Tourists’ Willingness to Pay for Holiday Trip Characteristics: A Discrete Choice Experiment

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Abstract:

This paper studies the marginal rates of substitution and Willingness to Pay for holiday trip characteristics. By means of a Discrete Choice Experiment, we specifically examine how much individuals from four cities in Northern Spain are willing to pay for accommodation, mode of transport, travel time and length of stay. We estimate a Latent Class Model that allows us to account for taste heterogeneity based on sociodemographic characteristics. The welfare loss due to a tourism daily tax is also examined. Our results show that respondents place positive utility to travelling by plane, high-quality accommodation and longer stays. Specifically, they are willing to pay about €170 more for plane travelling with respect to the use of car, €120 for staying at a 4-star hotel relative to an apartment, and €760 for a 10-day trip relative to a 3-day one. We show that a daily tax of €1 per person would produce a larger welfare loss in coastal destinations.

Keywords: *Discrete Choice Experiment, Latent Class Model, Willingness to Pay, vacation choice, travel preferences*

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1. INTRODUCTION

A holiday trip is a multi-faceted decision that involves choosing several factors such as the mode of transport, the accommodation dwelling or the length of stay. The choice of a bundle of trip-features requires individuals to make trade-offs between the attributes. Understanding preferences for vacation together with the substitution rates at which individuals are willing to forego a trip feature to get another one constitutes an issue of economic relevance.

So far, the factors that pull tourists to holiday destinations have been largely studied (e.g. Nicolau and Más, 2006; Wong et al., 2017). However, studies based on revealed preferences have the weakness that the researcher only observes the *chosen* trip. That is, when modelling the choice of a holiday trip, we do not observe the full range of existing alternatives. This typically requires scholars to make some assumptions about the choice set from which individuals choose. Furthermore, choices in real life might be affected by several confounding factors that are unobserved from the researcher's perspective. We instead aim to study preferences for holiday trips through an experimental setting that controls for the characteristics of the non-chosen alternatives. A precise definition of the context and the environment in which decisions are made thus allows for a better identification of preferences.

We conduct a Discrete Choice Experiment (DCE) in which respondents are presented with a series of six hypothetical choice scenarios, each of them characterized by three types of destinations (coastal, urban and nature-based destination) plus a 'none-of-them' option. Each alternative is defined by a set of exogenous well-defined attributes. Participants are required to choose their preferred option in each scenario. Based on their choices, we estimate the associated marginal utilities that rationalize the data according to Random Utility Maximization Theory. Importantly, the repeated nature of the choice task has the advantage that tastes are identified based on choices from different combinations of attribute levels in each choice situation. Therefore, contrary to observational data in which the preferences for two attributes that usually vary together can be empirically indistinguishable, our experimental design allows us to separately identify the preferences for each attribute based on exogenous variability in the rest.

We estimate a Latent Class Model (henceforth LCM) that allows for preference heterogeneity being modelled as a function of sociodemographic characteristics such as gender, age, income, and education level. We derive marginal rates of substitution in the form of Willingness to Pay (WTP) estimates, which provide an economic valuation of the preferences for the attributes. In this way, our model explains how individuals trade attributes when choosing among different recreational sites.

A particular feature of our study is that our data comes from a sample of real-life couples recruited from the general population of four cities in Northern Spain. We have several motivations to select real life couples as our subject pool. Since preferences for vacation features might depend on trip companions and the season of the year, we framed the choice experiment in the specific context of a summer trip with their sentimental partner. Partners are accustomed to making decisions on behalf of each other. Hence, from the respondents' perspective, being confronted with a choice decision for a joint trip knowing that their partner is also making his own decision enhances the *salience* of the choice task. This makes it more in line with a real-life situation, and thereby reduces hypothetical bias. Remarkably, both partners make their choices individually and separately. Therefore, we elicit their *individual* preferences, without prejudice of the potential exercise of altruism towards their partner's preferences. This, in our view, enriches the practical relevance of our results.

Our paper contributes to the empirical literature on preferences for vacation attributes by shedding light on how individuals are willing to trade one attribute for another. Although there are some scholars who study WTP for coastal (e.g. Schuhmann et al., 2016), cultural (e.g. Figini and Vici, 2012) and nature-based recreation (e.g. Wuepper, 2017), these studies focus on specific features such as beach quality or the tenure of World Heritage status. We, instead, assess marginal rates of substitution for a more generic tourist trip, allowing the respondent to choose among coastal, urban and nature-based tourism alternatives. A second relevant feature of the paper is that we allow for preference heterogeneity in the form of latent classes. In this sense, our study is similar to Chen et al. (2019), who also conduct a choice experiment for addressing preferences for alternative package tours. However, we depart from them in that rather than deriving point estimates of the willingness to pay for each class we use a weighted estimator that gives information about the distribution of the WTP in the sample. We also conduct a simulation exercise to explore the welfare loss associated with the setting of a tourism daily tax.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the experimental setting and the choice experiment. This is followed by a description of the econometric modelling in Section 4. Section 5 outlines the model specification and reports the estimation results. Finally, Section 6 discusses the main findings and concludes.

2. LITERATURE REVIEW

2.1. Discrete Choice Experiments in tourism

There is a growing body of literature in tourism using experimental techniques for analysing cause-effect relationships. Among the different typologies, DCE stand as the most applied. Participants in a DCE are asked to choose their preferred alternative from a given exogenous choice set with two or more alternatives (apart from the 'none of them' option), each one characterized by a set of well-defined attributes. In this way, DCE are a useful technique for examining the trade-offs consumers make between alternatives depending on their attributes.

Over time, DCEs have been widely used in marketing (e.g. Louviere et al., 2008), transportation (e.g. Hess et al., 2007) or environmental valuation (e.g. Johnston et al., 2017). In the tourism literature, DCEs are nowadays a valuable and commonly employed methodology for eliciting tourists' preferences for hotels (e.g. Kim and Park, 2017), the role of personal interactions in Tourism Information Offices (e.g. Araña et al., 2016), improvements in transport infrastructures (e.g. Bimonte et al., 2016), the economic valuation of cultural heritage (Choi et al., 2010), conflicting preferences between local residents and tourists (Concu and Atzeni, 2012), or host city convention choice (e.g. Crouch et al., 2019), among others.

