The Impact of COVID-19 on Tourists' Length of Stay and Daily Expenditures

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Abstract:

This study evaluates the effect of the COVID-19 pandemic on tourists' length of stay and daily expenditures at a destination. The paper compares detailed microdata for visitors to a Northern Spanish region in the summer periods of 2019 (pre-pandemic) and 2020 (after the pandemic outbreak). We estimate the pandemic-induced impacts on the length of stay and expenditures per person for several categories using regression adjustment, inverse probability weighting regression, and propensity score matching. We find clear evidence of a drop in the length of stay of around 1.26 nights, representing a 23.8% decline. We also show that, although total expenditures per person and day have remained constant, there has been a change in the allocations for categories in the tourism budget.

Keywords: *COVID-19, travel patterns, inverse probability weighting, propensity score matching*

Declaration of interest: NONE

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1. INTRODUCTION

The COVID-19 pandemic is a shock that has disrupted the global economy in general, and in particular, the tourism sector. Quarantines, travel bans, and risks of contagion have caused many people to cancel their travel plans (Ugur and Akbiyik, 2020) or changed their behaviour to adapt to the new circumstances (Li et al., 2020). There is an emerging body of research concerned with the impacts of the COVID-19 pandemic on various outcomes, including the decrease in travel and leisure industry returns caused by daily cases and deaths (Lee and Chen, 2020), the social costs imposed on local communities (Qiu et al., 2020), the drop in demand for air travel (Gallego and Font, 2020), the economic effects on tourist destinations (US. Travel Association, 2021), or the relationship between COVID-19 exposure and travel intentions (Boto-García and Leoni, 2021), among others. However, little is known yet about the pandemic-induced changes in tourists' length of stay (hereafter LOS) and daily expenditures per person at the destination.

Several scholars indicate that COVID-19 will change tourists' habits and preferences towards the practice of more outdoor activities that guarantee social distancing (Osti and Nava, 2020) and possibly more sustainable forms of tourism (Hall et al., 2020). Meanwhile the infection risk exists, some people might avoid travelling (Neuburger and Egger, 2021) or engage in local trips (Zenker and Kock, 2020). Those who will continue travelling are predicted to adapt to the new circumstances, cutting down the length of their stay to reduce contagion probabilities and reassigning their daily expenditure to distinct categories. In this regard, travel spending has sharply decreased worldwide (US Travel Association, 2021). This has not only translated into lower revenues for the tourism industry but it has also caused a large loss in tax revenues for destinations (US Travel Association, 2021). Since the economic contribution of the tourism sector to regional GDP depends on tourists' length of stay and expenditure (Faber and Gaubert, 2019), it is important to quantify the impact of COVID-19 on the intensity (daily expenditure) and extensity (LOS) components of tourism revenues. This analysis becomes particularly important for the post-COVID-19 recovery because social distancing requirements and sustainability goals might require destinations to have fewer tourists but with longer stays and greater daily expenditure. As discussed in Sigala (2020), understanding the pandemic-induced changes in travel patterns would help in the development of policy responses to resume the tourism industry. The identification of the reallocation of expenditures across different categories would also help destination management organizations and local enterprises to adapt their supply to tourists' preferences in the new context.

The objective of this research is to uncover the effects of COVID-19 on tourists' LOS and their daily expenditures per person *at the destination,* both in total and in several disaggregated categories. Specifically, we focus on expenditures for accommodation, transportation, food and beverages in bars and restaurants, and other items including cultural and outdoor activities. Ideally, we would like to observe the behaviour of a given tourist both *before* and *after* the outbreak of COVID-19 to evaluate the change. Unfortunately, this is not possible since longitudinal datasets for individual tourists at specific destinations are seldom available.

Longitudinal datasets usually involve following the same individual over time but on different trips, which precludes a formal analysis if the trip involves distinct destinations. An alternative method of analysis is to derive a counterfactual for the non-COVID-19 state based on tourism outcomes immediately before the pandemic began.

To properly identify the causal effects of COVID-19, we adopt the so-called one-group *pretest–posttest design* within the potential outcomes (counterfactual) framework (Rubin, 1974). The outbreak of the pandemic shares several characteristics of a natural experiment: it consists of an exogenous shock (intervention) but observations of the treatment group (post-pandemic outbreak, meaning after the initial spread of the disease) and the control group (pre-pandemic) are not randomly assigned. This is because the pandemic affects the likelihood of selection in the treatment (post-pandemic outbreak travelling decisions). To address these caveats, we make use of three different methodologies: regression adjustment (RA), inverse probability weighting regression (IPWR), and propensity score matching (PSM). These strategies rely on assumptions that we formally test. These methods were originally developed in medical sciences, and they have become widely used in the field of economics (Dehejia and Wahba, 2002; Ding and Lehrer, 2010; Huber, 2014) and recently in tourism research (e.g. Mora-Rivera et al., 2019). In this sense, our identification strategy is similar to that of Bimonte and D'Agostino (2020), who analyse the effects of tourism development on residents' attitudes based on a pre-season and peak-season design that matches individuals before and after an event, based on characteristics.

The study contributes to the tourism economics literature by quantifying the pandemic-induced changes in tourists' length of stay and daily expenditures at the destination. Previous studies of the effects of health crises on tourism mainly focus on the changes in the time evolution of aggregate outcomes at the country level using panel data (Kuo et al., 2008; Page et al., 2012) or time-series analysis (Mao et al., 2010; Choe et al., 2020). At the micro-level, research on travellers' behaviour following a disease outbreak tends to rely on surveys collected after the crisis to ascertain travel intentions (Lee et al., 2012) and adaptative behaviours (Kim and Lee, 2020). However, to the best of our knowledge, there are no empirical studies that formally quantify the changes in tourists' expenditures and length of stay caused by the outbreak of COVID-19 disease at the individual level. This is relevant because aggregates mask the micro-level sources of the changes in tourists' behaviour. Therefore, the study provides the first micro-level characterization of how the length of the stay and daily expenditures have changed because of COVID-19 disease.

