Annals of Tourism Research 84 (2020) 102969

Contents lists available at ScienceDirect

Annals of Tourism Research

journal homepage: www.elsevier.com/locate/annals

Research Article

The shares method for revealing latent tourism demand

Juan L. Eugenio-Martin*, José M. Cazorla-Artiles

Universidad de Las Palmas de Gran Canaria, Spain

ARTICLE INFO

Associate editor: Yang Yang

Keywords:
Latent demand
Market shares
Target markets
Air connectivity
Marketing campaign

ABSTRACT

This paper develops an intuitive methodology to reveal latent tourism demand. The aim is to quantify its scale by distinguishing the pair of origin-destination and the kind of tourism. The methodology starts measuring the market size that depends on origin population size and their willingness to participate in outbound tourism. Additionally, it takes into account the varying preferences of each origin population for different kinds of tourism. Finally, it compares the current market share of tourism with the expected market share, which is estimated using a random parameter logit model. The study draws on data from EU-28 countries. It provides indicators to select target markets to be strengthened and design strategies based on better air connectivity or oriented marketing campaigns.

Introduction

The development of tourism destinations usually follows a life cycle (Butler, 1980). Once maturity is reached, some destinations seek sustainable policies that may constrain demand, or target tourists by adopting environmentally-friendly policies (Dolnicar, 2010; Dolnicar & Leisch, 2008). However, other destinations may be interested in alternative ways to increase tourism expenditure. Aggregate tourism expenditure at destinations results from multiplying the number of arrivals, expenditure per tourist per night, and the length of stay. Policymakers may pursue strategies to increase any of these variables. This paper focuses on the analysis of the number of tourist arrivals, and identifies key information that reveals the difference between current and potential tourist flow. This difference is known as latent tourism demand (Davies & Prentice, 1995).

This paper develops a new methodology to quantify latent tourism demand. The methodology distinguishes the kind of tourism, so that it provides information not only about the size of the untapped market but also the motivation for this tourism demand. It allows for better market segmentation by providing information about the nature of a marketing campaign (Perdue, 1996; Weaver, 2015) and its location.

The methodology was applied to EU-28 countries (as the EU at the time of the study included the UK) and tourism flow among all these European countries is considered. The analysis of the flow is based on an individual's 'main holiday' taken in a year and distinguishes four kinds of motivations: sun and beach, nature, city and culture. Latent tourism demand is estimated with a set of chained shares and the use of a random parameter logit model. The results reveal the latent demand for each pair of origin-destination and the kind of tourism. The results are illustrated by the use of tables, figures, heat maps and geographic maps.

Once latent demand has been identified and quantified, policymakers can employ this information to define target markets. Two of the main strategies for increasing the number of arrivals are marketing campaigns in key origin markets and new or strengthened air connectivity for attracting additional international tourists (see for instance, Seetanah, Sannassee, Teeroovengadum, & Nunkoo, 2019).

* Corresponding author.
E-mail addresses: juanluis.eugenio@ulpgc.es (J.L. Eugenio-Martin), jose.cazorla101@alu.ulpgc.es (J.M. Cazorla-Artiles).

https://doi.org/10.1016/j.annals.2020.102969
Received 25 June 2019; Received in revised form 25 May 2020; Accepted 28 May 2020
0160-7383/

On the one hand, better connectivity is expected to boost arrivals (Alderighi & Gaggero, 2019). For this reason, government subsidization of new air routes has been applied to several tourism destinations, either to airlines or airports (Barbot, 2006; Núñez-Sánchez, 2015; Ramos-Pérez, 2016). For instance, in some Italian airports, some low cost carriers have received discounts on landing and terminal charges, revenue-guarantee schemes, and co-marketing agreements (Laurino & Beria, 2014). This is a way to support or cover part of the fixed and/or operating costs of the airline, so that risk is reduced and they can be encouraged to operate the route. In some cases, the air company realizes the operation is profitable, and remains flying without any subsidy. In other cases, most of the loss is covered by the destination subsidization. The choice of the route is based on expected profit indicators, market size and the number of rivals (Oliveira, 2008).

On the other hand, tourism government institutions need to identify the origin markets and the kinds of tourism products that are best marketed (Hawes, Taylor, & Hampe, 1991; Kastenholz, 2004). It may happen that particular destinations have reached their cap demand for certain kinds of tourism, but there is still some latent demand for other kinds of tourism, or combinations. This is critical information to efficiently launch a marketing campaign. Leaving aside per capita expenditure and length of stay issues, tourism institutions need to take into account multiple variables for targeting markets, such as the size of the origin population, their willingness to participate in international tourism, their preferences for different kinds of tourism products, and the current market share. Thus, monitoring potential markets and identifying key market segments is required for the development of successful new marketing campaigns (Weaver, 2015) or policies that pursue better connectivity.

Literature review

The literature has extensively developed tourism demand models (Song, Qiu, & Park, 2019). However, applications or specific methodologies for estimating latent tourism demand are rare. Within the mainstream of tourism demand modelling, latent tourism demand may be understood by employing destination choice models either from an individual or aggregate perspective. In both cases, travel cost methods or gravitational models (Morley, Rosselló, & Santana-Gallego, 2014; Yang, Liu, & Li, 2019) provide the framework to estimate the determinants of destination choice. Random utility models are applied for the individual perspective (Nicolau & Más, 2005), while time series and panel data models are used for aggregated data (Li, Song, & Li, 2017).

On the one hand, the literature has developed micro-models that seek to understand a specific market, such as heritage attractions (Davies & Prentice, 1995) or nature-based tourism destinations (Huybers & Bennett, 2003). Most micro-models deal with the individual tourism participation decision. Thus, the analysis seeks to understand the underpinnings of non-participation, such as income (Eugenio-Martin & Campos-Soria, 2011), safety (Sönmez & Graefe, 1998) and/or distance (Kah, Lee, & Lee, 2016), so that lessons can be drawn to address individual constraints. Clustering potential visitors has also been considered in order to choose the preferred markets for achieving destination goals such as ecological sustainability or economic viability (Neuts, Romao, Nijkamp, & Shikida, 2016). Nevertheless, micro-models that can predict latent tourism demand have not yet been built.

On the other hand, macro-models pursue the understanding of latent tourism demand at aggregate levels concerning overall arrivals to countries (Botti, Goncalves, & Ratsimbanierana, 2012; Chen, Jang, & Peng, 2011). A popular method for targeting markets at aggregate level is portfolio minimum-variance theory. This is based on the financial portfolio model developed by Markowitz (1952). The method balances the expected return of an investment and the variance of such a return. For instance, in tourism it can be used to assess alternative target markets, taking into account indicators based on the expected return in terms of tourism expenditure together with the risk associated with its variance. Jang, Morrison, and O'Leary (2004) build several indices based on mean household tourism expenditure, segment size, and risk. Risk is measured with standard deviations and the authors consider expenditure risk and segment size risk. They also consider different kinds of tourism destination clusters, such as beach and sunshine lovers, city sightseers, culture and nature enthusiasts and visiting friends and relatives. Thus, they end up with a risk-adjusted expenditure index that can identify the target clusters. Jang (2004) extended this methodology to identify seasonal demand by segments and established an efficient segment mix solution to seasonal instability. Chen et al. (2011) then employed this methodology to identify an efficient frontier for targeting international markets taking into account their current growth rate and standard deviation. The authors also discuss the role that the variance-covariance matrix of growth rates may play, so that, negative cross-correlations are preferred. For instance, in the event of a crisis, positive cross-correlated countries will be affected similarly, whereas uncorrelated or negatively correlated countries may remain traveling. It is important to maintain a balance among origins, so that a sustainable number of tourists is reached. Similarly, Botti et al. (2012) and Rakotondramaro and Botti (2017) apply the same methodology to identify origin markets of interest from the French perspective. In the former paper, the number of overnight stays is applied, whereas in the latter paper the growth rate is employed. In both cases, such expected return is analyzed together with its standard deviation for optimal market identification and segmentation. Finally, Andriamasy and Rakotondramaro (2016) have highlighted the need for taking into account the 'non-normal distribution of variables' such as overnight stays. They suggest employing non-parametric techniques, so that the skewness and kurtosis properties of the distribution are also considered in the risk function.

All these models have focused on target market identification but have not provided information on the size of the market. As far as we know, there are no existent methodologies that measure the size of latent tourism demand. This paper contributes with a new method that can provide indicators on the identification and quantification of such latent demand.

Methodology

The methodology pursues the identification and quantification of the size of latent tourism demand distinguishing the pair of origin-destination and the kinds of tourism. The hypothesis is based on the decomposition of tourism demand into shares that are linked together, but can be estimated independently. Decomposition is a helpful tool because it offers more parsimonious destination choice modelling, and hence, allows for better identification and more accurate predictions.

Theory

Definition 1. Latent tourism demand is defined as the difference between current and expected demand.

$$L_{od} = \mathrm{E}[T_{od}] - T_{od} \tag{1}$$

where L denotes latent tourism demand, T denotes tourism demand, o denotes origin and d denotes destination. Thus, if $L_{od} > 0$, then the number of tourists may be increased, otherwise, if $L_{od} \leq 0$, then the market is saturated and it has reached its current potential.

Assumption 1. Total tourism demand at a destination can be decomposed into tourism demand motivated by different kinds of purposes.

$$T_{od} = \sum_{k} T_{odk}, \forall k \tag{2}$$

where k denotes the kind of tourism demand.