Most empirical studies concerned about individual preferences for leisure recreation using DCEs have focused on nature-based tourism (Shoji and Tsuge, 2015; Wuepper, 2017; De Valck et al., 2017). In this regard, the recreational demand literature has made important contributions on anglers and recreationists' preferences for destination choice using choice experiments (e.g. Boxall and Adamowicz, 2002). Similarly, other studies have focused on specific types of tourism activities such as coastal (Schuhmann et al., 2016; Talpur et al., 2018) or urban tourism (Dellaert et al., 1995, 1997; Figini and Vici, 2012). In doing so, respondents are generally consumers of the type of tourism being analysed and the choice experiments are designed for specific contexts. Since our purpose is to study preferences for vacation features considering different types of destinations, our study falls better within the body of research summarized below aimed at understanding preferences for generic holiday destinations.

2.2. Preferences for holiday destinations

Huybers (2003) conducts a DCE to a sample of Australian residents to address the drivers of short-break (3 days) domestic tourists' destination choices. Travel time, expenditure per person, accommodation amenities measured by the number of stars, the level of crowdedness, the presence of event/festival and the type of activities to engage in at the destination are the six attributes considered in a choice set with 6 alternative destinations. His results show that tourists attach great importance to the level of crowdedness and the quality of accommodation amenities, whereas travel time is not statistically significant. Additionally, the staging of an event or festival increases destination utility, with the summer period being the preferred one for travelling.

The vacation preferences of Dutch students are analysed by Grigolon et al. (2012). The portfolio choice considers four types of destinations (groups of cities based on geographic proximity), trip duration (daytrips, short and long holidays), travel party (alone, with partner, with family, with friends), mode of transport (car, bus/train, regular airlines and low-fare airlines) and type of accommodation (hotel/rented apartment, hostel, camping and friend's/relative's house). Since their aim is to explore students' preferences for low-fare airlines, only transport-specific attributes (mode, cost, travel time, time of the time, and time to get to the station/airport) are systematically varied. Therefore, preferences for transport are conditional on the remaining characteristics of the trip, which are freely chosen. However, a main limitation of their experiment is that costs other than transportation are not considered. The authors conclude that the mode of transport and transportation costs are the most important facets of the travel decision. Their results also indicate that i) destination utility increases with the duration of the trip, and ii) a hotel or a rented apartment are preferred over a hostel or a camping.

A novel DCE to study how destination and experience information affect holiday choices is conducted by Oppewal et al. (2015). Specifically, participants are presented first with a set of eight holiday destinations (place names) and then eight types of experiences, or vice versa. After that, choices are made from a reduced choice set with four options in each condition characterized by transport and accommodation attributes. Their results indicate that early exposure to a type of attribute enhances its importance, being the effect larger in the case of destination place names than for type of experiences. In line with expectations, travellers prefer longer stays and accommodations with more stars. Interestingly, experiences like 'relaxation, health and indulgence' and 'nature' are preferred over 'indigenous culture'.

Van Cranenburgh et al. (2014) study vacation behaviour under high travel cost conditions at the micro level. Their main aim is to see whether a rise in travel costs (three times larger than expected) would exert a large impact on travel destination choice. They use real-life destinations (cities, regions, and countries) in a DCE that pivots choice tasks using information on respondents' true consideration set. Basically, the choice set is endogenously created from respondents’ actual trip plans. They show that an increase in travel costs is more negatively valued for air travel than for road transport. Overall, vacationers exhibit diminishing marginal disutilities of travel costs. They also show that tourists prefer travelling by plane/bus/train (relative to car) and lodging in a market-based accommodation (relative to a tent or a caravan). Remarkably, utility increases with distance to origin. Using the same data, Van Cranenburgh (2018) further disentangles the heterogeneity in tourists’ sensitivity to travel costs using latent class analysis. Four classes of tourists are found. Whereas middle age and elderly tourists are highly inclined to change their vacation destination to closer locations, about 12% of respondents (those with high incomes) are not willing to change their choices even under a high travel cost scenario.

Finally, Chen et al. (2019) analyse heterogeneity in preferences for package tours using a DCE directed to mainland Chinese outbound tourists, which are classified into three groups according to their budget constraint. Alternative packages are described using labelled destinations based on the availability of free time, the number of designated stops and optional activities, the meals and attractions included, the type of flight and total cost. Some attributes take different levels for each budget segment. Using sociodemographic variables and trip motivations as class membership determinants, they find that only a few attributes are significant for explaining package choices. Specifically, direct flights are strongly preferred among the medium and high budget segment whereas the number of activities and designated stops in the itinerary are not relevant for any segment. Therefore, tourists seem to avoid too many transfers. Furthermore, the USA and Europe are preferred relative to Australia for one of the two classes identified, whereas the opposite holds for the other.

3. EXPERIMENTAL SETTING

In this section, we first describe the preliminary steps of the DCE related to the definition of attributes, alternatives, and experimental design. Second, we outline the data collection procedure, and finally we provide descriptive statistics.

3.1. Experimental Design

We conducted qualitative discussion focus groups with some experts in tourism and reviewed related studies to identify the most relevant characteristics for vacation choice. Individuals consider many dimensions when organizing a holiday trip. However, the greater the number of holiday trip characteristics considered, the higher the cognitive burden of choosing a specific type of destination. Therefore, the analyst needs to find a balance between making the hypothetical choice realistic without making it too complex.

This preliminary work led to the choice of the following five characteristics: i) the travel time required to reach the destination; ii) the mode of transport; iii) the length of the stay; iv) the type of accommodation; and vi) the total cost (including both transport and lodging costs). These choice attributes and their respective levels considered in the experiment are displayed in Table 1. To avoid including overlapping attributes such as distance (given the mode of transport, travel time and total cost) and to reduce inter-attribute correlation, we included the trip characteristics that are salient to most people. Although related studies consider more attributes, we kept them to a reduced number since Louviere et al. (2008), in the specific context of holiday choice, show that choice consistency decreases as the number of attributes increases.

Attribute	Levels	Acronym
Travel time	Less than 2 hours	*shortTT*
	Between 2-5 hours	*medTT*
	More than 5 hours	*longTT*
Mode of transport	Car	*car*
	Bus or Train	*bustrain*
	Plane	*plane*
Length of the stay	3 days	*3days*
	7 days	*7days*
	10 days	*10days*
Accommodation site	Full private apartment	*apartment*
	2-star hotel	*2starhotel*
	4-star hotel	*4starhotel*
Total cost (per couple)	€200	*Cost*
	€600	
	€1,000	
	€1,400	

Table 1.- Attributes and levels

The cost is the only attribute that is treated as continuous and the one with the highest number of levels (4). The monetary values were derived from existing market prices at the time of the data collection. The rest of the attributes are dummy coded. The specific attribute levels chosen (Table 1) mimic the ones used in Keane and Wasi (2013). They specifically used 3 and 5 hours for travel time, 7 and 12 days for length of stay, and 2-star and 4-star hotel for the type of accommodation.