The remainder of the paper is structured as follows. After this introductory section, Section 2 reviews the related literature. Next, Section 3 outlines the theoretical framework for the analysis. In Section 4 we present our case study, describe our dataset, and report some descriptive preliminary evidence on the changes in tourism patterns before and after the pandemic occurrence. Section 5 describes the methodology. In Section 6, we present and discuss the results. Finally, Section 7 summarizes the findings and provides some implications.

2. LITERATURE REVIEW

2.1. Effects of infectious disease on the tourism industry

In 2003, Asia experienced an outbreak of a SARS coronavirus epidemic similar to COVID-19, although with far fewer deaths (774) and infectious cases (8,096), according to the World Health Organization (hereafter WHO). A global alert issued by WHO asked governments to impose travel restrictions and urged individuals to avoid unnecessary trips. The fear of infection and quarantine measures led to a significant drop in international arrivals to the affected countries. Since then, other diseases like Ebola, swine flu, Middle East Respiratory Syndrome coronavirus (MERS), and influenza A (H1N1) have disrupted the tourism industry. A large body of literature examines the economic consequences of these diseases for the travel sector.

Kuo et al. (2008) investigate the impacts of both SARS and avian flu on tourist arrivals to Asian countries using time series and panel data analysis. They show that tourism demand in Asian countries was heavily damaged by SARS but not by the avian flu, and the effect is directly related to the number of infections in the country. Mao et al. (2010) study the recovery of tourist arrivals in Taiwan from Japan, Hong Kong, and the U.S. after SARS. They show that arrivals bounced back quickly to pre-SARS levels once the risks of SARS disappeared. Similarly, Tang and Wong (2009) show that the SARS crisis had only a transitory effect on international tourist arrivals to Cambodia.

Choe et al. (2020) quantify the economic impact of MERS on tourist arrivals in South Korea. They show that it led to a loss of 3.1 billion USD in receipts. Page et al. (2012) untangle the effects of the 2008 economic crisis and the swine flu on tourism in the United Kingdom from 14 countries using panel data analysis. Their results indicate that the swine flu alone was responsible for a decline of 1.6 million visitors in the second quarter of 2009. Preliminary evidence of the impact of COVID-19 on the Greek economy by Mariolis et al. (2020) shows a decrease in travel receipts in the range of 3.5 to 10.5 billion euros.

2.2. Tourists' response to health risks

Previous research in travel medicine and tourism shows that, when there is a risk of infectious disease, people either avoid travelling or adopt precautionary actions to minimise risk. The protection motivation theory (PMT) (Rogers, 1975) posits that, when confronted with threatening events such as environmental hazards or disasters, individuals change their behaviour to protect themselves; however, this depends on three factors: i) the severity of the risk, ii) the probability that the risk will affect them, and iii) the expected efficacy of the protective response.

Wang et al. (2019) apply PMT to understand tourists' coping strategies to mitigate health risks during travel. They report a low protective behaviour among those who are excessively optimistic and who avoid thinking about the consequences of the risk; this suggests that tourists' adaptative behaviour is heterogeneous. In this sense, Rittichainuwat and Chakraborty (2009) document that the perceived risk of disease is lower among travellers with prior experience and among novelty seekers, who might even attach value to high-risk destinations as part of their travel motivations. Travel risks also vary by gender, with females generally reporting more anxiety about natural disasters and physical risks (Park and Reisinger, 2010).

Several studies have examined tourists' travel patterns following a health crisis. Leggat et al. (2010) document that those who exhibited concern about the 2009 swine flu were more likely to cancel their trips. Cahyanto et al. (2016) find that cases of Ebola in the United States in 2014 induced Americans to avoid travelling – especially females and risk-averse people. Wen et al. (2005) report that, because of the 2003 SARS crisis, Chinese tourists changed their travel patterns and the types of tours they took. People started to be interested in outdoor activities and eco-tourism, and safety and hygiene became more important in the choice of destination than previously. Lee et al. (2012) examine the perceptions about the risk of travel of prospective international tourists to Korea in the aftermath of 2009 influenza A. They find that positive anticipated emotion is a key determinant of travel desire, but the perception of disease is not a significant predictor. They conclude that the risk of infection does not preclude international travel; rather, it induces people to engage in adaptative behaviour.

2.3. The impact of COVID-19 on tourists' travel patterns

Recent evidence for COVID-19 reveals that the pandemic has generated substantial travel anxieties (Neuburger and Egger, 2021) and fears (Bae and Chang, 2021). Between January 1, 2020, and the official declaration of the pandemic (March 12, 2020, WHO), many travellers had already cancelled or delayed their trips worldwide (Ugur and Akbiyik, 2020). From a psychological perspective, the studies by Kock et al. (2020), Miao et al. (2021) and Karl et al. (2021) illustrate how the pandemic has altered tourists' psyche, with health risks inducing prospective travellers to postpone their travel plans. In this sense, Pappas (2021) find that older people are much more worried about the risks of taking a holiday, which translates into lower holiday intention.

However, as in previous health crises, people developed different coping strategies that generally involve the adoption of cautious travel behaviour rather than travel avoidance. Zheng et al. (2021) document that, since the outbreak, individuals prefer independent short-distance trips. Self-driving tours within the province of residence are found to be the preferred travel options. Zenker and Kock (2020) also point to an increase in domestic tourism and a greater preference for lesser-known destinations. Li et al. (2020) report a decline in the intentions to use public transport coupled with an increase in the willingness to travel by car. They also find tourists who travel since the outbreak opt for shorter stays and that travel fears vary by sociodemographic status. Osti and Nava (2020) study destination loyalty during the pandemic and show that the most risk-sensitive tourists are less likely to visit seaside destinations, prioritizing mountain destinations instead. In this sense, the studies by Derks et al. (2020) and Day (2020) also report an increased preference towards outdoor activities in greenspaces. This can be explained by the psychotherapeutic benefits of nature-based tourism (Buckley and

Westaway, 2020), which is expected to become one of the most important market segments in the post-COVID-19 recovery.