Thus, the latent tourism demand of each pair of origin destination (od) can be understood in terms of kind of purpose, so that:

$$L_{odk} = \mathrm{E}[T_{odk}] - T_{odk}, \forall\ odk \tag{3}$$

In order to proceed with the methodology, it is necessary to clarify a number of definitions.

Definition 2. Share 1: The participation rate (S_1) is the ratio between the number of tourists from origin o and its population size (P).

$$\mathrm{S_{1o}} \equiv \frac{\mathrm{T_o}}{\mathrm{P_o}}$$

Definition 3. Share 2: The ratio of preferences for each kind of tourism (S_2) is the ratio between the number of tourists from origin o that are traveling for kind of tourism k with respect to the total number of tourists.

$$\mathrm{S_{2ok}} \equiv \frac{\mathrm{T_{ok}}}{\mathrm{T_o}}$$

Definition 4. Share 3: The market share (S_3) corresponding to the pair of origin-destination od for kind of tourism k is defined as the ratio between the number of tourists from origin o to destination d for kind of tourism k and the total number of tourists from origin o for kind of tourism k.

$$\mathrm{S_{3odk}} \equiv \frac{\mathrm{T_{odk}}}{\mathrm{T_{ok}}}$$

Theorem. *Tourism demand for each pair of origin-destination by kind of tourism can be decomposed into shares, so that:*

$$T_{odk} = P_o \bullet S_{1o} \bullet S_{2ok} \bullet S_{3odk} \tag{4}$$

The proof can be found in the Appendix.

Corollary. *The expected tourism demand of each pair of origin-destination by kind of tourism can be decomposed into shares, so that:*

$$\mathrm{E}[T_{odk}] = \mathrm{E}[P_o] \bullet \mathrm{E}[S_{1o}] \bullet \mathrm{E}[S_{2ok}] \bullet \mathrm{E}[S_{3odk}] \tag{5}$$

Substituting Eq. (5) into Eq. (3):

$$L_{odk} = \mathrm{E}[P_o] \bullet \mathrm{E}[S_{1o}] \bullet \mathrm{E}[S_{2ok}] \bullet \mathrm{E}[S_{3odk}] - P_o \bullet S_{1o} \bullet S_{2ok} \bullet S_{3odk}, \forall\ odk \tag{6}$$

Eq. (6) represents different ways of market growth or decrease. For simplicity, it can be explained using comparative statics component by component, such as:

Component 1. Population changes.

Ceteris paribus, if origin population varies, the latent demand also varies, so that:

$$L_{odk,t+1} = (\mathrm{E}[P_{o,t+1}] - P_{o,t})\bullet S_{1o,t}\bullet S_{2ok,t}\bullet S_{3odk,t}$$

Component 2. Participation rate changes.

Over time, origins may increase their participation rate in tourism. For instance, this may occur under income changes, so that:

$$L_{odk,t+1} = P_{o,t}\bullet(\mathrm{E}[S_{1o,t+1}] - S_{1o,t})\bullet S_{2ok,t}\bullet S_{3odk,t}$$

Components 1 and 2 provide dynamics to the latent demand. Population and/or the participation rate may increase over time. However, aggregate S_2 and S_3 always equal one. They may be redistributed but they cannot grow over time. Destination policymakers cannot influence either origin population size, or origin participation rate, or S_2 preferences distribution over kind of tourism.

Component 3. Changes on preferences for each kind of tourism.

In the short run, the preferences for each kind of tourism are unlikely to change. However, in the long run, they may change, so that, ceteris paribus, the latent demand can be written as:

$$L_{odk,t+1} = P_{o,t}\bullet S_{1ok,t}\bullet(\mathrm{E}[S_{2o,t+1}] - S_{2o,t})\bullet S_{3odk,t}$$

Component 4. Market shares changes.

Destination policymakers cannot influence on $\mathrm{E}[P_o]\cdot\mathrm{E}[S_{1o}]\cdot\mathrm{E}[S_{2ok}]$, but they can influence on $\mathrm{E}[S_{3odk}]$. Thus, if such expectations are treated as constants, Eq. (3) can be rewritten as:

$$L_{odk} = \mathrm{E}[T_{odk}] - T_{odk} = P_o\bullet S_{1o}\bullet S_{2ok}\bullet\mathrm{E}[S_{3odk}] - P_o\bullet S_{1o}\bullet S_{2ok}\bullet S_{3odk}$$

$$L_{odk} = P_o\bullet S_{1o}\bullet S_{2ok}\bullet(\mathrm{E}[S_{3odk}] - S_{3odk}),\ \forall\ odk \tag{7}$$

Empirical approach

The empirical approach deals with the estimation of the expected value of each component, i.e.: $\mathrm{E}[P_{o,\ t+1}]$, $\mathrm{E}[S_{1o,\ t+1}]$, $\mathrm{E}[S_{2o,\ t+1}]$ and $\mathrm{E}[S_{3odk}]$.

The Component 1, $\mathrm{E}[P_{o,\ t+1}]$, requires an understanding of population dynamics. The population can be understood by employing time series analysis, and there is a vast literature on this topic (Wilson & Rees, 2005). The research conducted has discovered that population is influenced by the size of different age cohorts (Shang, 2012), and immigration or migration processes (Cushing & Poot, 2003). However, understanding the dynamics of Component 1 is beyond the scope of this paper.

The Component 2, $E[S_{1o,\ t+1}]$, requires an understanding of tourism participation dynamics. The literature has considered this topic from an individual or household approach with Probit or Tobit models (see for instance, Van Soest & Kooreman, 1987; Melenberg & Van Soest, 1996; Alegre & Pou, 2004). These models show that disposable income is usually the main determinant for tourism participation. Thus, it makes sense to think of GDP (Gross Domestic Product) as the main determinant at aggregate level (Halicioglu, 2010; Kim, Park, Lee, & Jang, 2012), despite the fact that the sensitivity of different origins under GDP changes is different (Eugenio-Martin & Campos-Soria, 2014; Smeral, 2012).

The Component 3, $E[S_{2o,\ t+1}]$, pursues the understanding of preferences on different kinds of tourism destinations, and has been little studied. However, approaches taken include nested multinomial logits (Eymann & Ronning, 1997), and sequential choice (Nicolau & Más, 2008).

Components 1, 2 and 3 are relevant for understanding long run dynamics, whereas Component 4 is key for understanding short run effects. For illustrative purposes, this paper shows models that estimate the determinants of Components 3 and 4. However, the key for estimating the short run latent tourism demand is related with Component 4. Indeed, policymakers can mainly influence Component 4.

Random parameter logit model

In order to model the destination choice of Component 4, an aggregate or an individual approach can be taken. At the aggregate level, a fractional regression model can be applied (Gómez-Déniz, Pérez-Rodríguez, & Boza, 2019). This model has the advantage that the dataset can be easier to handle and modelling can be parsimonious. However, it may miss some socioeconomic attributes that may enrich specification and accuracy. For this reason, we have considered a microeconometric approach instead. Destination choice at individual level has been studied with Multinomial Logit Models (Huybers, 2003), and with Random Parameter Logit Models (Nicolau, 2008) if heterogeneity among tourists is relevant.

The methodology is based on a behavioural model where the tourist chooses the destination that provides the highest level of utility, denoted by U. In this sense, individual i would choose destination d if and only if: $U_{id} > U_{ig}\ \forall\ d \neq g$. Nevertheless, these utility levels are unobservable. The only known aspects are certain socioeconomic characteristics of the individuals, denoted by S_i, and some attributes of the set of destinations, denoted by A_d. From the information available, we can construct a function $V_{id} = V$

(S_i, A_d), which represents the indirect utility that destination d provides to individual i. Thus, the utility can be decomposed as: $U_{id} = V_{id} + \varepsilon_{id}$, where ε_{id} denotes the unobserved part of utility for tourist i when she visits destination d. Thus, the probability that tourist i chooses to visit destination d is:

$$P_{id} = \Pr(U_{id} > U_{ig}, \forall\ d \neq g) = \Pr(V_{id} + \varepsilon_{id} > V_{ig} + \varepsilon_{ig}, \forall\ d \neq g) = \Pr(\varepsilon_{ig} - \varepsilon_{id} < V_{id} - V_{ig}, \forall\ d \neq g)$$

In logit models such error differences are assumed to be independently and identically distributed extreme value. As reported by Train (2009), within a random parameter logit model (RPLM), the probability that tourist i visits destination d is given by: $P_{id} = \int \left(e^{V_{id}(\beta)} / \sum_g e^{V_{ig}(\beta)}\right) f(\boldsymbol{\beta})\mathrm{d}\beta$, where $\boldsymbol{\beta}$ is the vector of parameters associated with each component of the utility function and $f(\boldsymbol{\beta})$ is the mixing distribution, which allows for modelling tourists' heterogeneous concern with respect to different determinants. If we assume that the utility is linear in β, then the probability can be written as: $P_{id} = \int \left(e^{\alpha_{id} + \beta_i' x_{id}} / \sum_g e^{\alpha_{ig} + \beta_i' x_{ig}}\right) f(\boldsymbol{\beta})\mathrm{d}\beta$.