A relevant decision for the design of a DCE experiment is the number of alternatives. Under utility maximization, the higher the number of options, the higher the probability for respondents to find a suitable choice (Oehlmann et al., 2017). However, complexity affects choice consistency (DeShazo and Fermo, 2002). Furthermore, providing respondents with a large choice set might make them feel overwhelmed, a phenomenon known as ‘choice overload’ (e.g. Park and Jang, 2013). To avoid cognitive burdens, respondents are presented with three alternatives per choice task plus a ‘none of them’ option. This is done to avoid forcing them to choose any of the alternatives if none of them are attractive enough. This is standard practice in DCE in general (Oehlmann et al., 2017) and in the context of holiday choice in particular (Huybers, 2003; Grigolon et al., 2012; Bimonte et al., 2016) to ensure realism.

These three alternatives are presented as ‘types’ of destinations: coastal, urban, and nature-based tourism. This is done to eliminate potential prior knowledge biases that may arise due to destination image or familiarity if we used real destination names. Similar to Bimonte et al. (2016) and Chen et al. (2019), respondents are confronted with six different choice tasks, creating a panel structure for our data. Oehlmann et al. (2017) note that as the number of choice tasks increases, the probability of respondents opting for the ‘none of them’ also rises, possibly due to fatigue effects. Choice cards are displayed in the transposed form (i.e. one row per alternative and one column per attribute) to facilitate row wise comparison and to enhance consistency with Random Utility Maximization (Sándorf et al., 2018).

The vacation context was defined as 15 holiday days with a partner during any period in the summer season (June-September). Most importantly, we told participants that in making their individual decision they have full freedom to choose their preferred option. This was intended to identify their *individual preferences* rather than the *couple’s preferences*. Since there is some evidence that children can exert some influence in family holiday decisions (e.g. Thornton et al., 1997), we emphasized that neither children nor relatives are allowed to participate in the couple trip. Moreover, the cost involves the total cost of accommodation (breakfast included) and transportation, and travel time refers to the transit time between departure and arrival at the destination.

As recommended by the DCE literature, we pre-tested the questionnaire, the choice task, and the attribute levels with a pilot study. It was conducted in February 2019. A total of 17 couples (i.e. 34 individuals) participated. Subsequently, a D-efficient design was generated in NGENE (Choice Metrics, 2012) to find the optimal design. The priors used were obtained from the pilot study. We imposed some constraints on the attribute level combinations to avoid dominant alternatives (i.e. cases in which one destination is clearly superior to the other). Our experimental design of 18 rows comprises three blocks so that each respondent faced six choice tasks. An example of a choice card is presented in Figure 1.

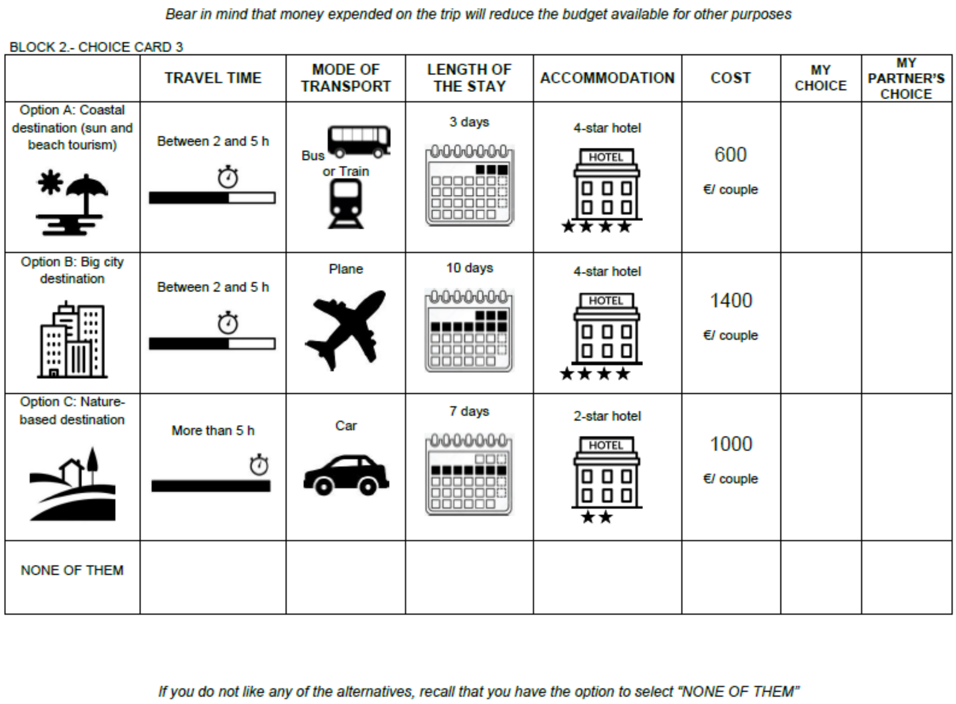

Figure 1.- Example of the DCE

The data were collected in face-to-face interviews, and the choice task was presented to respondents in paper format in a randomized order (Börger, 2016; Oehlmann et al., 2017). Finally, all the choice cards included two reminders about the household budget constraint, and if they do not like any of the three options they could select 'none of them'.

3.3. Data collection

The DCE was conducted together with a parallel study on intra-household decision making. Our recruitment procedure follows the ones by Munro and Popov (2013) and Cochard et al. (2016). We recruited a fairly representative sample of established couples over 18, regardless of whether they were married or they had children. Couples were recruited through flyers, brochures, social networks and word-of-mouth from four cities in the North of Spain (Oviedo, Gijon, Avilés and Bilbao). In the announcements, we stated that we were looking for stable couples to participate in a research study for a better understanding of preferences for a holiday choice. We also indicated that each participant would receive a fixed amount of money for participation (€10) plus a variable sum of money depending on choices from a Public Good Game (not included in this work). Each individual was paid individually and anonymously at the end of each experimental session.

The experimental protocol was the following. Upon arrival at the lab, subjects were given a random ID code that identified the couple and the individuals within it (e.g. 44B). Before the experiment started, participants were gathered in a large room and informed about two important issues. First, they were guaranteed that their answers to the questionnaire would remain unknown to their partner. This follows Ashraf (2009), who pointed to the necessity of hiding participants' answers from their partners to maintain 'plausible deniability' when couples exited the experiment. Second, we conducted a brief introductory talk in which subjects were told about the purpose of the study and the structure of the experimental session. Participants were informed that participation was voluntary and that the collected information would only be used for research purposes.