Li et al. (2021) discuss in detail tourists' behavioural adaptation to COVID-19, indicating it is heavily dependent on sociodemographic characteristics, cultural background and psychological aspects. Zhang et al. (2020) show that, under the threat of infectious disease, risk aversion makes tourists to develop more negative emotional responses to disadvantaged price inequality (i.e. paying more than a reference group pays), thereby increasing their perceived price unfairness.

Due to the increasing concerns about hygiene, people are less attracted to crowded environments (Kock et al., 2020), prefer private dining facilities (Kim and Lee, 2020), and look for accommodations with limited interaction (Shin and Kang, 2020). Tourists seek open spaces, minimize the distance travelled and look for lesser-known destinations (Jeon and Yang, 2021). This has given rise to so-called 'untact tourism', by which tourists protect themselves from infection by minimising interpersonal interactions (Bae and Chang, 2021). As a result of all these preference shifts, tourists are likely to change their allocation of money across expenditure categories and to reduce the length of their stay.

3. THEORETICAL FRAMEWORK

Assume individuals allocate available time and income to leisure and non-leisure activities and that preferences over recreational and non-recreational goods (services) are weakly separable (Deaton and Muellbauer, 1980). Given their preferences, a subset of the population decides to take a vacation trip and each individual chooses where to go according to destination hedonic characteristics and subjective preferences over them (Lancaster, 1966).

Consider now a tourist destination that receives n travellers[1]. Assume also we have two time periods: immediately before and immediately after a pandemic disease outbreak. The new state of the world changes i) the marginal rate of substitution between tourism travelling and other leisure activities due to risk aversion (Chen et al., 2011), and ii) the latent utility of each destination depending on its epidemiological situation because health security increases its weight in the preference order (Bae and Chang, 2021; Zheng et al., 2021). As such, the composition of travellers to a given destination differs between the two periods because the shock changes travel preferences heterogeneously across the population (Wang et al., 2019).

Let us now focus on the pre-pandemic outbreak period. Once at the chosen destination, tourists allocate disposable income to several expenditure categories j such as accommodation, transportation or outside accommodation food and beverage. Since at this point all tourists face

[1] The number of travellers that a destination receives is the sum of the subset of the population who travels and for whom the destination probabilistic demand is strictly higher than any other alternative destination within the traveller's feasible choice set.

the same prices, an Engel-type expenditure function for each individual i (for $i = 1, \dots, n$) and category j (for $j = 1, \dots, J$) can be expressed as follows:

$$E_i{}^{j\,pre} = f(M_i, \tau_i{}^j) \tag{1}$$

where M_i is disposable income and $\tau_i{}^j$ are subjective preferences over each category j, which are assumed to be a function of a vector of sociodemographic and trip-related characteristics ($\tau_i{}^j = \beta_j X_i$) that act as preference shifters (Pollak and Wales, 1981)[2].

Following Brida and Scuderi (2013), let us assume expenditure takes a multiplicative form as follows:

$$E_i{}^{j\,pre} = exp^{\alpha_j} M_i{}^{\gamma_j} exp^{\beta_j X_i} exp^{\omega_j} \tag{2}$$

where α_j is an item-specific constant term capturing population mean expenditure per category j, γ_j is an elasticity parameter, β_j is a vector of parameters capturing preference differences by sociodemographic group and trip-related factors, and ω_j are zero-mean idiosyncratic terms affecting expenditure that are assumed to be uncorrelated with the rest of the variables. If we take logarithms:

$$\ln E_i{}^{j\,pre} = \alpha_j + \gamma_j \ln M_i{}^{pre} + \beta_j X_i{}^{pre} + \omega_j \tag{3}$$

Similar to Fleischer and Rivlin (2009), Fleischer et al. (2011) and Aguiló et al. (2017), expenditure per category can be decomposed into personal daily expenditure ($e_i{}^j$) and tourist's length of stay (LOS_i) so that:

$$E_i{}^{j\,pre} = e_i{}^j LOS_i \tag{4}$$

Therefore, equation (3) is expressed as:

$$\ln e_i{}^{j\,pre} + \ln LOS_i{}^{pre} = \alpha_j + \gamma_j \ln M_i{}^{pre} + \beta_j X_i{}^{pre} + \omega_j \tag{5}$$

As shown in Aguiló et al. (2017), the linear equation (5) can be further decomposed into its two components in the following manner:

$$\ln e_i{}^{j\,pre} = a_j + \delta_j \ln M_i{}^{pre} + b_j X_i{}^{pre} + \omega_{1j} \tag{6}$$
$$\ln LOS_i{}^{pre} = \mu + \theta \ln M_i{}^{pre} + \eta X_i{}^{pre} + \omega_{2j} \tag{7}$$

[2] The expenditure function for each item j emerges from an item-specific conditional tourism demand function in the spirit of Pollak (1971). Commodities are partitioned into subsets so that each item is a different branch from the utility tree.

where $\alpha_j = a_j + \mu$; $\gamma_j = \delta_j + \theta$; $\beta_j = b_j + \eta$ and $\omega_j = \omega_{1j} + \omega_2$, with $\omega_{1j} \perp \omega_2$. In this way, total expenditure in each category j is decomposed into its intensity (daily expenditure) and extensity (LOS) components.