One advantage of the RPLM is the flexibility to address heterogeneity. Such heterogeneity can be related with the varying sensitivities of tourists with respect to different determinants. For instance, in the case of sun and beach tourism demand analysis, the distance may play a heterogeneous role depending on the origin climate, such that tourists who live in countries with poor climate may be more willing to travel longer distances (e.g. north to south) than those who live in countries with better climate. In this case, the parameter associated with distance is expected to be negative, but it may be lower (in absolute terms) for those who are willing to travel longer distances. In that case, the parameter can be specified to shift depending on the origin climate. Similarly, the variance of the random parameters can be modelled according to other determinants. For instance, income is usually a determinant that explains heteroscedasticity because higher income households have a wider set of choices than those with less. Hence, each coefficient m can be modelled such that: $\beta_{mi} = \beta_m + \delta_m' z_i + \sigma_m \nu_{mi}$, where z are the determinants that may shift the coefficients and ν_{mi} are individual and choice specific unobserved random disturbances. Moreover, as stated above, such disturbances may be heteroscedastic, and such heteroscedasticity may depend on certain determinants. Thus, $\mathrm{Var}[\nu_{mi}] = \sigma_{jm}{}^2[\exp(\omega_m' h_i)]^2$ (see Hensher, Rose, & Greene, 2005: 605–620, for further details).

Illustration

This paper analyzes the latent tourism demand of the EU-28 countries. The dataset employed is the microdata surveyed for elaborating Flash Eurobarometer 432. The survey was conducted in January 2016 in relation with traveling during 2015. It comprised 30,105 observations in total, wherein 27,070 observations corresponded to European households belonging to the EU-28 countries, and the remaining observations correspond to Iceland, Macedonia, Moldova, Montenegro and Turkey.

The respondents state their main holiday destination and their main reason for going on holiday. In the construction of the dataset, we assume that the main holiday is linked with the main reason for going on holiday. The analysis below focuses on the main international holiday of each household. Moreover, the micro dataset of households is aggregated so that we end up with EU-28 origin markets and EU-28 destination markets. This illustration works on Eq. (7), where the participation rate refers to the outbound tourism market within the EU-28, so that:

$$L_{odk} = P_o \bullet S_{1o}^{EU28} \bullet S_{2ok}^{EU28} \bullet (\mathrm{E}[S_{3odk}^{EU28}] - S_{3odk}^{EU28})$$

Components 1 and 2: outbound tourism demand market size

The starting point is to identify the outbound tourism population size of the origin market. Origin market population is multiplied by the outbound tourism participation rate within the EU-28 (${S_{1o}}^{EU28}$), so that the number of tourists is revealed. Table 1 shows the participation rates of European countries, distinguishing between total participation rate ($S_{1,\ o}$), domestic participation rate (${S_{1,\ o}}^d$), international participation rate (${S_{1,\ o}}^i$) and participation rate within the EU-28 countries (${S_{1,\ o}}^{EU28}$). France and Greece are the countries with the highest domestic participation rate (0.51), followed by Bulgaria (0.48) and a set of sun and beach destinations such as Croatia (0.47), Italy (0.46) and Spain (0.45). On the international participation rate side, Luxembourg (0.80) shows the highest rate, followed by Denmark (0.63), Slovenia (0.62) and Austria (0.60), whereas East and South-European countries show lower rates, such as Italy (0.21), Spain (0.20), Romania (0.16), Bulgaria (0.11) and Greece (0.10). Finally, according to the international participation rate within EU-28 countries, the ranking is pretty similar to the international one. At the top of the ranking Luxembourg (0.65), Slovenia (0.57) and Cyprus (0.53) are located, whereas at the bottom of the ranking are Spain (0.14), Romania (0.14), Bulgaria (0.09) and Greece (0.08).

Component 3: market size by kind of tourism

Component 3 identifies different preferences of origin markets for different kinds of tourism. Interviewees were asked for their first motivation when traveling for holidays and their main holiday destination. That information is sample weighted so that a distribution of preferences can be obtained for each origin country. Overall, enjoying sun and beach destinations and visiting friends and relatives are the main purposes of European international tourism in the EU-28. This share is multiplied by the outbound tourism

Table 1
Component 2: Shares of tourism participation (S_{1o}) of EU-28 countries.

Origin country	$S_{1,\ o}$	$S_{1,\ o}{}^{d}$	$S_{1,\ o}{}^{i}$	$S_{1,\ o}{}^{EU28}$
Austria	0.81	0.21	0.60	0.43
Belgium	0.63	0.08	0.56	0.45
Bulgaria	0.59	0.48	0.11	0.09
Croatia	0.68	0.47	0.21	0.15
Cyprus	0.75	0.18	0.56	0.53
Czech Republic	0.75	0.32	0.43	0.34
Denmark	0.83	0.20	0.63	0.46
Estonia	0.69	0.25	0.44	0.34
Finland	0.83	0.36	0.47	0.35
France	0.77	0.51	0.26	0.16
Germany	0.77	0.26	0.51	0.35
Greece	0.61	0.51	0.10	0.08
Hungary	0.59	0.38	0.21	0.19
Ireland	0.79	0.21	0.58	0.46
Italy	0.66	0.46	0.21	0.15
Latvia	0.63	0.20	0.43	0.34
Lithuania	0.58	0.29	0.30	0.24
Luxembourg	0.81	0.00	0.80	0.65
Malta	0.57	0.07	0.49	0.42
Poland	0.66	0.38	0.28	0.22
Portugal	0.50	0.28	0.22	0.17
Romania	0.47	0.31	0.16	0.14
Slovakia	0.66	0.22	0.44	0.36
Slovenia	0.77	0.15	0.62	0.57
Spain	0.65	0.45	0.20	0.14
Sweden	0.84	0.36	0.49	0.31
The Netherlands	0.77	0.20	0.58	0.45
United Kingdom	0.71	0.24	0.47	0.29

Table 2
Component 3: Shares of kind of tourism preferences of main holidays by origin markets (S_{2ok}).

	Sun & beach	Health	City	Sport	Nature	Culture	VFR	Events	Other
Austria	0.32	0.05	0.15	0.07	0.11	0.14	0.12	0.03	0.01
Belgium	0.23	0.04	0.10	0.07	0.21	0.09	0.18	0.02	0.06
Bulgaria	0.32	0.04	0.09	0.03	0.12	0.08	0.24	0.03	0.03
Croatia	0.08	0.05	0.33	0.03	0.07	0.12	0.19	0.09	0.05
Cyprus	0.14	0.03	0.21	0.02	0.04	0.07	0.31	0.10	0.09
Czech Republic	0.40	0.09	0.03	0.08	0.17	0.05	0.10	0.03	0.04
Denmark	0.27	0.03	0.15	0.07	0.14	0.12	0.11	0.05	0.06
Estonia	0.11	0.03	0.10	0.10	0.07	0.18	0.26	0.04	0.12
Finland	0.18	0.09	0.28	0.06	0.06	0.06	0.21	0.04	0.03
France	0.27	0.05	0.20	0.04	0.12	0.15	0.14	0.02	0.02
Germany	0.30	0.06	0.09	0.07	0.14	0.10	0.15	0.02	0.04
Greece	0.06	0.03	0.26	0.03	0.07	0.15	0.29	0.05	0.06
Hungary	0.22	0.10	0.13	0.04	0.07	0.09	0.24	0.05	0.06
Ireland	0.40	0.02	0.14	0.07	0.03	0.06	0.16	0.05	0.06
Italy	0.13	0.04	0.27	0.01	0.04	0.26	0.16	0.04	0.04
Latvia	0.07	0.10	0.10	0.10	0.14	0.08	0.24	0.13	0.03
Lithuania	0.16	0.02	0.12	0.05	0.17	0.17	0.23	0.05	0.02
Luxembourg	0.25	0.05	0.09	0.04	0.13	0.10	0.27	0.03	0.03
Malta	0.01	0.12	0.09	0.05	0.09	0.15	0.18	0.12	0.19
Poland	0.29	0.02	0.18	0.07	0.11	0.06	0.21	0.03	0.02
Portugal	0.23	0.09	0.07	0.00	0.05	0.16	0.27	0.06	0.05
Romania	0.22	0.02	0.10	0.01	0.13	0.09	0.34	0.00	0.07
Slovakia	0.42	0.12	0.04	0.03	0.08	0.07	0.13	0.05	0.06
Slovenia	0.60	0.01	0.07	0.03	0.06	0.07	0.10	0.02	0.05
Spain	0.08	0.02	0.19	0.03	0.06	0.29	0.25	0.03	0.04
Sweden	0.32	0.19	0.07	0.03	0.03	0.11	0.16	0.04	0.04
The Netherlands	0.31	0.00	0.07	0.04	0.24	0.15	0.11	0.02	0.06
United Kingdom	0.36	0.01	0.10	0.03	0.06	0.09	0.21	0.03	0.11
Mean EU-28	0.24	0.05	0.14	0.05	0.10	0.12	0.20	0.05	0.05