After that, participants were separated into two different rooms (at random). They were given the set of six portfolio choices together with an example for the purpose of illustration. Confronted with the four-option choice set, they were required to mark their preferred option for a trip with their partner. While completing the choice tasks they could not communicate. They had to make their choices alone as if they had the full power to decide. This is similar to Huybers (2003).

After completing the DCE, respondents individually answered a questionnaire about sociodemographic characteristics and previous travel frequency.

3.4. Descriptive statistics

Prior to the data collection, we conducted Monte Carlo simulation exercises to identify the minimum sample size for parameter identification (available upon request). Our estimates indicated that we needed at least 240 respondents for reliable parameter identification.

In total, we conducted 10 sessions with approximately 13 couples per session. Our DCE was successfully completed by 131 couples (i.e. 262 individuals). Importantly, most respondents (90%) had never taken part in an experiment before. Table 2 presents summary statistics of the sample along with the description of the variables.

Starting with sociodemographic features, the average age of respondents is 32.4 years, ranging from 18 to 89. About 60% have university education, with half of the sample (53.8%) currently employed. In terms of after-tax monthly income, the sample is quite balanced, with 27% having no income, 13% earning less than €500 per month, 30% receiving between €500 and €1,500, 22% earning between €1,500 and €2,500 and only 5% earning more than €2,500. Approximately 28% of respondents are married and 25% have children. The vast majority of the respondents are Spanish (97%). Regarding the length of their relationship, more than half of participants (53%) have been together for less than 5 years, while a non-negligible 15% have been in a relationship for more than 25 years.

Variables	Description	Mean	SD	Min	Max
female	=1 if female	0.50	0.50	0	1
age	age (in years)	32.4	13.9	18	89
educ1	=1 if primary education	0.07	0.26	0	1
educ2	=1 if secondary education	0.31	0.46	0	1
educ3	=1 if high education	0.61	0.48	0	1
working	=1 if employed	0.53	0.49	0	1
unempl	=1 if unemployed	0.06	0.24	0	1
inactive	=1 if inactive (housewife or retired)	0.07	0.26	0	1
student	=1 if student	0.32	0.46	0	1
income0	=1 if NMII*=0	0.27	0.44	0	1
income1	=1 if 0<NMII≤€500	0.13	0.34	0	1
income2	=1 if €500<NMII≤€1,500	0.30	0.46	0	1
income3	=1 if €1,500<NMII≤€2,500	0.22	0.41	0	1
income4	=1 if NMII>€2,500	0.05	0.22	0	1
income	=0 if NMII=0; =1 if 0<NMII≤€500; =2 if €500<NMII≤€1,500; =3 if €1,500<NMII≤€2,500; =4 if NMII>€2,500	1.61	1.25	0	4
married	=1 if married	0.28	0.45	0	1
children	=1 if has children	0.24	0.43	0	1
numchildren	Number of children	0.42	0.77	0	3
natspain	=1 if Spanish	0.97	0.15	0	1
rel_less5	=1 if relationship <5 years	0.53	0.49	0	1
rel_5_15	=1 if relationship between 5 and 15 years	0.24	0.43	0	1
rel_15_25	=1 if relationship between 15-25 years	0.06	0.25	0	1
rel_more25	=1 if relationship >25 years	0.14	0.35	0	1
likeshol	=1 if likes going on holidays	0.96	0.18	0	1
travelled	=1 if travelled for leisure purposes in last 12 months (at least one overnight stay)	0.87	0.33	0	1
domtrips	=1 if prefers to travel domestically (vs abroad)	0.24	0.42	0	1
preftravcou	=1 if prefers to travel exclusively with partner when going on holidays (as opposed to alone or with friends/relatives)	0.52	0.50	0	1
nevertra	=1 if never or hardly ever goes on holidays	0.11	0.31	0	1
onceytr	=1 if goes on holidays once a year	0.29	0.45	0	1
twiceytr	=1 if goes on holidays twice a year	0.35	0.48	0	1
moretr	=1 if goes on holidays three times a year or more	0.23	0.42	0	1
iprefcoastal	=1 if in general prefers coastal destinations	0.32	0.47	0	1
iprefurban	=1 if in general prefers urban destinations	0.27	0.44	0	1
iprefnat	=1 if in general prefers nature-based destinations	0.10	0.30	0	1
noclearpref	=1 if respondent does not have a clear preference for any time of destination	0.27	0.44	0	1
partbefore	=1 if participated in a similar study before	0.10	0.30	0	1

Table 2.- Summary statistics of the sample (N=262)
*Note: NMII stands for net monthly individual income

Although our sample is not perfectly representative of the population in the four cities, their characteristics are reasonably well-aligned with the subpopulation of interest: those who participate in tourism activities. Compared to microdata from the Residents Travel Survey

(Spanish National Statistics Institute), in our sample the educated and young people are slightly overrepresented and married people underrepresented.

Concerning trip preferences, most participants declare they like going on holidays (96%), and 87% went on a leisure trip with their partner at least once in the last year. Only 24% of the sample state that prefer travelling domestically than abroad, whereas 52% declare preferring travelling with their partner in comparison to alone or with friends/relatives. As for travel frequency, 11% state they never or hardly ever go on holidays, 29% say they go on holidays once a year, 36% report they travel for leisure twice a year, and 23% indicate they usually take a trip three times a year or more. Finally, 32% prefer coastal locations. Urban destinations are preferred by 28% of the sample, while nature-based ones are the main option for only 10% of respondents. The remaining 27% do not exhibit a clear preference for either of the three.

Each respondent answered six different choice cards with four alternatives each. Therefore, the total number of observations is $6\ x\ 262 = 1{,}572$. Coastal is chosen in 35% of the choice tasks, closely followed by urban tourism (32%). Nature-based destinations are selected in 20% of the cases while 'none of them' is chosen in about 11% of the choice cards.

4. ECONOMETRIC MODELLING

4.1. Random Utility Maximization

The theoretical basis for Discrete Choice Modelling can be found in Lancaster's Theory of Value (Lancaster, 1966). According to this framework, individuals derive utility from the attributes of goods, so that different characteristics lead to different levels of utility. Preferences for goods' characteristics are assumed to be separable so that the overall utility is expressed as a weighted sum of the utilities of the characteristics.

