time span, geographic data position of Gijón (longitude, latitude and altitude) and the UTC zone, the software computes the corresponding values of vapour pressure (hPa), global radiation (W/m2) and mean radiation temperature (ºC) needed to calculate the PET.

Table 3 presents the values of the original weather variables used to construct the indexes for each day in the sample. Figure 3 plots the values of the TCI and PET weather indexes.[8] As shown, the profile of the two indexes is quite similar. Considering only the time span during which the ship stopped at the city, May, 16th was the most uncomfortable day in the sample (TCI=35; PET=8.8). The day with the best weather conditions was 10th August according to the TCI (TCI=94; PET=19.2) and 27th October based on PET (TCI=83; PET=19.3). Nonetheless, the differences between these two days are minimal. In the rest of the days, atmospheric conditions could be deemed as 'comfortable'.

[8] The specific values of the TCI (and its five subindexes) and PET indexes are shown in Table A1 in Supplementary Material.

Cruise ship	Date	Max. temp. (ºC)	Min. relative humidity (%)	Mean temp. (ºC)	Mean relative humidity (%)	Total rainfall (mm)	Sunshine duration (hours)	Wind speed (m/s)	TCI	PET
Seabourn Soujourn	13/05/2013	16.8	71	15.9	79	0	11.6	5.1	76	16.2
Seabourn Pride	16/05/2013	13.7	59	12.4	82	49	1.1	4.2	35	8.8
Adventure of the Seas	27/05/2013	15.4	76	14.6	85	0	4.1	5.4	59	12.5
Silver Cloud	02/06/2013	17.2	74	16.2	83	0	11.8	5.5	75	15.8
Quest for Adventure	10/08/2013	23.4	72	19.8	82	0	12.0	6.1	94	19.2
Bremen	27/09/2013	24.4	40	20.1	79	0	0.0	3.7	75	17.3
Seabourn Pride	27/09/2013	24.4	40	20.1	79	0	0.0	3.7	75	17.3
Adventure of the Seas	01/10/2013	21.1	81	20.6	88	16	3.1	3.0	77	18.1
Infinity	27/10/2013	23.6	39	20.33	67	0	4.2	2.9	83	19.3
Average		20.0	61.33	17.78	80.44	7.22	5.32	4.40	72.11	16.06

Table 3.- Summary statistics of weather variables per day

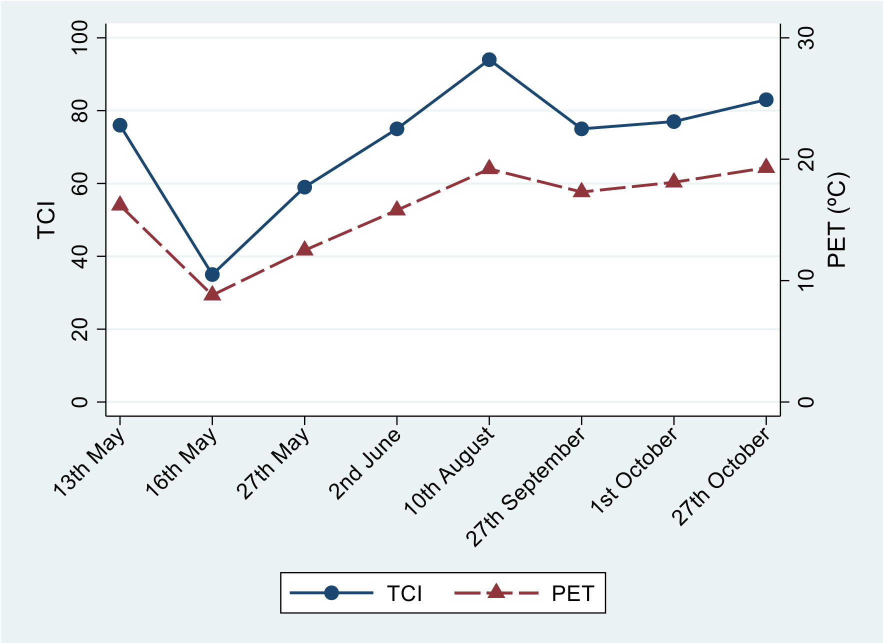

Figure 3.- TCI and PET weather indexes values in the sample

4. METHODOLOGY

4.1.Econometric modelling

We aim to understand the relationship between the weather indexes introduced before and the expenditure made by cruise passengers during their visit. The fact that a share of people exhibits zero expenditure (17.7% of the sample) requires some special modelling issues. Since the dependent variable is censored, the Tobit regression (Tobin, 1958) is the most appropriate approach. The model formulation is the following:

$$y_i^* = \alpha + \beta Weather_i + \theta X_i + \epsilon_i \qquad \text{for } i = 1, \dots, N \tag{2}$$

where y_i^* is a latent unobserved variable representing the expenditure that tourist would like to undertake, α is a constant term to be estimated, $Weather_i$ is the corresponding weather indicator that varies across individuals depending on the day and period they stayed onshore, β is the key parameter of interest, X_i is a set of control variables, θ is the associated vector of parameters to be estimated and ϵ_i is a normally distributed error term with zero mean and variance σ.

The observation mechanism relates the observed expenditure y_i to the model in (2) as follows:

$$\begin{cases} y_i = y_i^* & if \;\; y_i^* > 0 \\ y_i = 0 & if \;\; y_i^* \leq 0 \end{cases} \tag{3}$$

The parameter estimates of the non-linear Tobit model are inconsistent in the face of both non-normality and heteroskedasticity (Arabmazar and Schmidt, 1982). To alleviate the former, we employ the inverse hyperbolic sine transformation (IHS) to the dependent variable.[9] The IHS transformation of a variable y takes the following form:

$$I(y,\gamma) = \frac{1}{\gamma}\sinh^{-1}(\gamma y) = \frac{1}{\gamma}\log\left[\gamma y + (\gamma^2 y^2 + 1)^{0.5}\right] \quad (4)$$

where γ is a scalar parameter to be estimated.

The transformation becomes linear as γ approaches 0 and logarithmically as γ increases. Apart from rendering the estimation of the transformed variable robust to non-normality of the original error terms, the IHS transformation has the additional advantage that it deals with extreme values because of being smooth and continuous and applies to the entire real support (Brown et al., 2015).

Concerning potential heteroskedasticity, we parametrize the disturbance variance as follows:

$$\sigma_i{}^2 = exp(Z_i{}'\delta) \quad (5)$$

where Z_i is a set of individual characteristics and δ is the associated vector of parameters to be estimated. The exponential transformation ensures the variance is positive.

4.2.Model specification

As discussed before, we alternatively measure weather's comfort through TCI and PET indexes. It is important to highlight that weather conditions are exogenous to tourists' on-site expenditure decisions. In our setting, the existing atmospheric conditions at the time cruise passengers stop at the port of call are given. Therefore, the parameter β in equation (2) measures the causal impact of the real time weather conditions.

Concerning the control variables to include in the regression, we follow the vast empirical literature on cruise passengers' expenditure at ports of call and consider gender (Marksel et al., 2017; Di Vaio et al., 2018), age (Henthorne, 2000; Domènech and Gutiérrez, 2020; Baños and Tovar, 2021), income (Brida et al., 2012; Casado-Díaz et al., 2021), nationality (Brida et al., 2014; Baños and Tovar, 2019), the size of the travel party (Brida et al., 2015; Baños and Tovar, 2019), the length of the stopover (Brida et al., 2012; Casado-Díaz et al., 2021) and the cruise ship size (Di Vaio et al., 2018; Casado-Díaz et al., 2021). Given the relatively small sample size

[9] One typical transformation to make the data resemble the normal distribution is to take logs and make some scale adjustment to avoid undefined values when the dependent variable takes value zero. However, the choice of an arbitrary number for the reescalation has the risk that a 'zero' value in the log scale is not equivalent to the same value in the untransformed scale (Brown et al., 2015).

we work with and for the sake of parsimony, we specifically include: i) a dummy for being a female (*Female*), ii) age (in years), iii) a dummy for earning up to €2,000 per month (*Low income*), iv) the number of people in the travel group (*Travel party*), v) a dummy indicator for whether the cruise ship can accommodate between 2,000 and 3,500 passengers (*Large ship*), and vi) three dummies for whether the cruise passenger is from North America (*North American*), from a European country other than the United Kingdom and Germany (*Other European*) or from Asia, Latin America, Africa or Australia (*Other nationality*). German and British cruise passengers are therefore collapsed in the reference category.