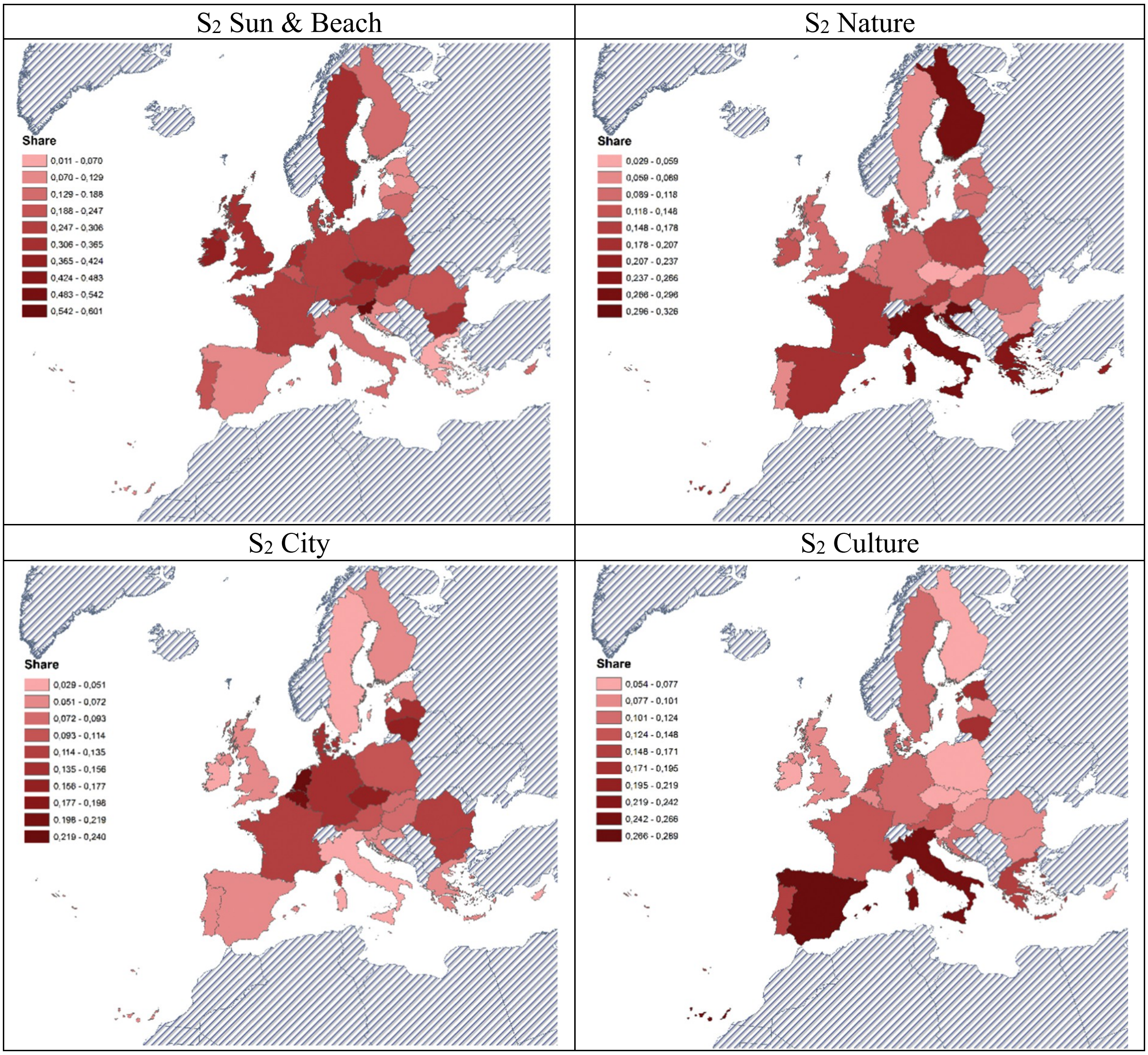

Fig. 1. S_2 shares of kind of tourism preferences by origin market (2015).

demand market size to reveal the origin market size by kind of tourism. Table 2 shows the details of each origin market, so that each raw must sum 1.

The results are very interesting. Slovenia leads the sun and beach preferences (60%), Sweden leads the health preferences (19%), Croatia leads the city preferences (33%), Estonia leads the sports preferences (10%), The Netherlands leads the nature preferences (24%), Spain leads the culture preferences (29%), Romania (34%) leads the visiting friends and relatives' preferences, and Latvia (13%) leads the events international traveling preferences. A visual result is shown in Fig. 1 using a Geographic Information System.

The determinants of Component 3 are estimated with a Multinomial Logit model. The results are shown in Table 4. For simplicity, it shows the marginal effects of sun and beach, nature, city, culture and visiting friends and relatives' preferences. However, it should be noted that other kinds of motivations such as events, sports, health and spa, and other are also included in the modelling, but not reported.

Each origin market S_{2ok} share is averaged over each individual who belong to origin o, so that:

$$\mathrm{E}[S_{2ok}] = \sum_{i} P_{ik,o}/n_o \quad \forall\ ok$$

where $p_{ik,\ o}$ denotes the estimated probability that individual i visits the kind of destination k, given that she lives in origin o, and n denotes sample population size. Moreover, under a multinomial logit model, the probabilities are defined in terms of the odd ratios based on the indirect utility function V_{ik}, which is conditioned upon origin o:

Table 3
Determinants of Component 3 (kind of tourism decision of main holidays). Marginal effects of multinomial logit regression of EU-28 countries.

	Sun and beach	Nature	City	Culture	VFR
Gender	−0.013	0.0172**	−0.004	−0.024**	−0.029***
	(0.010)	(0.007)	(0.007)	(0.007)	(0.009)
Age	−0.001***	0.0005	−0.0002	0.001***	−0.0004
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
GDP pc	0.0000006*	0.0000006**	−0.0000008***	0.0000008***	−0.0000008**
	(0.0000003)	(0.0000002)	(0.0000003)	(0.0000002)	(0.0000003)
Origin cultural attractiveness	0.0007*	−0.00004	0.0007***	0.001***	−0.0008**
	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
Origin climate	−0.040***	0.001	0.006***	0.013***	0.010***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Occupation (only significant ones)					
Student	−0.110*	−0.053	0.069	0.133***	0.020
	(0.060)	(0.048)	(0.045)	(0.045)	(0.057)
Other (manual worker)	−0.076	−0.137***	0.134	−0.062*	0.053
	(0.194)	(0.045)	(0.206)	(0.034)	(0.220)
Seeking a job	−0.079	−0.084*	0.022	0.044	0.129***
	(0.064)	(0.048)	(0.045)	(0.042)	(0.061)
Other (self-employed)	−0.050	−0.025	0.038	0.089*	−0.021
	(0.070)	(0.055)	(0.051)	(0.050)	(0.063)
Professional	−0.017	−0.010	0.031	0.075**	−0.070
	(0.060)	(0.047)	(0.041)	(0.038)	(0.053)
General management	0.049	−0.045	0.011	0.084*	−0.087
	(0.068)	(0.050)	(0.046)	(0.045)	(0.057)
Civil servant	−0.0009	−0.027	0.053	0.081**	−0.067
	(0.060)	(0.047)	(0.041)	(0.037)	(0.053)
Retired	−0.046	−0.025	0.025	0.078**	0.003
	(0.058)	(0.046)	(0.040)	(0.036)	(0.053)
Number of observations	7368	7368	7368	7368	7368

Standard errors in brackets.
*** Level of significance 1%.
** Level of significance 5%.
* Level of significance 10%.

$$P_{ik,o} = e^{V_{ik,o}(\beta)} / \sum_{h} e^{V_{ih,o}(\beta)}$$

The indirect utility function is specified in linear form such as:

$$V_{ik,o} = U(g_i, a_i, i_o, c_o, cl_o, o_i)$$

where g_i denotes gender and is a binary variable that takes value 1 if the interviewee is a man, a_i denotes age, i_o denotes income at the origin region, which is proxied with regional gross domestic product per capita in purchasing power parity at NUTS2 level, c_o denotes origin cultural attractiveness, which is measured by the number of World Heritage UNESCO sites, cl_o denotes origin climate, which is measured by the yearly climate index as defined by Eugenio-Martin and Campos-Soria (2010). The index takes into account monthly temperature and rain conditions within a double hurdle fashion, so that linear and overriding issues are avoided. The climate variable index can lie between 0 and 12 depending on the number of months with "good" climate at origin, and o_i denotes occupation.

The results in Table 3 show that origin climate is a key determinant for sun and beach tourism preferences, so that origin countries with poorer climate show higher preferences for traveling for sun and beach purposes, whereas residents of origins with better climate indices look for other kinds of destinations. It is also interesting to highlight that origin climate does not have a significant influence on any other kind of tourism. Additionally, the degree of cultural attractiveness in origin countries has proved to be a push factor for preferring city or cultural destinations.

Moreover, there are some gender differences. Men are more interested in visiting nature-based destinations, whereas women are keener to visit cultural destinations and traveling for visiting friends or relatives. The results also show that, on average, younger tourists are more likely to choose sun and beach destinations; but this switches to cultural destinations when tourists get older. On top of that, young tourists who are also students moderate their preferences in favor of cultural destinations instead of sun and beach destinations. Finally, tourists who live in regions with lower income are more likely to spend their holidays visiting friends and relatives or city destinations. Willingness to spend holidays visiting friends and relatives increases if the individual is seeking a job.

Component 4: market share by kind of tourism

For simplicity, the paper focuses on the main kinds of tourism: sun and beach (24.19% of European travelers), city (13.71%), culture (11.82%), and nature-based tourism (9.96%). Visiting friends and relatives (19.87%) is also relevant, but this illustration is

Table 4
Component 4: Current destination market share of main holidays by kind of tourism ($S_{3dk}{}^{EU28}$) (EU-28, 2015).