The traditional way to model discrete choices follows from Random Utility Maximization (RUM) developed by McFadden (1974). In line with microeconomic theory, agents choose the option that maximizes their utility conditional on the budget constraint. The true underlying decision process is unknown, but utility maximization is likely to be a valid approximation. Consistent with Lancaster's characteristics model, the econometrician thus links observed choices to the attributes that characterize the available alternatives. However, individuals do not only have different tastes over the attributes, but they might also exhibit random behavior. For this reason, RUM postulates that the underlying utility function is the sum of a systematic (V_{ijt}) and a random component (ε_{ijt}):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (1)$$

The random component ε_{ijt} is independent and identically distributed across individuals (*i*), alternatives (*j*) and choice situations (*t*). The systematic component (V_{ijt}) is a linear-in-parameters function of the *K* attributes that describe each alternative *j* in each choice situation *t* (X_{kijt}) and their associated vector of parameters (β_k) to be estimated, so that $V_{ijt} = \sum_{k=1}^{K} \beta_k X_{kijt}$. Individuals choose the alternative *j* that produces the highest level of utility (i.e. $U_{ijt} > U_{imt} \ \forall j \neq m$).

Following Haab and McConnell (2002), given a budget constraint and a marginal disutility of price, the marginal rate of substitution between attribute *k* and *cost* measures the willingness to pay for that attribute (WTP_k) as follows:

$$WTP_k = \frac{\beta_k}{-\beta_{cost}} \quad (2)$$

where β_k is the marginal utility of attribute k and β_{cost} is the marginal (dis)utility of cost.

4.2. Allowing for Preference heterogeneity: Latent Class Model

It has been recognized the convenience of allowing for taste heterogeneity in discrete choice modelling to avoid bias in coefficient estimates. The typical way to do so is by means of the Random Parameter Logit (RPL) and the Latent Class Model (LCM). LCMs have a long tradition in the recreational demand literature and DCEs (Boxall and Adamowicz, 2002; Shoji and Tsuge, 2015; Araña et al., 2016; Chen et al., 2019). It is assumed in these models that the population is composed of discrete (unobserved) groups or classes of individuals with homogeneous preferences within each class, but different preferences across classes (Kamakura and Russell, 1989).

There is no consensus about whether taste heterogeneity is better represented by means of random parameters or latent classes. Sen (2009) favors the use of the latter while Keane and Wasi (2013) find that models with random heterogeneity outperform latent class modelling in terms of model fit. By contrast, authors like Greene and Hensher (2003) and Hynes et al. (2008) conclude that neither of them is strictly preferred. The LCM offers the advantage of imposing less parametric structure on heterogeneity and lower computational burden at the cost of blocking individuals into groups with homogeneous preferences. Another advantage of the LCM is the possibility of estimating the size (shares) of each class. Nevertheless, the adequacy of each approach is highly case dependent.

Let us assume that the population is composed of several classes of individuals with different preferences. Conditional on membership to class c for $c = 1, \ldots, C$, and according to (1), the utility each individual *i* obtains for each alternative *j* in choice situation *t* is expressed as:

$$U_{ijt|c}{}^{*} = ASC_{jc} + \beta_c' X_{ijt} + \varepsilon_{ijt|c} \quad (3)$$

where X_{ijt} is a vector of observed attributes that varies over alternatives, individuals, and choice situations, β_c is a vector of parameters to be estimated for each class that measure the marginal utilities of the attributes, ASC_{jc} is a set of alternative-specific constants for each class that gather residual utility not captured in X_{ijt} (one of them is normalized to zero for identification), and $\varepsilon_{ijt|c}$ is the random error term.

The error term is assumed to be Type I Extreme Value distributed (Gumbel) so that the difference between the errors of two alternatives leads to a logistic distribution. Let $y_{ijt|c}$ be a binary indicator of whether individual *i* who belongs to class *c* chooses option *j* in choice situation *t*. Given the parameters for each class (i.e. β_c), the conditional probability of respondent *i*'s sequence of choices is given by the product of logit probabilities:

$$P_i = Pr(y_{ijt}|c, X_{ijt}) = \prod_{t=1}^{T} \prod_{j=1}^{J} \frac{\exp(ASC_j + \beta_c' X_{ijt})}{\sum_{j=1}^{J} \exp(ASC_j + \beta_c' X_{ijt})} \quad (4)$$

Individuals are assigned to classes probabilistically. Although class membership can be modelled semi-parametrically based on a constant term (Scarpa and Thiene, 2005), the most common way is to assign individuals to classes based on sociodemographic characteristics (Z_i) using a semiparametric multinomial logit structure (e.g. Araña et al., 2016; Chen et al., 2019). Hence, the class allocation function is expressed as follows:

$$\pi_{ic} = \frac{\exp(\mu_c + \lambda_c' Z_i)}{\sum_{c=1}^{C} \exp(\mu_c + \lambda_c' Z_i)} \quad (5)$$

where π_{ic} is the probability that respondent *i* belongs to class *c*, μ_c is a set of constants to be estimated for each class (normalized to one in one class for identification) and λ_c is a vector of parameters to be estimated for *c-1* classes. It holds that $\sum_c \pi_{ic} = 1$ and $\pi_{ic} > 0$.

Therefore, the unconditional probability of a sequence of choices over *t* choice situations is:

$$P_i = Pr(y_{ijt}|X_{ijt}) = \sum_{c=1}^{c} \pi_{ic} \prod_{t=1}^{T} \prod_{j=1}^{J} \frac{\exp(ASC_j + \beta_c X_{ijt})}{\sum_{j=1}^{J} \exp(ASC_j + \beta_c X_{ijt})} \quad (6)$$

Contrary to the RPL model, choice probabilities in the LCM do not require integration, so estimation is done by standard Maximum Likelihood (ML).

5. EMPIRICAL ANALYSIS

5.1 Model specification

Consistent with RUM theory, conditional on belonging to class *c*, the latent utility of alternative *j* for individual *i* in choice situation *t* (equation 2) is specified as follows:

$$\begin{aligned} U_{ijt|c}{}^{*} = \; & ASC_{jc} + \beta_{1c}\, medTT_{ijt} + \beta_{2c}\, longTT_{ijt} + \beta_{3c}\, bustrain_{ijt} + \beta_{4c}\, plane_{ijt} \\ & + \beta_{5c}\, 7days_{ijt} + \beta_{6c}\, 10days_{ijt} + \beta_{7c}\, 2starhotel_{ijt} + \beta_{8c}\, 4starhotel_{ijt} \\ & + \beta_{9c}\, Cost_{ijt} + \varepsilon_{ijt|c} \end{aligned} \quad (7)$$

where $\varepsilon_{ijt|c}$ is the Type I Extreme Value distributed error term, ASC_{jc} are alternative-specific constants to be estimated for each class, $medTT$, $longTT$, $bustrain$, $plane$, $7days$, $10days$, $2starhotel$ and $4starhotel$ are the dummy coded attributes defined before, and the β are a set of parameters to be estimated for each class. The omitted reference categories are $shortTT$, car, $3days$ and $apartment$ (Table 1).