The reasons for opting for this specific model specification are the following. First, in preliminary checks, we documented no expenditure differences between passengers with middle or high income. No differences were detected between British and German passengers. The same applies to tourists travelling in small-medium or super-sized ships (Table A3 in Supplementary Material). Therefore, we only control for expenditure differences between low-income earners and the rest, and travellers in large ships and the rest to save degrees of freedom.[10]

Regarding the variables that model variance heteroskedasticity, we select age in years (*Age*) and the length of the stopover (*Stopover length*).[11] This is because preliminary checks using *binscatter* non-parametric analysis (Cattaneo et al., 2021) suggest larger variability in expenditure levels across the elderly segment and among those who stayed for longer (see Figures A2 and A3 in Supplementary Material).

5. RESULTS

5.1.Findings

Table 4 presents the coefficient estimates and t-statistics of the Tobit regression model with the IHS transformation considering three distinct model specifications. In Model 1, we omit the weather variable and explain onshore expenditure by the sociodemographic and trip-related characteristics typically used in the literature. Models 2 and 3 expand this by including the TCI and the PET weather indexes, respectively. The regressions have been performed in LIMDEP software version 11.

We find that both weather indexes positively impact cruise passengers' onshore expenditure. This implies that atmospheric conditions at the destination affect onshore expenditure conditional on sociodemographic and cruise characteristics. As shown, tourist expenditure at a

[10] We also tested the inclusion of a squared term for *Age* and *Travel party* to allow for non-linear effects. None of the squared terms resulted statistically significant (available upon request), so we excluded them for the sake of parsimony.
[11] This variable is exogenous to passengers' expenditure decisions but tends to be associated with the number of passengers and the sailing distance from the previous port, among others (Chen and Nijkamp, 2018).

destination is positively affected by the weather encountered. Both the traditional atmospheric-based TCI index and the more recent comfort-based PET index agree to point out that marginal improvements in ambient comfort turn into greater expenditure. This result relates to the findings by Becken and Wilson (2013), Helbich et al. (2014), Hewer et al. (2017) and Wilkins et al. (2018) documenting that weather affects on-site destination tourism-related decisions. Furthermore, based on the AIC information criteria, the inclusion of either of the weather indexes improves model fit.

Concerning the rest of the variables, onshore expenditure does not significantly vary depending on gender, age or travelling in a group. In this sense, the literature is inconclusive about the role of age and travel party composition; authors like Baños and Tovar (2019) find that older tourists tend to spend more; others like Brida et al. (2015), Di Vaio et al. (2018) and Casado-Díaz et al. (2021) show the opposite pattern while Marksel et al. (2017) do not find a significant relationship. Similarly, whereas Brida et al. (2013; 2015), Baños and Tovar (2019, 2021) and Casado-Díaz et al. (2021) find that passengers in groups spend more, Parola et al. (2014) do not find such association.

Low-income travellers spend significant less, in line with Brida et al. (2012), Parola et al. (2014) and Baños and Tovar (2021). Interestingly, those in large ships spend significantly less than those in small/medium or supersized ones. This finding is quite puzzling but robust, since it remains under different model specifications. One possible explanation could be that small/medium ships are the most luxury ones while supersized ships have all type of amenities and services inside them so that large ships might be of comparatively less quality. In any case, since there is only one large cruise ship in our sample (*Infinity*), this negative effect might be capturing any ship-specific factor. Therefore, we refrain from interpreting this finding in terms of a cruise size effect. Finally, British and German passengers (reference category) appear to be the ones who spend the least, with those coming from North America, other European countries (although the coefficient estimate is only significant at 10% significance level) or the rest of the world spending significantly more money at the city. In this respect, expenditure differences by country of origin have been largely documented in previous studies (Brida et al., 2012; Marksel et al., 2017; Baños and Tovar, 2019; Casado-Díaz et al., 2021).

Importantly, we find that the variance of the error term significantly increases with age and the length of the stopover. That is, onshore expenditure becomes more extreme and volatile as the period the ship stopped at the city and passenger's age increases. This result indicates that, within large stopovers, each cruise passenger either spends nothing or spends a large amount at the destination. This likely reflects engagement into very different types of activities during long stops that result in very distinct expenditures (e.g., guided tour versus walking throughout the streets). Similarly, the variability in expenditure is found to be larger among elderly cruise passengers. This falls in line with some prior research that document age-specific effects affecting the unobserved error term when estimating expenditure functions (Wakabayashi and Hewings, 2007). Recall that in the Tobit context neglected heteroskedasticity results in inconsistent parameter estimates.