	Sun & beach	Nature	City	Cultural
Austria	0.01	0.09	0.05	0.04
Belgium	0.01	0.00	0.02	0.02
Bulgaria	0.02	0.01	0.00	0.01
Croatia	0.13	0.07	0.03	0.02
Cyprus	0.03	0.00	0.01	0.00
Czech Republic	0.00	0.01	0.01	0.03
Denmark	0.00	0.04	0.03	0.01
Estonia	0.00	0.00	0.01	0.00
Finland	0.00	0.01	0.00	0.01
France	0.07	0.14	0.16	0.19
Germany	0.00	0.06	0.09	0.06
Greece	0.17	0.05	0.04	0.05
Hungary	0.01	0.01	0.04	0.02
Ireland	0.00	0.01	0.01	0.02
Italy	0.10	0.17	0.15	0.21
Latvia	0.00	0.01	0.00	0.00
Lithuania	0.00	0.00	0.00	0.00
Luxembourg	0.00	0.01	0.00	0.00
Malta	0.01	0.00	0.01	0.01
Netherlands	0.01	0.04	0.03	0.02
Poland	0.00	0.02	0.01	0.01
Portugal	0.05	0.05	0.05	0.05
Romania	0.00	0.01	0.01	0.02
Slovakia	0.00	0.03	0.01	0.00
Slovenia	0.00	0.00	0.00	0.00
Spain	0.34	0.09	0.11	0.10
Sweden	0.00	0.04	0.02	0.01
United Kingdom	0.01	0.03	0.09	0.06
Total	1	1	1	1

aimed at policies and since policymakers cannot make much difference in attracting this kind of tourism, it has been ruled out of the exercise.

Table 4 shows the current destination market share by kind of tourism (S_{3dk}). In the sun and beach tourism market, Spain concentrates 34% of demand, followed by Greece (17%), Croatia (13%) and Italy (10%). In the nature-based tourism market, Italy leads the market share with 17%, followed by France (14%), Spain (9%) and Austria (9%). The city-based tourism market is led by France (16%) together with Italy (15%), and followed by Spain (11%), the United Kingdom (9%) and Germany (9%). Finally, culture-based tourism market is headed by Italy (21%) together with France (19%) and followed by Spain (10%), Germany (6%) and the United Kingdom (6%). All these results are shown in Table 4, but they can also be seen and compared using the Geographic Information System, as shown in Fig. 2.

The expected S_3 values lie within 0 and 1, so that they may be estimated by employing a random parameter logit model. This model provides great flexibility to deal with the heterogeneity. Aggregate expected share is obtained after averaging individual probabilities over origins such that:

$$E[S_{3od,k}] = \sum_i P_{iod}/n_o \ \forall \ k$$

The individual probability of choosing destination d depends on the indirect utility function that each pair of origin-destination provides to the individual, so that under RPLM:

$$P_{iod} = \int \left(e^{V_{iod}(\beta)} / \sum_g e^{V_{iog}(\beta)} \right) f(\beta) \mathrm{d}\beta$$

Specifically, the indirect utility model specification can be expressed as:

$$V_{iod}(\beta) = U(q_d, p_{od}, d_{od} \mid g_i, a_i)$$

where q_d denotes the destination quality for enjoying destination d, which is proxied with an alternative specific constant (ASC). The ASC works as a benchmark for each P_d, which will be shifted depending on the moderators of the individual and his or her place of residence (Huybers, 2003), p_{od} denotes the relative prices, which is proxied as the ratio between the purchasing power parities of each pair of origin-destination, d_{od} denotes the distance between origin and destination, which are measured as the Euclidian distance between the centroid of each origin at NUTS2 level and the destination at country level. The relevance of distance is not

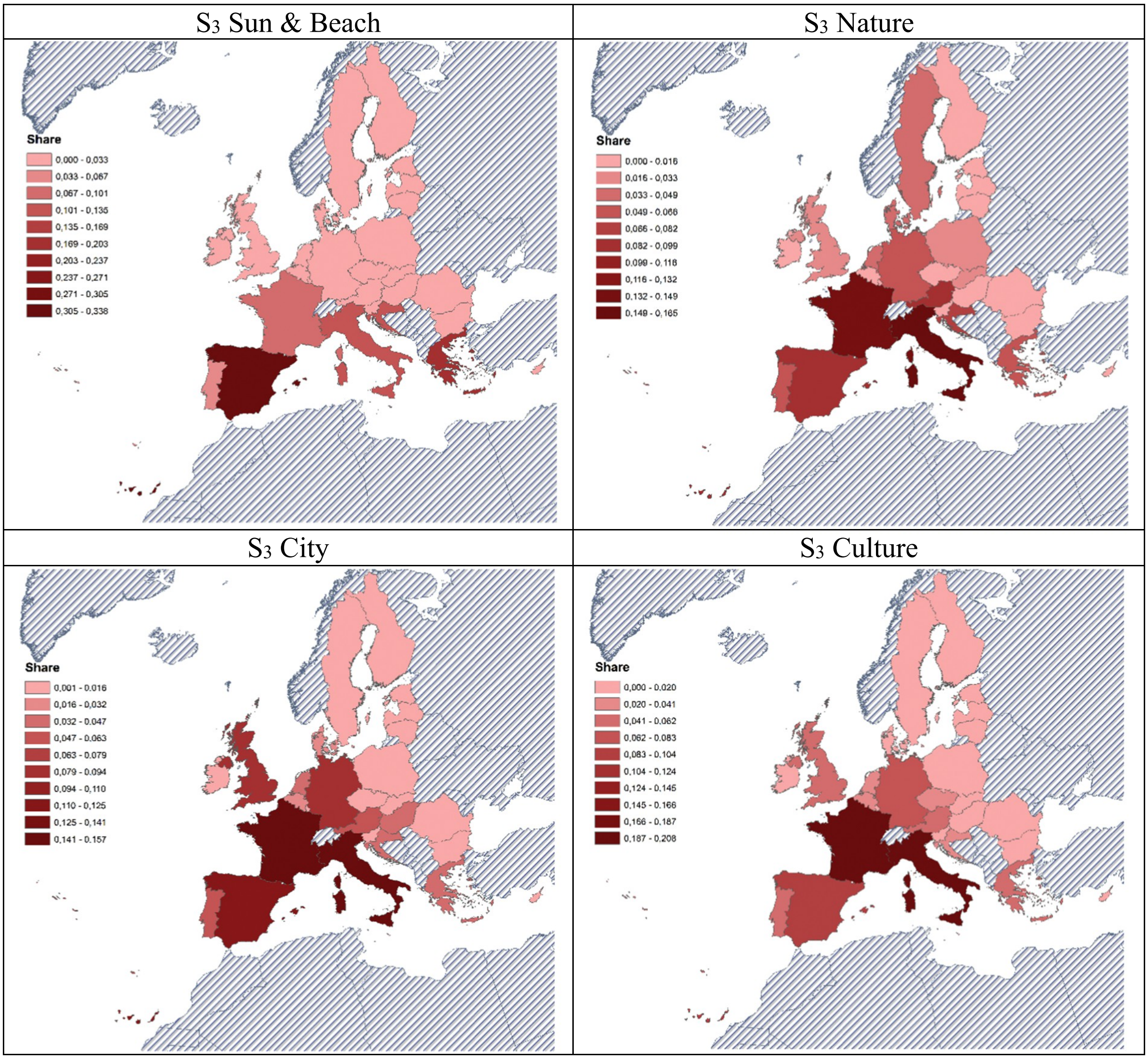

Fig. 2. Average tourism market share (S_3) spatial distribution by kind of destination (2015).

homogeneous (Nicolau, 2008) and it is expected to decay (McKercher & Lew, 2003). Moreover, it varies with the origin country (McKercher & Mak, 2019) with a high degree of heterogeneity (Sun & Lin, 2019). In this paper in order to address such previous findings, the distance decay effect is modelled with a normal random parameter. In our model we have considered that the parameter shifts according to the origin climate. Thus, it is expected that the distance parameter be negative, but reduced (in absolute terms) depending on how poor the origin climate is. Moreover, the heterogeneity is also modelled with income, because higher income is associated with higher heterogeneity and higher random parameter variance.

Finally, socioeconomic variables such as gender and age enters the model to control for individual socioeconomic characteristics. The results are shown in Table 5 and distinguish the four kinds of tourism destinations employed in this paper. For simplicity, the 28 coefficients of each ASC, as well as each of the 28 coefficients of each of the socioeconomic variables are omitted in the table. Overall, they show significant differences across destinations especially in terms of ASC, some slight differences in terms of age, and fewer differences concerning gender. In all cases, the coefficient of the relative prices is negative and significant, so that relative cheaper baskets of goods and services work as a pull factor, as expected. The same applies to the coefficient of distance which is also negative and significant in all the regressions. The origin climate shifts (in absolute terms) the distance coefficient significantly downwards for sun and beach and nature-based tourism destinations. It proves that poor origin climate works as a push factor to travel further. This effect occurs in the kinds of destinations that are more climate dependent, i.e. nature or sun and beach. However, it does not apply to city or cultural destinations where climate dependency can be overcome. Finally, it should be noted that distance random parameter

Table 5
Determinants of Component 4: Destination choice of main holidays. Random parameter logit model by kind of tourism destination.