To model class membership, we consider the following sociodemographic characteristics in the allocation function (5): gender, age, high education level (vs. primary/secondary education) and individual net income:

$$Z = (female, age, higheduc, income)$$

Before model estimation, the number of classes needs to be determined. Table 3 presents the (consistent) Akaike Information Criteria (cAIC and AIC), Bayesian Information Criteria (BIC) and log likelihood values (log L) for two, three and four classes. The AIC indicates four classes and cAIC and BIC indicate two classes. On the one hand, some authors suggest that AIC over-estimates the number of classes and, on the other hand, others document that BIC tends to favour a small number of classes, especially in small sample sizes (McLachlan and Peel, 2000). Furthermore, Scarpa and Thiene (2005) and Hynes et al. (2008) indicate that, in choosing the number of classes, the statistical criteria and the significance of the parameter estimates needs to be tempered by the researcher's own judgement of the suitability of the model. Since we aim to capture groups of individuals with different preferences for the attributes, we consider taste heterogeneity to be better represented in our data by three segments.

	2 Classes	3 Classes	4 Classes
Log L	-1,695.4	-1,637.0	-1,600.9
K	29	46	63
AIC	3,448.8	3,366	3,327.8
cAIC	3,633.2	3,658.6	3,728.5
BIC	3,604.2	3,612.6	3,665.5

Table 3.- Information criteria statistics

5.2. Results

Table 4 presents the parameter estimates for a baseline Multinomial Logit model (MNL) together with the three class LCM. Standard errors are Huber-White heteroskedasticity-consistent. The estimation has been done in R using both *Apollo* (Hess and Palma, 2019) and the *gmnl* package (Sarrias and Daziano, 2017). We first discuss the estimates for the MNL model, and we then turn to the LCM. For computational reasons, in both models the *cost* attribute is rescaled by 1/100 (in hundreds of euros).

The MNL is usually used as a benchmark model. Consistent with descriptive statistics, respondents exhibit a stronger preference for the coastal alternative (ASC_1), *ceteris paribus*. Since the DCE was framed for a trip during the summer season, this is an expected result. The urban destination (ASC_2) is the second preferred option, followed by the nature-based alternative (ASC_3). Strikingly, travel time is not significant for explaining destination choices and there are no differences between travelling by car (base category) or by bus or train. However, respondents prefer to travel by plane. Consistent with expectations, tourists prefer longer stays and trip cost exerts a negative effect on utility. Concerning accommodation type, 4-star hotels are significantly preferred over apartments (base category) and 2-star hotels.

Focusing on the LCM estimates presented in Table 4, we conclude that class 2 is the largest (50%), followed by class 3 (40%) and class 1 (10%). For identification, the class allocation parameters were set to zero for class 1 so that the parameters for classes 2 and 3 are interpreted relative to it. Class 1 is more likely to be composed of relatively elderly females with university education and low income. By contrast, class 2 mainly comprises young males with middle/high income and non-university education. Class 3 is similar to class 2; but class 3 is more balanced in terms of age and gender and composed of a greater proportion of individuals with high income and non-university studies.

For respondents in class 1, the length of the stay and trip cost are the only attributes that drive their vacation choices. These individuals prefer longer stays and are deterred by cost. None of the remaining attributes are statistically significant. This suggests that this group of individuals might exhibit some sort of lexicographic preferences by which they only attend to some attributes in their decision-making. Nevertheless, this group represents a small share of the sample (10%).

By contrast, individuals in class 2 attach great importance to the type of destination, everything else being equal. Coastal destinations are strongly preferred, followed by urban and nature-based tourism. The plane is preferred to other modes of transport, *ceteris paribus*, while travel time is not statistically significant. Also for this group, longer vacation duration constitutes a desirable feature. However, the type of accommodation does not significantly affect their utilities. Put another way, respondents in class 2 appear to be indifferent with respect to the accommodation type. Regarding cost, this variable exhibits a negative effect on utility as economic theory dictates. Note here that price sensitivity is relatively larger for this segment than for those in class 1.

For individuals assigned to class 3, the destination labelling also matters in their choices. However, these individuals attach greater value to urban tourism and to nature-based destinations than to coastal ones. Like those in class 2, respondents in class 3 prefer travelling by plane than by car, bus, or train. Longer stays are also preferred, but the marginal utilities of this attribute are the lowest in magnitude compared to the other classes. Contrary to the other two segments, individuals in this class place positive value to 4-star hotels relative to apartments. Cost negatively impacts utility, although this group of respondents appears to be the least price sensitive.

	MNL			LCM								
				Class 1			**Class 2**			**Class 3**		
Variables	Coefficient		Rob.SE	Coefficient		Rob.SE	Coefficient		Rob.SE	Coefficient		Rob.SE
ASC1	1.554	***	0.176	-0.736		1.176	3.339	***	0.507	1.943	***	0.430
ASC2	1.383	***	0.182	-0.646		1.548	2.108	***	0.491	2.712	***	0.449
ASC3	0.877	***	0.183	-1.572		1.232	1.403	***	0.463	2.365	***	0.491
medTT	0.029		0.090	0.007		0.622	-0.129		0.238	0.139		0.183
longTT	-0.031		0.081	-0.490		0.478	0.018		0.197	-0.139		0.203
bustrain	0.018		0.078	-0.488		0.584	0.086		0.174	0.097		0.128
plane	0.278	***	0.068	0.348		0.471	0.468	**	0.188	0.294	**	0.115
7days	1.298	***	0.106	1.731	***	0.401	2.270	***	0.294	0.904	***	0.206
10days	1.419	***	0.109	1.808	***	0.432	2.621	***	0.343	0.883	***	0.261
2starhotel	-0.170	*	0.093	-0.419		0.618	0.004		0.171	-0.289	*	0.161
4starhotel	0.235	***	0.085	0.006		0.575	0.175		0.273	0.391	***	0.145
Cost	-0.186	***	0.015	-0.197	**	0.099	-0.272	***	0.040	-0.177	***	0.040
Class membership												
const							4.580	***	0.411	3.273	***	0.427
female							-0.739	***	0.205	-0.509	**	0.205
age							-0.090	***	0.008	-0.045	***	0.007
higheduc							-0.587	**	0.252	-1.093	***	0.248
income							0.258	***	0.091	0.300	***	0.088
LC probabilities				0.108			0.504			0.405		
N	262						262					
Observations	1,572						1,572					
Log Likelihood	-1807.7						-1637					

Table 4.- MNL and LCM parameter estimates
*** p<0.01, ** p<0.05, * p<0.1

Overall, we find that all respondents attach positive utility to longer stays, in line with related studies (Grigolon et al., 2012; Van Cranenburgh et al., 2014; Oppewal et al., 2015). Consistent with microeconomic theory, the higher the total cost of an alternative, the lower the likelihood of that alternative being chosen. Nevertheless, price sensitivities seem to differ across classes. For some individuals, the plane is significantly preferred over the car, as reported in Van Cranenburgh et al. (2014) and Grigolon et al. (2012). Concerning the type of accommodation, respondents in classes 1 and 2 do not show a significant preference for hotels relative to apartments. This mimics the findings by Schuhmann et al. (2016) in the context of beach recreation. However, individuals in class 3 significantly prefer 4-star hotels. This is also found in Dellaert et al. (1997) and Oppewal et al. (2015).