As introduced earlier, the outbreak of a pandemic disease changes the population composition of travellers. Therefore, the sociodemographic profile of the sample in the pre-pandemic period (X_i^{pre}) could be different from that in the post-pandemic outbreak period (X_i^{post}). This happens because the risk of contracting the disease changes both tourism participation likelihood (Pappas, 2021) and destination probabilistic demand with a preference shift towards short-distance trips (Zheng et al., 2021; Miao et al., 2021) and outdoor activities (Osti and Nava, 2020; Buckley and Westaway, 2020). In addition to this, tourists are expected to change their allocation of the budget constraint across expenditure categories and how long to stay because COVID-19 disease: i) induces travellers to perform distinct activities at the destination than before (Gössling et al., 2020), and ii) causes each time unit at the destination to become more 'costly' through the utility loss caused by increased exposure to disease (Wang et al., 2019). Therefore, daily expenditure per category and LOS after the pandemic outbreak can be expressed as follows:

$$\ln e_i{}^{j\,post} = \widetilde{\alpha}_j + \widetilde{\delta}_j \ln M_i{}^{post} + \widetilde{b}_j X_i{}^{post} + v_{1j} \quad (8)$$

$$\ln LOS_i{}^{post} = \tilde{\mu} + \tilde{\theta} \ln M_i{}^{post} + \tilde{\eta} X_i{}^{post} + v_{2j} \quad (9)$$

The parameters in (8) and (9) are allowed to differ from those in (6) and (7), respectively.

4. DATA

4.1. Case study

The Principality of Asturias is a Northern Spanish region with about one million inhabitants and an area of 10,600 square kilometres (see Figure 1). It has a long tradition as a leading region for rural tourism in Spain (Barke, 2004), partly due to the quality labels of their rural cottages (Bilbao and Valdés, 2016). In the last several decades, it has consolidated its popularity as a nature-based destination. Asturias is known for its beautiful landscapes and forests, unspoiled coastline, natural surroundings, gastronomy, and historical culture (Goya, 2020). It welcomes around 7.6 million visitors each year (5.3 million tourists and 2.2 million same-day visitors), generating an estimated gross added value of about 2.3 billion euros (Tourist Information System of Asturias [SITA], 2020). The tourism sector represents almost 11% of its GDP and 12.7% of total employment (SITA, 2020).

Figure 1.- Asturias geographical position within Spain

Asturias is chosen as the case study to evaluate the impacts of COVID-19 on tourism outcomes for various reasons. Apart from the significant contribution of tourism to its regional economy, during summer 2020 it was the autonomous community with the lowest accumulated incidence of COVID-19 cases in Spain. According to official Spanish Health Ministry records, in July, August, and September 2020, the 14-day accumulated incidence per 100,000 inhabitants was 0.00, 10.46, and 46.54, respectively. By contrast, the national mean during those months was 8.47, 62.94, and 211.84, respectively. These low figures, and its character as a nature-based destination where people can enjoy many outdoor activities, made it a more attractive option than usual. Indeed, Asturias was the Spanish region with the highest hotel occupancy rate during July 2020 (50.1%) and the second-highest in August (62.8%) (INE, 2020).

Whereas other well-known Spanish sun and beach destinations like Mallorca or the Canary Islands suffered inter-annual drops in the number of arrivals of around 80% during July and August 2020, Asturias decreased the number of visitors by only 20% during those months (INE, 2020). Because this region showed greater resilience immediately after the first wave of the pandemic, it constitutes a relevant case to study the changes in tourism outcomes.

4.2. Dataset

The dataset used in our study is provided by SITA (http://www.sita.org/). This research institute belongs to the University of Oviedo, and it surveys a representative sample of visitors through the whole year to develop tourism statistics. For the collection of data, both tourists and same-day visitors are approached at sightseeing spots and collective establishments by trained enumerators and are asked to complete a questionnaire. They are asked for information about their trip, including the mode of transport, the type of accommodations chosen, the length of stay or their expenditures. They are also asked to provide sociodemographic data like age, education or labour status.

The sampling protocol uses a mixture of quota and pure random sampling. Quotas are based on existing information about the typical number of visitors to the region by season, municipality, travel purpose, type of visitor, and type of accommodations (private vs. market-based). This information is drawn from official records by the National Statistics Institute, which collects data from hotels, campsites, holiday dwellings, youth hostels, and rural accommodation occupancy surveys. Based on this, a specific number of surveys per strata is determined in advance to be collected each period. This is complemented by a share of surveys that follow random sampling.

Once the data are collected, sampling weights are constructed to ensure the data are valid for inference. We refer the reader to Aroca et al. (2013) for a discussion of their importance in tourism research. Sometimes it is quite difficult to sample some segments, which might lead to avidity bias. Furthermore, the quotas are defined beforehand according to past statistics. When there is a change in the distribution of tourists' characteristics (e.g., an increase in the number of people staying in private accommodations relative to the prior year), observations must be weighted to ensure representativeness. Consequently, sample weights are calculated for each person, based on official data. Observations are then weighted by the inverse of the likelihood of being sampled under a perfect sampling protocol to remove disproportionate representation of population segments.

The fieldwork in summer 2020 took place between 26th July and 20th September. At that time, there were no movement restrictions in Spain. A total of 890 valid surveys were collected during these eight weeks. To ensure a comparable analysis, we restrict the number of questionnaires from summer 2019 to those collected during the same period as in 2020 ($n = 1{,}599$). We exclude visitors coming for non-leisure purposes ($n = 692$), those who stay at a second residence or a friends' or relative's house ($n = 272$), and questionnaires with missing values ($n = 271$). Our final sample involves 1,610 individuals (975 for summer 2019 and 635 for summer 2020).

4.3. Descriptive evidence

From the survey responses, we define the following variables of interest: i) length of stay (nights), ii) total expenditures, iii) expenditures for accommodations, iv) expenditures for food and beverage (outside the accommodations), v) expenditures for transportation within the region, and vi) expenditures for other items, including such things as cultural and outdoor activities, shopping and souvenirs. All the expenditure variables are expressed in euros per person and day.

Table 1 presents the characteristics of the samples for the summers of 2019 (pre-pandemic) and 2020 (post-pandemic outbreak). We also report the results for t-tests (for continuous variables) and proportion tests (for dummy variables) to compare the differences between the two periods. The Appendix presents kernel density plots of the distributions of these variables before and after the pandemic. We document that total expenditures, expenditures for food and beverage, and expenditures on other items (per person and day) are significantly greater in summer 2020 than in 2019. By contrast, there are no apparent differences in the LOS or expenditures for accommodations and transportation. However, this simple mean comparison might be misleading since we do not consider potential differences in both the population and the sampling characteristics before and after the pandemic.