	Sun and beach	Nature	City	Culture
Nonrandom parameters				
Relative prices	−9.6763***	−10.0308***	−3.8573***	−4.8433***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Alternative specific constant	(…)	(…)	(…)	(…)
Gender	(…)	(…)	(…)	(…)
Age	(…)	(…)	(…)	(…)
Random parameters				
Distance	−0.0010***	−0.0021***	−0.0019***	−0.0019***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Derived standard deviation of the parameter distribution	0.0004***	0.0007***	0.0003***	0.0002**
	[0.0000]	[0.0000]	[0.0015]	[0.0346]
Heterogeneity in mean				
Origin climate	−0.0003***	−0.0002***	0.00005	0.0001***
	[0.0000]	[0.0001]	[0.1096]	[0.0011]
Heteroscedasticity in random parameters				
Income	0.00003***	0.00002***	0.00003***	0.00003***
	[0.0000]	[0.0000]	[0.00003]	[0.0000]
Pseudo R^2	0.5046	0.4587	0.3038	0.2947
Maximum likelihood	−5997,02	−3868.42	−3152.16	−3266.33
Number of observations	3636	2148	1362	1393
Replication for simulated probabilities	100	100	100	100

P-values are in square brackets.
*** Denotes 1% significance level.
* Level of significance 5%.

Table 6
Illustrative example: Latent tourism demand from UK to Spain for sun & beach purposes.

	Concept	Formulae	Value
Component 1	Population size	P_o	65,128,861
Component 2	Outbound tourism participation rate in EU-28	${S_{1o}}^{EU28}$	0.29
	UK outbound market size in EU-28		18,887,370
Component 3	Preferences on sun & beach destination	${S_{2ok}}^{EU28}$	0.36
	UK outbound sun & beach market size in EU-28		6,799,453
Component 4	Expected market share	$E[{S_{3odk}}^{EU28}]$	0.39
			2,651,786
	Current market share	${S_{3odk}}^{EU28}$	0.54
			3,671,705
	Latent demand estimate	${L_{odk}}^{EU28}$	−1,019,919

standard deviation is significant and that income works as a moderator of such value (heteroscedasticity) proving correct its relationship with a wider set of choices and probabilities.

The model is employed to estimate the expected S_3 share for each pair of origin-destination and for each kind of tourism. The difference between the expected S_3 and the current S_3 reveals how far each pair of origin-destination is from its potential demand. That figure is a market share which can be translated into a tourists figure according to Eq. (7).

How does the methodology work in this illustration?

An example is provided below. Table 6 shows how the method works for the case of main holiday flow between the UK and Spain for sun and beach purposes.

In 2015, the UK had a population of 65,128,861 people. However, 29% of its population travel abroad to destinations within the EU-28 for their main holidays. This leaves an origin market size of 18,887,370 international tourists traveling within the EU-28. Moreover, sun and beach destinations are popular, representing 36% of the outbound tourism demand market share. This represents a market size of 6,799,453 tourists. Moreover, the Spanish market represents 54% of outbound British market for sun and beach purposes, so that 3,671,705 British traveled there during 2015 for their main holiday. However, according to the model, the expected market share should be around 39%. Thus, its current market share is larger than the expected share. This means that British market traveling to Spain is pretty well covered by air connectivity, or marketing campaigns, as compared to other European origin markets.

Similar results are obtained for all pair of origin-destinations within the EU-28, for the four main kinds of tourism purposes. The details are shown below in Figs. 3, 4, 5, and 6. These figures show a heatmap for each pair of origin-destination and each kind of

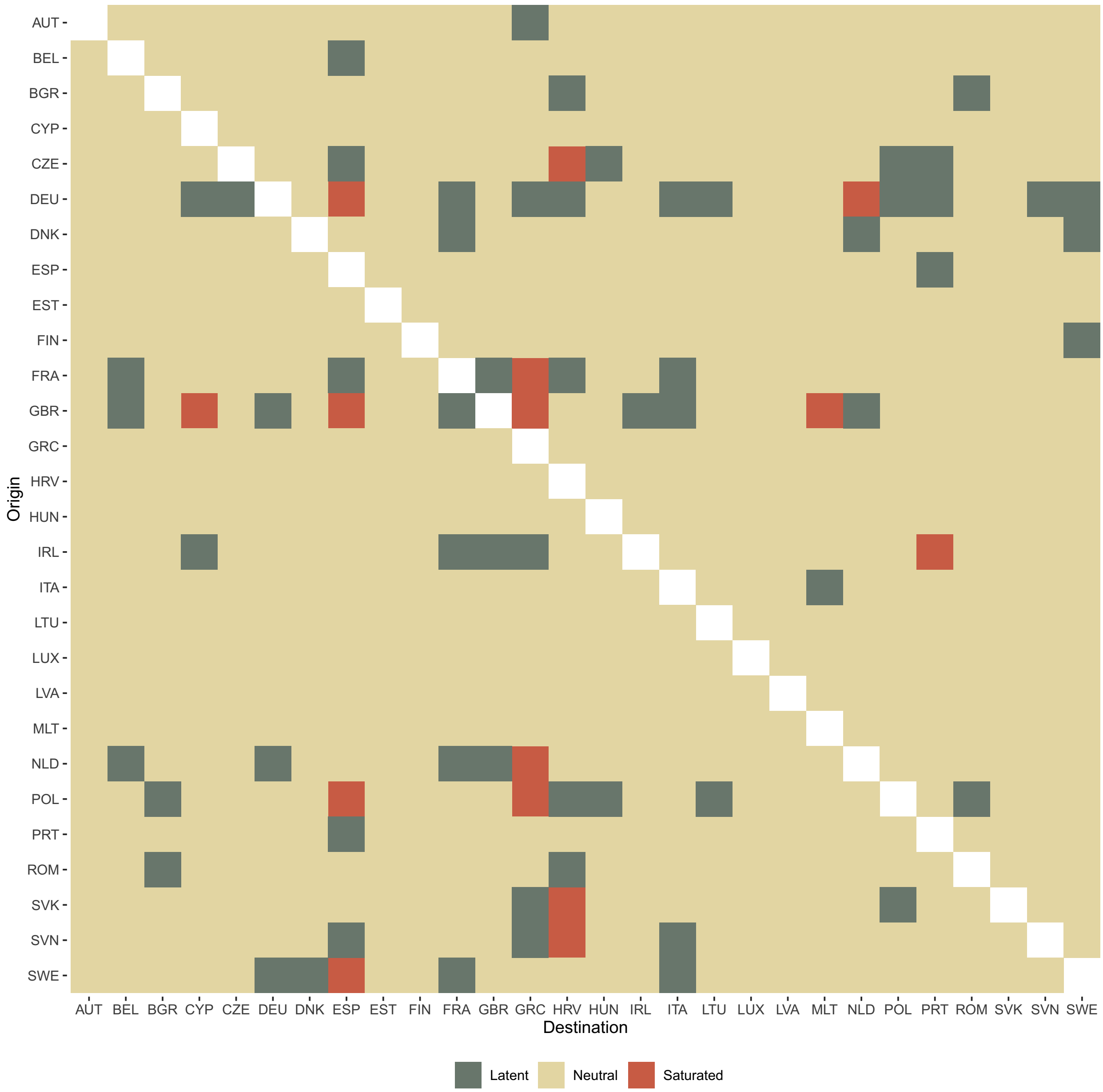

Fig. 3. Heat map of the latent and saturated demand of sun and beach destinations.

tourism destination. Green cells represent a pair of origin-destination with positive latent tourism demand. Specifically, those selected represent 10th percentile of all pairs with positive values. Similarly, red cells represent saturated flow between such pairs of origin-destination. The remaining pale yellow cells represent not so relevant pairs in terms of latent or saturated markets.

Further details for top latent tourism demand origins are shown in Table 7. This shows the top 3 latent tourism demand origins by destinations and purposes. For sun and beach destinations, the main latent demand markets revealed (origin to destination) are the United Kingdom – France (1,562,410 yearly travelers); United Kingdom – Italy (382,960); and Germany – Greece (286,577). For nature-based tourism destinations, latent tourism demand is revealed in the routes between Germany – France (374,017); Poland – Czech Republic (211,933); and Germany – Czech Republic (211,383). City destinations main figures are Italy – Spain (469,677); Spain – Portugal (306,898); and Germany – France (288,307). Finally, cultural destinations can grow for the following routes: Spain – Italy (508,719); Italy – Spain (428,120); and Germany – France (320,660).

Overall, the results show the relevance of German origin market for two reasons, i.e. large population and a high level of willingness to participate in EU-28 tourism. Currently, there is latent demand for sun and beach tourism in Greece for the German