Possibly the most intriguing result is the non-significance of travel time. This is also reported in Dellaert et al. (1997) and Huybers (2003). It could be the case that, although after-tax monthly income enters the class allocation function, our model is not properly controlling for the increasing disutility of travel time one would expect as income increases. To explore this, we estimated a MNL model in which $medTT$ and $longTT$ were interacted with income. However, none of the interactions were significant at the 95% significance level. Furthermore, following empirical evidence in the transportation literature (Guevara, 2017), the (dis)utility of travel time could differ by mode of transport. We estimated a MNL model with interactions between the levels of mode of transport ($bustrain$ and $plane$) and travel time ($medTT$ and $longTT$). As before, none of the interactions were statistically significant. This is in line with Dellaert et al. (1997).

Although the focus groups pointed to travel time as a key determinant of vacation choice, our results indicate that respondents do not pay enough attention to that attribute in their choice decision process. One possible explanation could be that the choice framing is 15 holiday days with partner during the summer season. In this setting, the travel time might not play a role.

5.3. Willingness to pay estimates

Based on the estimates in Table 4, we derive the WTP for each attribute for each class. Since individuals' class membership is probabilistic, it seems necessary to derive a measure of the *unconditional* WTP for the attributes based on the intensity of class membership. A weighted average of individual specific WTP can be computed as the average of the WTP estimates for each class weighted by the predicted class membership probabilities (e.g. Hoyos et al., 2015) as follows:

$$\widehat{WTP_{ik}} = \sum_{c=1}^{C} \hat{\pi}_{ic} \; WTP_{k,c} \tag{8}$$

Table 5 presents descriptive statistics of $\widehat{WTP_{ik}}$ estimates except for $medTT$, $longTT$, $bustrain$ and $2starhotel$. Since these attributes are not significant in any of the three classes, their WTP is not computed. This follows common practice (e.g. Greene and Hensher, 2013).

	Min	1st Q	Median	Mean	3rd Q	Max
WTP_{plane} (€)	168.4	169.8	170.4	170.3	170.9	173.4
WTP_{7days} (€)	607.6	690.2	711.3	706.1	729.4	773.6
WTP_{10days} (€)	625.1	738.7	768.6	764.3	798.4	845.0
$WTP_{4starhotel}$ (€)	69.24	107.4	119.1	120.8	129.25	169.6

Table 5.- Unconditional WTP estimates

Focusing on the mean values, respondents exhibit a large WTP for increasing the length of stay from 3 days (base category) to 7 and 10 days (€706 and €764, respectively). Although the different trip durations increase by about the same length (3 days), it is interesting that the WTP for 10 days stay is not the double of the WTP for 7 days, but of about the same magnitude. This highlights the existence of non-linearities in the marginal utility for length of stay. Regarding preferences for the mode of transport, respondents are on average willing to pay €170 for travelling by plane in comparison to the use of a car, *ceteris paribus*. Finally, individuals are willing to pay, on average, about €120 for lodging at a 4-star hotel relative to an apartment. Bear in mind that the cost attribute reflects the total cost of the trip for a couple rather than for a single individual.

5.4. Welfare analysis

There is some evidence that tourism imposes negative externalities on residents in the form of congestion, crime, noise, or waste (Biagi and Delotto, 2014; Meleddu, 2014). In this respect, there is an ongoing discussion in the literature about different taxing schemes aimed at reducing the negative impact of tourism congestion on host communities (e.g. Gago et al., 2015).

Suppose that policy makers were considering the possibility of introducing a tourism daily tax of €1 per person in only one of the types of destinations considered in our analysis (e.g. coastal destination). How would vacationers' welfare be affected by this? A theory-consistent way to explore this is to calculate the *Hicksian* compensating variation (i.e. the hypothetical transfer of money required to keep individuals on the same indifference curve they were before the tax setting).

The introduction of a daily tax per person in one of the alternatives is a price change that produces both a substitution (through altering choice probabilities) and an income effect. This leads to a change in consumer surplus that is obtained by integrating the uncompensated probabilistic demand for each alternative with respect to the price change, and then transforming it from *utils* to money. Consistent with Small and Rosen (1981), the compensating variation is given by:

$$CV = \frac{1}{\alpha}\left[\ln \sum_{j=1}^{J} exp^{V1} - \ln \sum_{j=1}^{J} exp^{V0}\right] \tag{9}$$

where $V1$ and $V0$ are the deterministic part of the utility function for each alternative after and before the tax, α is the marginal utility of money that converts the change in welfare into monetary values, and $\ln \sum_{j=1}^{J} exp^{V}$ is the *logsum* or inclusive value that corresponds to the expected maximum utility level. In this way, through the systematic component of utility (V_{ijt}), the compensating variation is a function of the characteristics in the choice set (X_{kijt}) and the distribution of preferences in the population (β_c). In applied work, the marginal utility of income is assumed to equal the negative of the marginal disutility of cost (i.e. $\alpha = -\beta_{cost}$).

Since preferences are assumed to be heterogeneous, this price change would produce a distribution of compensating variations rather than a single value. Considering the probabilistic nature of class membership, the CV for three latent classes is:

$$CV_i = \sum_{c=1}^{C} \pi_i \frac{1}{-\beta_{cost|c}}\left[\ln \sum_{j=1}^{J} exp^{V1|c} - \ln \sum_{j=1}^{J} exp^{V0|c}\right] \tag{10}$$

Let us consider two possible scenarios. Scenario 1 (SC1) is characterised by a 7-day trip with a total cost of €600, setting the rest of the attributes to the base category (i.e. travel time is less than 2 hours, mode of transport is the car, and accommodation is a full private apartment). We introduce a daily tax per person in alternative *j* that translates into an additional cost of €7. Similarly, Scenario 2 (SC2) refers to a 10-day trip with a cost of €1,000 and we introduce the same type of tax, also setting the rest of the attributes to the base levels. Therefore, this would translate into an additional cost of €10 in the latter case.