Dependent variable: Expenditure	Model 1		Model 2		Model 3	
Explanatory variables	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Constant	16.4107***	3.07	5.2071	1.11	5.9278	1.30
TCI			0.1915***	3.26		
PET					0.8373***	3.27
Female	-0.2491	-1.27	-0.3363	-0.28	-0.2821	-0.24
Age	0.0007	0.02	-0.0347	-0.73	-0.0416	-0.88
Low income	-3.2747*	-1.94	-3.3962**	-2.06	-3.4336**	-2.08
Travel party	-0.3296	-1.29	-0.1660	-0.68	-0.1230	-0.51
North American	6.0684***	3.69	6.6519***	4.14	6.6213***	4.15
Other European	4.8934*	1.66	4.9891*	1.79	4.8628*	1.74
Other nationality	12.4445***	2.60	12.1141***	2.61	12.0620***	2.66
Large ship	-16.3234***	-8.58	-19.5709***	-9.32	-20.2223***	-9.14
Variance equation						
Age	0.0077***	2.79	0.0081***	2.98	0.0081***	3.02
Stopover length	0.1798***	5.56	0.1719***	5.44	0.1715***	5.43
γ	0.0651***	7.23	0.0654***	7.24	0.0657***	7.23
Observations	588		588		588	
Uncensored	484		484		484	
Log-L	-2083.5		-2076.9		-2075.4	
AIC	4190.9		4180.1		4176.8	
AIC/N	7.127		7.109		7.103	

Table 4.- Coefficient estimates from Tobit regression with IHS transformation
Note. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

The estimated value of the parameter γ for the IHS transformation is positive and statistically different from zero. This means that both a naïve untransformed Tobit or an ad-hoc logarithmic transformation would be inappropriate. The IHS transformation decreases the asymmetry of the expenditure variable towards zero, thereby making regression residuals to compile with a normal distribution and producing consistent parameter estimates.

To gain a better intuition about the magnitude of the effects, Table 5 reports the marginal effects $\left(\frac{\partial E(y_i^*|X_i)}{\partial x_i}, \forall x_i \in X_i\right)$ for model specifications 2 and 3 in Table 4. As shown, they are quite similar. These marginal effects are interpreted as the average expenditure per person increase (in €) if there is a marginal change in the corresponding variable. For the case of dummy variables, it refers to the average expenditure difference with respect to the reference category. Starting with the TCI weather index, onshore expenditure per person increases by €1.6 per ten unit increase in the index. This implies that a change from a day with average weather conditions (TCI=71.4) to one with 'ideal' weather conditions (e.g., 10th August, TCI=94) would translate into a €3.61 increase in expenditure per person (ΔTCI*0.214=22.6*0.16=€3.61), which represents around 11% of mean expenditure. Similarly, onshore expenditure increases by €7.0 per ten unit increase in the PET index (degree Celsius). For instance, a shift from average weather conditions (PET=18.3ºC) to 'ideal' (e.g., 10th August, PET=21.9ºC) would rise average expenditure per person by €2.52 (ΔPET*0.70=3.6*0.70=€2.52).

Explanatory variables	**Model 2**	**Model 3**
TCI	0.1620***	
PET		0.7082***
Female	-0.2846	-0.2386
Age	-0.0294	-0.0352
Low income	-2.8736**	-2.9041**
Travel party	-0.1405	-0.1041
North American	5.6282***	5.6004***
Other European	4.2213*	4.1130*
Other nationality	10.2498***	10.2021***
Large ship	-16.5590***	-17.1041***

Table 5.- Marginal effects of the Tobit regression with IHS transformation
Note. *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

The estimates also indicate that low-income passengers spend around €2.9 less per person, on average. Those from Asia, Latin America, Australia or Africa are the ones who most spent onshore (around €10.2 more than British and German passengers) followed by North American passengers (€5.6 more). We also document that cruise passengers travelling in a large ship (*Infinity*) spend on average about €17 less than those coming in small/medium and supersized ships.