Examining the remaining characteristics of the samples, in 2020 there is a lower proportion of highly educated, employed, and foreign tourists but a greater share of unemployed individuals, tourists travelling in couples, and people lodged in the central area. Interestingly, there is a change in the type of activities undertaken, with notable increases in visits to beaches and mountaineering/trekking. By contrast, visits to villages have declined, likely due to the shift towards outdoor activities with reduced interpersonal interaction since the start of COVID-19, as shown by previous studies following a health crisis (e.g. Wen et al., 2005).

	2019		2020			
Outcome Variables	**Mean**	**SD**	**Mean**	**SD**	**z**	**p-value**
LOS (nights)	4.473	6.048	4.889	6.413	-1.300	0.193
Expenditure per person and day (euros):						
Total	63.016	32.149	68.842	34.972	-3.371***	<0.001
Accommod.	23.260	22.119	24.550	23.483	-1.102	0.2706
Food and Bever.	24.807	13.938	27.230	15.934	-3.130***	0.001
Transport	4.435	4.984	4.516	3.561	-0.382	0.702
Other Items	10.511	8.683	12.543	8.101	-4.779***	<0.001
Sociodemographic Characteristics						
Primary studies	0.084		0.099		-1.035	0.300
Secondary studies	0.108		0.099		0.608	0.543
Vocational training	0.150		0.239		-4.467***	<0.001
University education	0.656		0.562		3.804***	<0.001
Age	42.296	13.109	41.659	12.498	0.969	0.332
Male	0.533		0.547		-0.144	0.885
Civil servant	0.157		0.182		-1.353	0.175
Employee	0.440		0.370		2.785***	0.005
Self employed	0.091		0.114		-1.543	0.122
Student	0.116		0.099		1.110	0.266
Housekeeper	0.073		0.074		-0.012	0.989
Unemployed	0.014		0.051		-4.381***	<0.001
Retired	0.062		0.058		0.352	0.724
Other labor	0.044		0.048		-0.441	0.658
Spanish tourist	0.610		0.644		-1.369	0.170
Foreign tourist	0.063		0.023		3.672***	<0.001
Local tourist	0.326		0.332		-0.255	0.798
Distance to origin	436.898	933.547	355.310	447.040	2.054**	0.040
Trip characteristics						
Travel party	3.508		2.982		3.249***	0.001
Alone	0.016		0.039		-2.858***	0.004
Couple	0.410		0.466		-2.212**	0.027
Family	0.330		0.300		1.240	0.214
Friends	0.227		0.188		1.856*	0.063
Other people	0.015		0.004		1.988**	0.046
First-time	0.327		0.313		0.579	0.562
Car	0.587		0.588		-0.052	0.959
Public transport	0.066		0.048		1.478	0.139
Other transport	0.350		0.360		-0.404	0.686
Weekend	0.576		0.440		5.318***	<0.001
West	0.174		0.212		-1.913*	0.055
Centre	0.346		0.466		-4.795***	<0.001
East	0.478		0.321		6.273***	<0.001
Type of accommodation						
Hotel	0.378		0.374		0.148	0.882
Rural house	0.090		0.100		-0.706	0.480
Camping	0.074		0.070		0.301	0.763
Hostel	0.051		0.050		0.079	0.936
Private (market-based)	0.073		0.064		0.712	0.476
Activities performed						
Active tourism	0.075		0.137		-3.994***	<0.001
Mountaineering/trekking	0.096		0.181		-4.941***	<0.001
Visit villages	0.687		0.573		4.661***	<0.001
Visit Museums	0.086		0.163		-4.740***	<0.001
Beach	0.264		0.552		-11.651***	<0.001
Shopping	0.051		0.137		-6.024***	<0.001
Observations	975		635			

Table 1.- Sample characteristics before and after the pandemic outbreak

5. METHODOLOGY

Let T denote a binary treatment variable that takes value 1 for summer 2020 (hereafter 'treated' units) and 0 for summer 2019 (hereafter 'control' or 'non-treated' units). Let Y refer to the observed values of a variable of interest (e.g., LOS), and let X represent a set of population characteristics to be described later (i.e., gender, age, education). Adopting the potential outcomes framework developed by Rubin (1974), Y_1 is a random variable that refers to the potential value of the outcome when $T = 1$ and Y_0 is the potential value when $T = 0$. The causal effect of the treatment (pandemic outbreak) is given by the difference in potential outcomes $(Y_1 - Y_0)$, so the observed outcome (Y) is expressed as follows:

$$Y = TY_1 + (1 - T)Y_0 \tag{10}$$

The average treatment effect (ATE) of intervention T is given by:

$$ATE = E(Y_1 - Y_0) \tag{11}$$

Therefore, the ATE measures the difference in average outcomes by shifting the population from the normal ($T = 0$) to the post-pandemic outbreak state ($T = 1$)[3].

The pandemic outbreak is a random and exogenous shock, so this can be considered a natural experiment. Nevertheless, a simple comparison of the differences in means of the variables of interest *before* (summer 2019) and *after* (summer 2020) COVID-19 (i.e., $E[Y|T = 1] - E[Y|T = 0]$) is not appropriate for assessing the causal effect of the pandemic on tourism patterns for two reasons. First, as discussed before, the pandemic likely affects both the decision to travel and the choice of destination, with these effects being also contingent on individual characteristics (Cahyanto et al., 2016; Zheng et al., 2020; Li et al., 2020b). As a result, the two populations (and therefore the samples) might have different characteristics that have to be accounted for. In other words, the differences of means in the previous section might stem from a *composition effect*. Second, the potential outcomes might not be independent of the treatment because of *confounding effects*; there might be common factors that affect the outcome and the treatment assignment (self-selection).