Based on the LCM estimates presented in Table 4, we calculate the compensating variation in each scenario for each individual in the sample assuming the price change occurs: i) only for the coastal alternative; ii) only for the urban alternative; and iii) only for the nature-based alternative. Table 6 presents the CV monetary estimates (in Euros) for each class and the overall CV weighted one for the three alternatives and the two scenarios following equation (12). The negative sign here indicates a reduction in welfare.

		Scenario 1 7 days €600	Scenario 2 10 days €1,000
Price change in coastal destination	CV Class 1	-1.86	-1.99
	CV Class 2	-4.79	-6.74
	CV Class 3	-1.43	-1.97
	Mean of Weighted CV	-2.99	-4.10
Price change in urban destination	CV Class 1	-2.04	-2.02
	CV Class 2	-1.39	-1.95
	CV Class 3	-3.10	-4.26
	Mean of Weighted CV	-2.19	-2.93
Price change in nature-based destination	CV Class 1	-0.80	-0.86
	CV Class 2	-0.68	-0.96
	CV Class 3	-2.19	-3.01
	Mean of Weighted CV	-1.33	-1.80

Table 6.- Compensating Variation estimates under the two scenarios

Individuals in class 2 are the most affected by a tax in coastal destinations in both scenarios. However, in the case of a tax either in the urban or in the nature-based alternative, individuals in class 3 experience the largest welfare loss. Nevertheless, the magnitude of the loss in consumer surplus differs across the two scenarios. Focusing on the mean of the weighted CV, Scenario 2 corresponds to the highest amount of money needed to give individuals back to the original utility levels. Interestingly, the compensating variation is larger in the coastal alternative, followed by the urban and the nature-based ones. An exploratory analysis of the shape of the distribution of the CV further indicates that that there is greater heterogeneity in the welfare loss caused by the tax in the coastal alternative relative to the others. This is consistent both with descriptive statistics and the results from the MNL model in Table 4. Additionally, the estimated compensating variations largely depart from the price change in each scenario. If choice probabilities were insensitive to price, then the CV would equal the value of the tourism tax.

It is important to highlight that, firstly, the closed-form formula of the CV heavily relies on the following assumptions: i) disturbances enter additively in the utility function and are independent of the explanatory variables; ii) the policy change does not affect the individual's draw for the Extreme Value distribution; and ii) the marginal utility of income is constant. Secondly, we cannot ascertain which choice alternative would be chosen by a given respondent after the tax setting. Instead, we only assess the change in choice probabilities for each alternative after the introduction of the tax only in one of them, ceteris paribus. More importantly, the analysis explicitly considers the change in the choice probabilities for the non-choice option. Accordingly, the estimated compensating variations consider potential corner solutions after the price change.

6. CONCLUSIONS

In this paper, we have conducted a Discrete Choice Experiment for studying the relative importance of vacation attributes in holiday destination choice. We have recruited a sample of couples from four cities in Northern Spain and asked them to choose individually and separately in a lab their preferred option for a joint trip.

We have estimated a Latent Class Model that allows for preference heterogeneity and find that about half of the sample is classified into one class, characterized by young males with moderate income and non-university education. These individuals assign a great value to the length of the stay, to travelling by plane with respect to the use of a car and are highly sensitive to cost. The second big class comprises about 40% of the sample, also with relatively more males and young people. However, respondents in this class seem to have higher income compared to the previous class. This class places lower importance on travelling by plane, length of stay and cost relative to the former group, but derives positive utility from staying at a 4-star hotel. Finally, the remaining 10% belong to a third class to which elderly females with high education and low income are more likely to belong. This group does only pay attention to the length of the stay and to trip cost.

Based on the model estimates, we have derived a weighted average of the Willingness to Pay across classes. We have found that respondents are willing to pay about €170 for plane travel with respect to a car, €120 for staying at a 4-star hotel relative to an apartment, and €760 for a 10-day trip relative to a 3-day one. As a final empirical exercise, we have computed the compensating variation for the hypothetical setting of a daily tax of €1 per person in each of the destinations in two different scenarios. We have derived the distribution of compensating variations needed to give respondents back to their original utility levels. We have shown that a daily tax in the coastal destination would lead to the largest loss in welfare. Nevertheless, the estimated compensating variations are always lower than the corresponding rise in prices, suggesting relevant substitution patterns in choice probabilities across destinations after the tax setting.

The study has some features that distinguish it from related studies. Contrary to data obtained from surveys, the experimental procedure has allowed us to have information on the non-chosen options and to control for the environment and context in which choices are made. In contrast to other studies that use students or pre-recruited panellists, our sample comprises real-life married and non-married couples from the general population. Also unlike related studies, individuals are required to make their individual choices among three of the most common types of destinations (coastal, cultural and nature-based) rather than limiting the analysis to one of them.

Our main contribution is the analysis of the heterogeneity in tourists' preferences for travel portfolios. Unlike similar choice experiments, we have derived an unconditional estimator of the willingness to pay estimates that is individual-specific based on class membership probabilities. Therefore, we have explored the distribution of the monetary marginal rates of substitution in the sample. Most similar studies lack this type of analysis and concentrate on the WTP point estimates within classes without exploring its distribution. Different from prior literature, based on the estimated probabilistic demands we have performed a simulation analysis of the welfare loss caused by a daily tourism tax. We have taken advantage of the experimental setting to study the impacts of a policy intervention.

The understanding of how much money vacationers are willing to pay for holiday attributes is policy relevant. On the one hand, our results could be valuable for travel and tourism agencies for the design of travel packages and their pricing. Our findings highlight the importance attached to length of stay relative to transportation or accommodation features. In fact, the preferences for the length of the stay are non-linear. Accordingly, tourism operators should be aware that tourists' willingness to pay for a trip does not increase with length of stay in a linear way. On the other hand, policy makers need to consider the welfare losses induced by the setting of a tourism daily tax. We show that the effect of this tax on consumer surplus depends on the type of destination, being more harmful for a coastal destination than for urban or nature-based ones.

Our study has some limitations. First, young and educated people are slightly overrepresented and married couples underrepresented. We acknowledge this sampling bias as a potential limitation of this research. Second, our analysis is conditional on the alternatives and the attributes presented in the choice task. In real-life situations, couples have the possibility of finding any suitable combination of vacation hedonic attributes. Nevertheless, it is precisely the impossibility of having information on the non-chosen alternatives what hinders the analysis of preferences using revealed preference data. We instead encompass the study of marginal rates of substitution by exogenously restricting the choice set and identifying preferences conditional on that. Finally, although we collect information on choices made by the two members of the couple, we devote our attention to the estimation of individual preferences separately. Further investigation on this and the modelling of joint choices is part of our future research agenda.

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