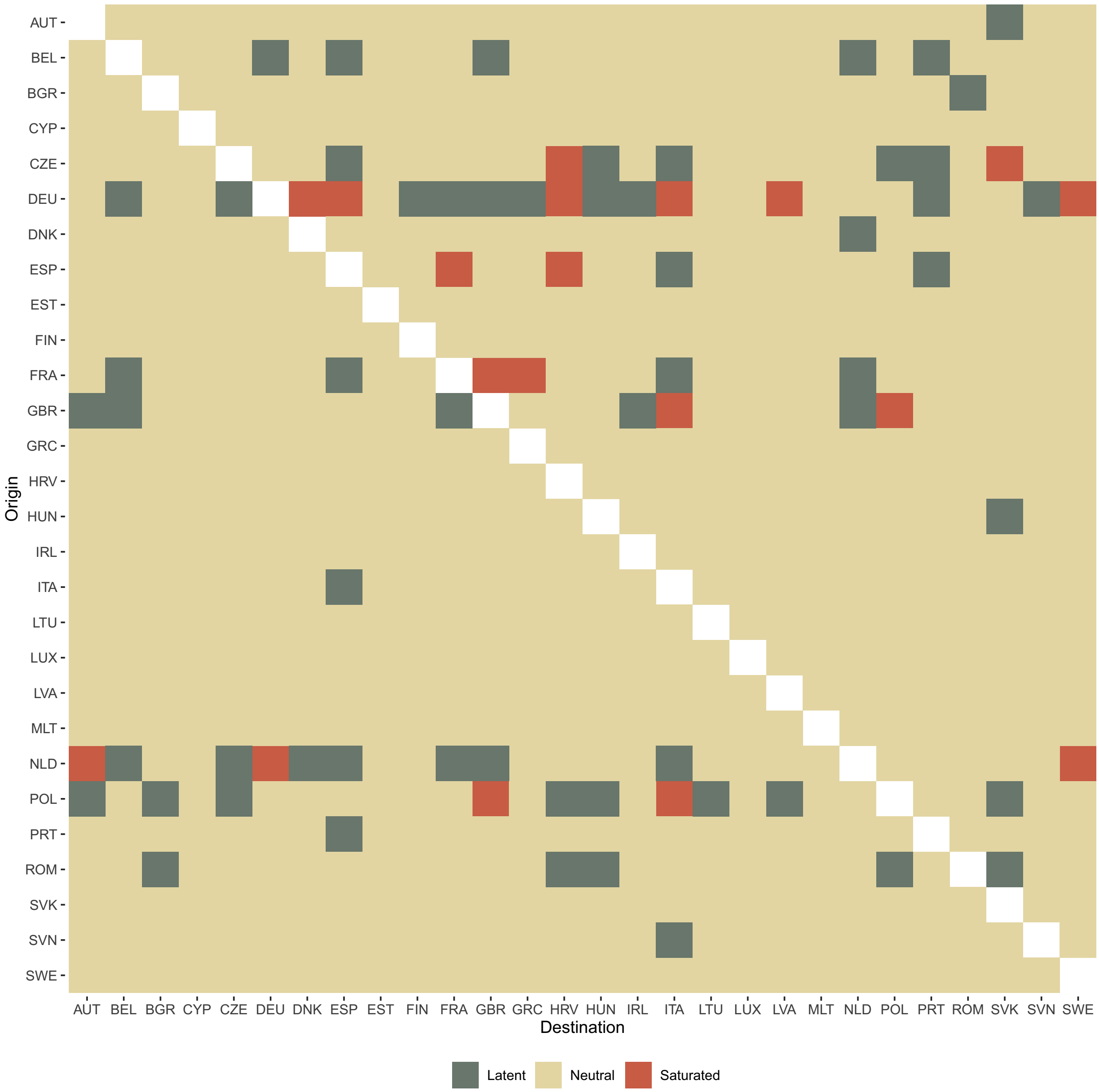

Fig. 4. Heat map of the latent and saturated demand of nature-based destinations.

market, and opportunities for further growth can be explored in France if they target tourists with interests in nature, cities and/or cultural tourism. Moreover, Spain has shown its dominance in sun and beach tourism within the EU-28, especially for the British market where the model shows that such flow is currently saturated. However, the model also reveals that alternative destinations such as French and Italian sun and beach markets may have larger demand from the United Kingdom.

Conclusion

The methodology reveals latent tourism demand and provides a figure that quantifies its size. Such information is very useful as an aid to target markets. It distinguishes demand by kind of tourism for each pair of origin-destination, so that it is informative at the time of designing a marketing campaign. It also identifies location for the campaign and the nature of the campaign, so that one or several motivations can be stressed to pull tourists from that origin more efficiently. Additionally, the whole set of motivations can be added to define latent tourism demand for each pair of origin-destination. This figure can be used to aid decisions on strengthening or

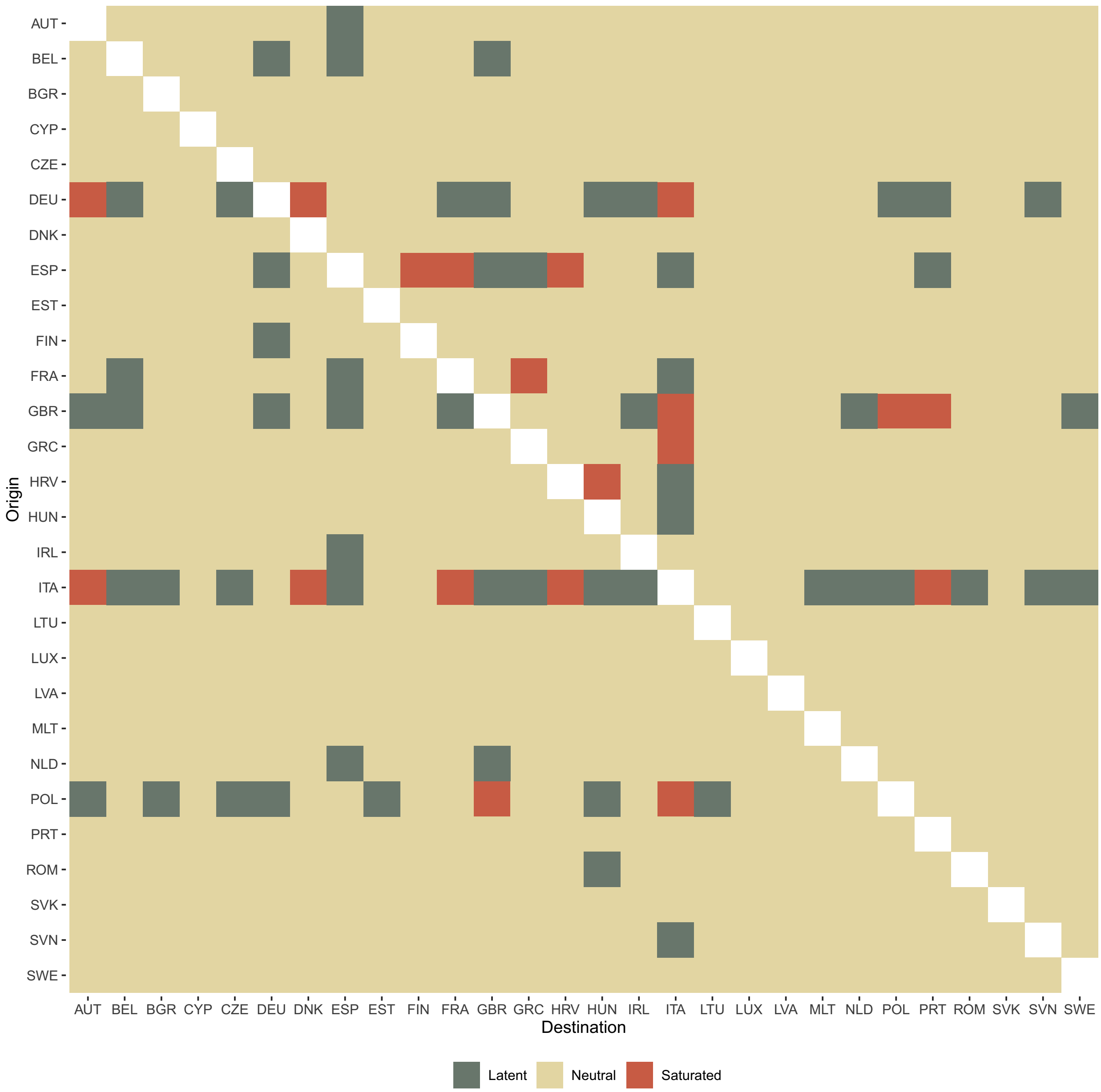

Fig. 5. Heat map of the latent and saturated demand of city destinations.

opening new air routes. Thus it can be used as a tool for targeting origin markets. The methodology also provides information on pairs of origin-destinations that are larger than the expected value. For these cases it may not be necessary to perform further marketing promotion or improve air connectivity.

The method is very intuitive and not very demanding in terms of dataset requirements because it disentangles tourists' decision making into several stages that can be explained independently and later rejoined for the final calculation. It is an advantage for short run policymaking because policymakers do not need to understand all stages except the last.

It should be noted that the profile of tourists matter to the destination, especially in terms of length of stay and expenditure per tourist and night. Other tourists' characteristics such as behavior or respect for the environment are very important for targeting markets. All this information needs to be incorporated to make a comprehensive and more informative decision. A way of aggregating is linking the potential arrivals with their expected expenditure and length of stay, so that added value measures, such as aggregate expenditure and GDP can also be anticipated. They can be used to provide an ex-ante economic valuation of subsidization policies of new air traffic routes as well as the return on tourism marketing campaigns.