5.2. Robustness checks

We conducted a battery of robustness checks. First of all, as shown in Table 1, the share of respondents over total passengers varies across cruise ships. As mentioned before, our sample is representative of cruise passengers that decide to disembark and visit the city, a choice decision that we cannot model and take as given. However, if such decision is affected by the encountered weather conditions, we face the risk that our estimates of the weather effects on expenditure suffer from sample selection problems. To examine this, we have compared the share of surveys collected per cruise with the weather conditions to inspect whether there is a clear connection between the two. Figures A4 and A5 in Supplementary Material present scatterplots of the share of surveys on maximum and mean temperature, minimum and mean humidity, precipitation, sunshine duration and wind speed. As shown there, there is a weak association between the weather variables and the share of respondents surveyed per cruise. Therefore, the decision to disembark appears not to be driven by weather conditions. As such, the potential bias from sample selection is likely to be negligible.

Second, as discussed in subsection 3.3, the use of synthetic weather indexes has the problem that it imposes a specific functional form in which the different weather variables enter the index construction. As a check, we re-estimated the model by replacing the weather indexes with each of the underlying variables in separate regressions.[12] The estimation results are presented in Tables A4 and A5 in Supplementary Material. It appears that temperature is the weather indicator that mostly affects expenditure. Sunshine duration is only significant at 90% confidence level whereas rainfall, wind speed and humidity are not found to significantly affect onshore expenditure. This is consistent with Wilkins et al. (2018), who document that temperature is the most influential predictor of spending.

Third, even though the heteroskedastic Tobit regression with the IHS transformation deals with extreme values and is robust to non-normality in the error term, we re-estimated our model specification using the censored least absolute deviations (CLAD) proposed by Powell (1984). This estimator is also robust to departures from homoskedasticity and normality. The parameter estimates and bootstrapped confidence intervals are presented in Table A6 in Supplementary Material. The estimates are similar, pointing again at a positive and significant effect of weather conditions on onshore expenditure and therefore providing robustness to our findings.

Fourth, to examine potential non-linear effects in the influence of weather on expenditure, we split the range of the TCI and PET indexes into three intervals and re-estimate the model including dummy variables (Tables A7 and A8 in Supplementary Material). We document that, in line with Table 4, expenditure is significantly greater when weather conditions are very good or ideal as opposed to acceptable/cool. In other words, atmospheric conditions seem to exert a monotonically increasing effect on expenditure, at least in our case study.

Fifth, a recent study by Aihounton and Henningsen (2021) show that regression results from IHS-transformed variables are sensitive to the units of measurement. We re-estimated the model using total travel group expenditure as the dependent variable instead of expenditure per person. The results are shown in Table A9 in Supplementary material. We find the estimates are similar in sign and significance as compared to those in Table 4 with the exception that now age becomes statistically significant. Apart from this, our core findings are sustained, implying they are not sensitive to potential scaling issues.

Finally, we re-estimated the model separately for those travelling alone/in a couple (n=389) and those in groups of three people or more (n=199). The coefficient estimates and marginal effects are shown in Tables A10-A13 in Supplementary Material. The results for solo travellers and couples are similar to the main analysis, with the difference that age turns significant with negative sign for explaining mean expenditure but not its variance. Interestingly, weather is non-significant for explaining expenditure among people travelling in groups of more than 2

[12] As documented in the literature (e.g., Auffhammer et al., 2013), the weather variables are highly correlated (see Table A2 in Supplementary Material). This precludes their joint inclusion in the regression equation.

people. Accordingly, those in large groups seem to be insensitive to weather conditions when making their expenditure decisions.

6. CONCLUSIONS

6.1.Summary of findings

This paper examines the role played by weather conditions on cruise passengers' onshore expenditure at a port of call. Whereas many studies pay attention to the relationship between climate and tourism demand, we analyse the impact of real time on-site atmospheric conditions on tourists' unplanned behaviour. We take advantage that cruise stopovers are time limited and take place at a given date so that weather conditions are exogenous to them. Once arrived at the port of call, cruise passengers decide how much to spend in the city depending on their moods, which might be contingent on weather (Murray et al., 2010).