To properly estimate the causal effect of the pandemic on tourism patterns, we make use of three well-known techniques from program evaluation literature: i) regression adjustment (RA), ii) inverse probability weighting regression (IPWR), and iii) propensity score matching (PSM). Reviews of these techniques are provided by Imbens and Wooldridge (2009) and Abadie and Cattaneo (2018).

[3] It is important to highlight here that we take the decision to travel and the choice of destination as given. As such, the population of interest are tourists who travel to Asturias before and after the pandemic outbreak. We thank an anonymous referee for highlighting this point.

5.1. Regression adjustment (RA)

In the absence of independence between the treatment and the outcome, the average treatment effect can be identified upon conditional independence on observables (*weak unconfoundedness*) so that:

$$(Y_1, Y_1) \perp T|X \tag{12}$$

The ATE is expressed as:

$$ATE = E[E(Y|X, T = 1) - E(Y|X, T = 0)] \tag{13}$$

A common way to estimate Equation (13) is through regression analysis. We regress the observed outcome variable Y on X separately for treated ($T = 1$) and non-treated ($T = 0$) units in a unified framework as follows:

$$\begin{aligned} Y_0 &= \alpha_0 + \beta_0 X + \epsilon_0 \quad if\ T = 0 \\ Y_1 &= \alpha_1 + \beta_1 X + \epsilon_1 \quad if\ T = 1 \end{aligned} \tag{14}$$

The predicted values for the outcomes ($\widehat{Y_1}$ and $\widehat{Y_0}$) are the potential outcomes under treatment and control. The difference in means between the two predictions given X is a valid estimator of the average treatment effect.

Please note the analogy between the regression model for the pre- and post-pandemic outbreak periods in equation (14) and the models in equations (6-8) and (7-9). Since we lack information about disposable income (M), this variable is proxied by education level, occupation and age.

5.2. Inverse probability weighting regression (IPWR)

The ATE derived from the RA method might be affected by the *population* composition of treated and untreated units. For instance, some segments might be more present in the treated than in the control group, making the average difference in predicted outcomes sensitive to that. IPWR allows the researcher to weight observations by the inverse of the probability of receiving the treatment. In this way, the identification of the treatment effect explicitly recognises that individuals with a high (low) probability of being observed in summer 2020 must receive a lower (higher) weight.

It is important to clearly distinguish between the *sampling weights* discussed earlier and the *treatment weights* to which we now refer; the former are weights that consider the sampling variability for a given population, whereas the latter control for changes in the composition of the underlying population. Accordingly, sampling weights reflect, for instance, that people with primary studies are less willing to take the survey, and therefore those observations must receive greater weight. Treatment weights gather the fact that, independent of the sampling, people with low education are less likely to travel after the outbreak of the pandemic.

IPWR proceeds in two stages. First, we compute the probability of receiving the treatment conditional on X using a Probit model (i.e. $Pr(T=1|X)$). Second, the predictions for the treated and control groups are weighted by the estimated first-stage probabilities in the computation of the ATE as follows:

$$ATE = \frac{1}{\widehat{Pr(T=1|X)}}(\widehat{Y_1}|X, T=1) - \frac{1}{\widehat{Pr(T=1|X)}}(\widehat{Y_0}|X, T=0) \tag{15}$$

This method is sometimes called the 'doubly robust' estimator because it considers both differences in the likelihood of being in the treatment group through $\widehat{Pr(T=1|X)}$ as well as differences in the effects of the characteristics of the population in the two groups (β_0 and β_1). Since we also consider sampling weights, this estimator can be labelled as 'triply robust'. Besides, consistency requires only one of the two models to be correctly specified. The reader is refereed to Li et al. (2018) for further technical details about this estimator and to Ding and Lehrer (2010) and Huber (2014) for empirical applications.

5.3. Propensity score matching (PSM)

An alternative method to regression analysis is the matching estimator. This procedure consists of matching one-to-one each individual *i* in the treatment group with an individual *j* in the control group who is as similar as possible (i.e., has the same characteristics). The behaviour of the so-called neighbour (*match*) is used as the counterfactual for the identification of the treatment effect.

The matching can be performed based on covariates (direct matching) or on the propensity score introduced above. Rosenbaum and Rubin (1983) show that matching on the propensity score ensures conditional independence in the same fashion as matching directly based on characteristics. PSM has the additional advantages that it reduces the dimensionality of the matching procedure and results in less bias (Abadie and Imbens, 2006). For these reasons, we match individuals only according to their propensity scores.

The proper implementation of the PSM method requires that the propensity scores fulfil the 'common support' condition (i.e. $0 < Pr(T=1|X) < 1$). A probit guarantees that the fitted probabilities lie on the unit interval, but they should not be located on the extremes because the matching requires an overlap between fitted scores for treated and control units (i.e., all individuals in the sample with the same characteristics must have a certain probability of being treated or untreated). Note that IPWR uses the reciprocal of that probabilities, so the weight becomes unreasonably large if the probability is close to zero. Furthermore, $Var(T|X)$ is maximised when $Pr(T=1|X)=0.5$, and it decreases as the probability moves towards the tails (Abadie and Cattaneo, 2018). A detailed derivation of the properties of the PSM matching estimator is provided in Dehejia and Wahba (2012) and Abadie and Imbens (2016).

4.4. Control variables

We define the same vector of explanatory variables X for modelling the propensity scores and as control variables in the RA and IPWR methods. Specifically, we consider the variables presented in Table 1:

- *Sociodemographic characteristics*: age (in years), gender (a dummy for being male), level of education (dummies for secondary studies, vocational training, and university studies, with primary studies acting as the reference category), labour situation (distinguishing between civil servant, employee, unemployed, student, housekeeper and retired, with the reference category collapsing self-employed people), and place of origin, measured as the Euclidean distance in kilometres between the place of residence and Oviedo (the capital city of Asturias), both in levels and in a squared form.
- *Trip-related factors*: a dummy for being a first-time visitor, travel companions (two dummies for travelling in a couple or with the family, being alone or with other people being the reference category), size of the travel party (number of people), a dummy for travelling to the destination by car (public transport and other transportation modes are collapsed in the reference category), market-based type of accommodations (two dummies for lodging at a hotel or a rural house, with the other options collapsed in the omitted category), and the geographic area for the destination where the tourist stays (two dummies for east and west, being the centre of Asturias the reference category).
- *Type of activities undertaken*: dummy indicators for whether the tourist partakes in tourism activities, goes to the beach, visits museums, visits villages, does some shopping, or goes for mountaineering/trekking.
- *Temporal factors*: controls for the month (August and September) and whether the trip takes place during a weekend.

6. RESULTS

6.1. Main Findings

Table 2 presents the estimated ATE of COVID-19 on the six different tourism outcomes considered: LOS and expenditures per person and day, considering total expenditures, and expenditures for accommodations, food and beverage in bars and restaurants, transportation and other items (all in logs). The log transformation allows us to interpret the estimates for the expenditures as semi-elasticities. For the RA and IPWR estimators, we use a Poisson regression for LOS and Ordinary Least Squares for the expenditure variables. We report only the estimates of the ATE; the coefficient estimates for the RA and the propensity scores are available from the authors upon request.

We find that the LOS decreased, on average, by 1.26 nights in 2020 relative to 2019 according to the RA method. When we weight the estimates by the treatment likelihood using the IPWR method, this figure becomes -1.6 nights. Nevertheless, the matching estimator using the propensity scores points to a lower decrease (-0.9 nights). Averaging the three estimates, the pandemic-induced decline in the LOS, *ceteris paribus,* is -1.25 nights. This represents a 23.4% fall (-1.25/5.29) relative to the summer of 2019. This result is consistent with Li et al. (2020), who note that since the pandemic people prefer shorter stays to minimise the risk of contagion.

		ATE	
Outcome	RA	IPWR	PSM
LOS	-1.261**	-1.623***	-0.899***
	(0.553)	(0.503)	(0.328)
Log Expenditure: Total	0.014	0.007	0.013
	(0.020)	(0.020)	(0.027)
Log Expenditure: Accommod.	-1.340***	-1.315***	-1.187***
	(0.192)	(0.178)	(0.233)
Log Expenditure: Food and Bever.	0.075	0.063	-0.066
	(0.061)	(0.071)	(0.102)
Log Expenditure: Transport	0.547***	0.523***	0.331***
	(0.080)	(0.078)	(0.071)
Log Expenditure: Other Items	0.126**	0.128**	0.150**
	(0.059)	(0.061)	(0.066)
Observations	1,610	1,610	1,610

Table 2.- Average Treatment Effects (ATE) using RA, IPWR and PSM.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Regarding the total expenditures (per person and day), all three methods indicate there are no significant differences between the two periods. However, when we decompose the expenditures into the different categories considered, interesting results emerge. Expenditures for accommodations decrease by around 1.3% whereas expenditures for transportation and other items increase by approximately 0.5% and 0.12%, respectively. This suggests that since the pandemic people opt for cheaper lodgings and/or hire fewer services at the accommodations. In contrast, tourists appear to have spent more money on transportation within the region in summer 2020. Finally, expenses in food and beverage remained constant.

The desire to avoid crowded spaces because of the risks of contagion and the absence of festivals or special events in the main cities of Asturias might have caused people to travel more within the region and to partake in more outdoor activities. This is in line with evidence by Day (2020), Osti and Nava (2020) and Derks et al. (2020) showing that the pandemic has increased individuals' desire to recreate in green spaces, forests, and remote locations. The invariance of expenses in food and beverage could be due to counteracting factors. On one hand, people might avoid eating in crowded dining rooms out of concern for their health, in line with Kim and Lee (2020). On the other hand, their increased mobility within the region might lead them to spend money on food and beverages outside their accommodations. As a result, there could be a change in the choice of bars and restaurants, but not in the amount spent.

In short, although the specific magnitudes differ slightly based on methodological differences, our findings consistently show that the decrease in expenditures for accommodations is offset by the increase in expenditures for transportation and other commodities, keeping the total expenditures per person and day constant.

6.2. Robustness checks

We perform some checks to our main analysis. First, we inspect the fulfilment of the 'common support' condition. Figure 2 plots the distributions of the propensity scores for treated and untreated units. As can be seen, there is sufficient overlap in the estimated scores across the two groups.

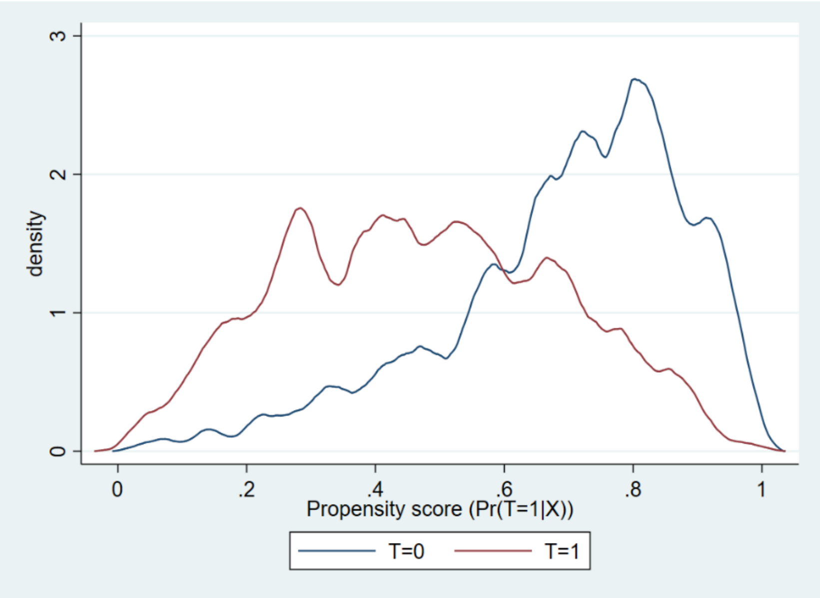

Figure 2.- Kernel density for propensity scores (common support condition)

Second, we examine the assumption of *conditional independence on observables* in the potential presence of unobserved factors. In such a case, the RA estimator for the potential outcomes is not consistent (Imbens and Wooldridge, 2009). To check this, we perform bivariate regressions in which both the outcome and the treatment dummy are jointly estimated, allowing the error terms to be correlated following a bivariate normal distribution. To ensure identification, we use Lewbel's heteroskedasticity-based instrumental variables (Lewbel, 2018). This procedure consists of artificially generating valid instruments to provide an additional source of variability to the potential endogenous treatment based on the data. If, conditional on X, there are still unobserved factors driving the relationship between the treatment and the outcomes, then the error terms are expected to be correlated. The correlation parameter is not statistically significant in any of these auxiliary regressions (available upon request). As such, our findings are not affected by undetected confounding effects.