Using survey data from cruise passengers at a port of call in Northern Spain (Gijón), we construct daily PET and TCI weather indexes based on hourly data and estimate a heteroskedastic Tobit model. Following the cruise expenditure literature, we control for several sociodemographic characteristics. We find consistent evidence that atmospheric conditions impact onshore expenditure decisions, particularly in the case of solo travellers and couples (which represents around two thirds of the sample). A random cruise passenger that lands at a port of call in a day with 'ideal' rather than average atmospheric conditions would increase her expenditure by €3.6 according to TCI index and €2.5 based on the PET index, on average. These figures can be deemed as negligible; this is partially due to the low values of onshore expenditure per person in the sample. In this vein, several authors argue that the contribution of cruise passengers to the local economy is very reduced (Larsen et al., 2013; Brida et al., 2015). Nonetheless, suppose the case of a 2,000 passengers cruise ship in which 80% disembarks. This would imply around €5,760 loss in tourism revenues for the local economy per cruise ship. If, for instance, 12 cruise ships stop at the port of call during the season, that would represent around €70,000 loss for a small port of call like Gijón. Therefore, even small differences in expenditure per person attributed to weather can result in non-negligible drops in tourism revenues.

Similar to previous studies on cruise passengers' expenditure, we also find that i) money spent on land is unrelated to gender, age and the size of travel group but lower among low-income passengers, and ii) average expenditure varies significantly depending on the country of origin. Importantly, by modelling the variance of the error term, we document that older people and those who stay for longer at the port of call are more volatile in their expenditure decisions; they either choose to spend almost nothing or a large amount.

6.2. Contribution

Our work contributes to the literature on expenditure at tourism destinations in several ways. First, we expand existing evidence on the factors that explain onshore cruise passengers' expenditure by investigating the role of weather. To the best of our knowledge, Douglas and Douglas (2004) is the only study that succinctly commented on the potential differences in expenditure due to atmospheric conditions. Second, contrary to other studies concerned about the effect of weather on tourist decisions that consider monthly or daily averages for large geographical areas, we use hourly information at a specific city in different days. As such, the weather data used better mimics the specific conditions encountered by tourists and reduces aggregation bias. Furthermore, rather than limiting the analysis to average temperature or rainfall, we also consider mean and maximum air temperature, wind speed, sunshine duration and mean and minimum relative humidity. With this information, we construct two alternative daily weather indexes, which provide consistent results. Finally, from a methodological perspective, we apply the inverse hyperbolic sine transformation to the expenditure variable to deal with problems of non-normality. To tackle heteroskedasticity, we model the variance of the error term as a function of age and the length of the stopover, showing that elderly people and those who stay for longer at the port are more volatile in their expenditure patterns. Importantly, our results are robust to the use of alternative estimators like CLAD and different model specifications.

6.3. Implications for destination management

Our findings have important implications for destination managers aimed at promoting coastal destinations as ports of call. Specifically, our results provide novel evidence for business managers and long-term planners about how onshore expenditure is sensitive to weather conditions. Although the size effects are modest, we show that pleasant weather translates into higher expenditure through invoked positive mood effects on cruise passengers. As such, destination managers should pay particular attention to weather forecasts. Given the usual low magnitude of onshore expenditures detected in the literature (Doménech and Gutiérrez, 2020; Brida et al., 2018), expenditure shifts caused by weather cannot be ignored. Knowing that a cruise ship will land at the city on a specific day and for a specific period, destination managers and tour operators should organize specific guide tours, provide transportation facilities or offer alternative leisure activities depending on the expected weather. In this vein, additional effort needs to be devoted to eluding cruise passengers to go back to the cruise too early. Coastal destinations strive for becoming a port of call and in some cases make important investments at their ports to host large cruise ships. Therefore, some contingency planning is needed to guarantee a minimum return from cruise tourism when weather conditions are unpleasant.

6.4. Limitations and avenues for future research

This study has some limitations that should be acknowledged. First, our data is only representative of the population of cruise passengers that disembark. Although this choice does not appear to be driven by weather in our dataset, incoming research should devote more attention to the influence of weather on the share of passengers that disembark. In this regard, the decision to remain at the ship during the stopover and motivations to disembark have received little attention in the literature. Second, we lack information about how much money the cruise passenger has already spent on the trip, either in terms of cruise fares or previous stopovers. This is likely to affect subsequent expenditure at ports of call and could be a valuable avenue for future research. Third, although there is some variability in the weather conditions encountered by cruise passengers in our case study, future studies should expand our work by exploiting the occurrence of unexpected extreme weather events. Finally, the analysis is based on a cross-sectional dataset of cruise passengers visiting a single city. If possible, future studies should consider tracking the behaviour of the same cruise passenger during several cruise stops at different ports of call. This will allow to better control for individual-specific unobserved heterogeneity and to study the dynamics in expenditure patterns across cities visited within the same trip.

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