6.3. Discussion

There is a large discrepancy between the descriptive statistics presented in Table 1 and the results derived from our analysis in Table 2 that deserves further discussion. The direct sample mean comparisons would wrongly lead us to conclude that i) there is a statistically significant increase in total expenditures and expenditures for food and beverage (per person and day) in summer 2020 compared to summer 2019, and ii) the number of overnight stays and expenditures for accommodations and transportation remain unchanged after the outbreak of the pandemic. However, the results of our estimation are quite different: i) there are no significant differences in total expenditures and expenditures for food and beverage, ii) tourists reduced the lengths of their stays in the aftermath of COVID-19, and iii) there has been a drop (increase) in expenditures at the accommodations (in transportation). Why are our results so different from simple summary statistics?

Several reasons can explain this apparently contradictory evidence. First, to make correct inferences when working with survey data, observations must be weighted by the sampling probability based on other sources of information about the composition of the population. Sample means attach equal weights to all the observations, whereas our analysis explicitly considers the sampling weights. Second, leaving the sampling issue aside, descriptive statistics only provide information about the values of the variables of interest before and after the outbreak of COVID-19. However, to properly identify the changes produced by the pandemic relative to the counterfactual outcomes were it not to have occurred, one must condition out both on i) the composition changes of the population, and ii) the confounding effects the population characteristics have. As a result, great care should be taken when analysing the pandemic-induced effects on the tourism industry using simple t-tests for comparison.

6. CONCLUSIONS

7.1. Summary of findings

This study is one of the first formal analyses of the impacts of the COVID-19 pandemic on two of the most important outcomes in tourism: tourists' length of stay and daily expenditures. We use survey microdata from tourists in a region in Northern Spain (Asturias) collected before the pandemic (in summer 2019) and after its outbreak (in summer 2020). Using formal econometric methods borrowed from the literature on program evaluation, we provide robust evidence that tourists' length of stay has decreased by around 1.26 nights, on average, representing a drop of 23.8%. Total expenditures per person and day have remained constant, but we document an interesting change in the distribution of expenditures across the different travel categories. Expenditures for transportation and other items including cultural events or outdoor activities have increased by 0.54% and 0.12%, respectively, whereas expenditures for accommodations have decreased by -1.34%. Accordingly, visitors to Asturias spent approximately the same in the summer of 2020 as they did before the pandemic. However, they have spent more of their budget visiting more areas within the destination and performing more activities, while lowering their expenditures for their accommodations.

To provide valid estimates about the causal impact of the pandemic on tourists' travel patterns, this study adopts the one-group *pretest–posttest design* within the potential outcomes (counterfactual) framework. We apply regression adjustment, inverse probability weighting regression and propensity score matching. These methods explicitly consider: i) the differences in the characteristics of the two groups and the corresponding confounding effects of these differences on the outcomes, ii) potential treatment assignment based on observable characteristics, and iii) sampling weights based on official records to recognise that some segments might not be properly represented in the sample.

7.2. Methodological implications

Our results have important implications for policy and practice. Methodologically, we have shown how misleading could be the conclusions derived from a simple comparison of sample means before and after the shock. Therefore, although they are informative, descriptive statistics must always be interpreted with care. This calls for controlling for changes in the population characteristics and the moderating effect of observable and unobservable sources of heterogeneity to avoid biased estimates of the changes in tourism patterns. In line with Aroca et al. (2013), we also highlight the importance of constructing and using sampling weights to ensure representativeness together with well-designed sampling protocols. Our study urges tourism researchers who are concerned about the effects of the pandemic on tourists' travel behaviour to conduct rigorous econometric analyses that properly isolate the effects they intend to capture. Our methodology can be easily applied to study the effects of the pandemic on other contexts and destinations.

7.3. Managerial implications

COVID-19 is expected to produce important effects on the tourism industry in the medium term. Even if most people in developed countries becomes vaccinated, social distancing will remain necessary for some time. Together with other sustainability goals related to climate change (UNWTO, 2021), the pandemic will therefore force tourist destinations to switch from mass tourism to more sustainable ways like ecotourism. In this context, the analysis of the intensity and extensity components of tourism revenues gains more relevance for destination managers since a tourist with a high daily expenditure is likely to be preferred than two tourists with half expenditures. Our estimates suggest that post-pandemic tourists are more mobile within the chosen destination after the outbreak of the pandemic. In line with the Protection Motivation Theory (Rogers, 1975), tourists engage in different coping strategies during health crises. Social distancing leads individuals to pursue more outdoor activities and eco-tourism (Wen et al., 2005). They prefer self-driving tours (Zheng et al., 2021) and avoid crowded environments (Kock et al., 2020). As our data show, tourists continue to travel, but they reduce the lengths of their stays, and they reprioritise the goods and services on which they spend their money. Their changes in preferences require enterprises in the hospitality and tourism industries to adapt to these new needs in kind. To attract resilient tourists, destinations need to offer services that match their preferences for social distancing. Tourists' increased demand for outdoor activities and private cars might foster the development of local guided tours, small groups, mountaineering activities, and multi-destination trips.

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Appendix. - Kernel density plots for the outcome variables pre-pandemic (2019) and post-pandemic (2020)