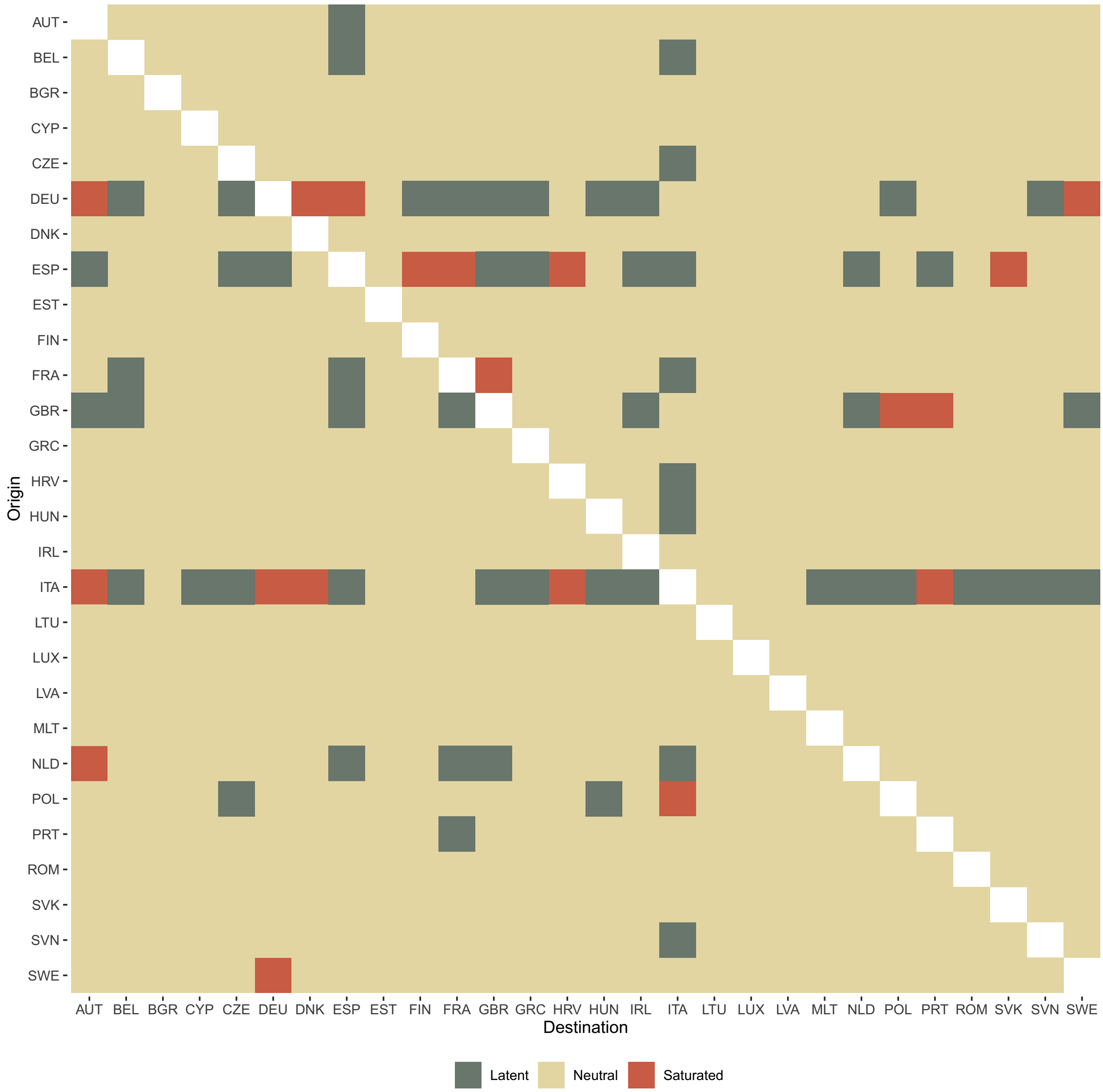

Fig. 6. Heat map of the latent and saturated demand of cultural-based destinations.

Further research may consider all the trips taken within a year rather than the main holiday only. This way the shares take into account holidays of all sorts of length, especially short breaks, which may increase the relative relevance of city trips. However, it also opens up new issues such as the way of comparing market shares with different lengths of stay. One alternative may be based on night shares; another alternative may disentangle the shares into short and long holidays. Policymakers may be interested in understanding both kinds of holidays and the analysis may provide them with different responses.

Other kinds of spatial focus can also be applied, such as domestic or international tourism markets. Similarly, the methodology can also be applied to any other sector where competition occurs, but restrictions in terms of logistics or marketing efforts are not homogeneous. Further research may also focus on a larger set of motivations by each individual. Additionally, Components 1 or 2 may be better understood with further research. Population forecasts can be included to understand age cohorts' variation and to link it with their holiday preferences.

Table 7
Top 3 latent tourism demand origins by destinations and purposes (number of tourists per year for main holidays within EU-28).

Origin	Destination	Latent demand	$E[S_{3odk}{}^{EU28}] - S_{3odk}{}^{EU28}$
Sun and beach			
United Kingdom	France	1,562,410	0.23
United Kingdom	Italy	382,960	0.05
Germany	Greece	286,577	0.03
Nature			
Germany	France	374,017	0.09
Poland	Czech Republic	211,933	0.23
Germany	Czech Republic	211,383	0.05
City			
Italy	Spain	469,677	0.19
Spain	Portugal	306,898	0.25
Germany	France	288,307	0.10
Culture			
Spain	Italy	508,719	0.27
Italy	Spain	428,120	0.18
Germany	France	320,660	0.10

Acknowledgment

We want to acknowledge the positive and constructive feedback of Sergio Ardila, Ofelia Betancor, Javier Campos, Federico Inchausti, Adela Moreda, Ubay Pérez and Pilar Socorro at an early stage, as well as two reviewers who certainly helped us to improve the quality of this paper. The usual disclaimer applies though.

We acknowledge the research grant ECO2016-80268-R funded by Ministerio de Economia y Competitividad in Spain.

Appendix A

Proof of Theorem

$$\mathrm{T_{odk}} = \mathrm{T_{odk}}$$

$$T_{odk} = P_o \frac{T_{odk}}{P_o} = P_o \frac{T_o}{T_o}\frac{T_{odk}}{P_o} = P_o \frac{T_o}{P_o}\frac{T_{odk}}{T_o} = P_o \frac{T_o}{P_o}\frac{T_{ok}}{T_{ok}}\frac{T_{odk}}{T_o} = P_o \frac{T_o}{P_o}\frac{T_{ok}}{T_o}\frac{T_{odk}}{T_{ok}};$$

$$\text{i. e. } T_{odk} = P_o \bullet S_{1o} \bullet S_{2ok} \bullet S_{3odk} \blacksquare$$

References

Alderighi, M., & Gaggero, A. A. (2019). Flight availability and international tourism flows. *Annals of Tourism Research, 79*, 1–16.
Alegre, J., & Pou, L. (2004). Micro-economic determinants of the probability of tourism consumption. *Tourism Economics, 10*, 125–144.
Andriamasy, L. R., & Rakotondramaro, H. H. (2016). Mean-variance-skewness in destination efficiency framework: The case of France. *European Journal of Tourism Research, 14*, 92–100.
Barbot, C. (2006). Low-cost airlines, secondary ariports, and state aid: An economic assessment of the Ryanair-Charleroi Airport agreement. *Journal of Air Transport Management, 12*(4), 197–203.
Botti, L., Goncalves, O., & Ratsimbanierana, H. (2012). French destination efficiency: A mean-variance approach. *Journal of Travel Research, 51*(2), 115–129.
Butler, R. W. (1980). The concept of a tourist area cycle of evolution: Implications for management of resources. *Canadian Geographer, 24*, 5–12.
Chen, M. H., Jang, S., & Peng, Y. J. (2011). Discovering optimal tourist market mixes. *Journal of Travel Research, 50*(6), 602–614.
Cushing, B., & Poot, J. (2003). Crossing boundaries and borders: Regional science advances in migration modelling. *Economics of Governance, 83*(1), 317–338.
Davies, A., & Prentice, R. (1995). Conceptualizing the latent visitor to heritage attractions. *Tourism Management, 16*(7), 491–500.
Dolnicar, S. (2010). Identifying tourists with smaller environmental footprints. *Journal of Sustainable Tourism, 18*(6), 717–734.
Dolnicar, S., & Leisch, F. (2008). Selective marketing for environmentally sustainable tourism. *Tourism Management, 29*(4), 672–680.
Eugenio-Martin, J. L., & Campos-Soria, J. A. (2010). Climate in the region of origin and destination choice in outbound tourism demand. *Tourism Management, 31*(6), 744–753.
Eugenio-Martin, J. L., & Campos-Soria, J. A. (2011). The role of income and the substitution pattern between domestic and international tourism demand. *Applied Economics, 43*(20), 2519–2531.
Eugenio-Martin, J. L., & Campos-Soria, J. A. (2014). Economic crisis and tourism expenditure cutback decision. *Annals of Tourism Research, 44*, 53–73.
Eymann, A., & Ronning, G. (1997). Microeconometric models of tourists' destination choice. *Regional Science and Urban Economics, 27*, 735–761.
Gómez-Déniz, E., Pérez-Rodríguez, J., & Boza, J. (2019). Modelling tourist expenditure at origin and destination. *Tourism Economics*. https://doi.org/10.1177/1354816619840845.
Halicioglu, F. (2010). An econometric analysis of the aggregate outbound tourism demand of Turkey. *Tourism Economics, 16*(1), 83–97.
Hawes, D. K., Taylor, D. T., & Hampe, G. D. (1991). Destination marketing by states. *Journal of Travel Research, 30*, 11–17.
Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis. A primer.* Cambridge: Cambridge University Press.
Huybers, T. (2003). Modelling short-break holiday destination choices. *Tourism Economics, 9*(4), 389–405.
Huybers, T., & Bennett, J. (2003). Environmental management and the competitiveness of nature-based tourism destinations. *Environmental and Resource Economics, 24*, 213–233.

Jang, S. C. (2004). Mitigating tourism seasonality – A quantitative approach. *Annals of Tourism Research, 31*(4), 819–836.
Jang, S. C., Morrison, A. M., & O'Leary, J. T. (2004). A procedure for target market selection in tourism. *Journal of Travel & Tourism Marketing, 16*(1), 19–33.
Kah, J. A., Lee, C., & Lee, S. (2016). Spatial-temporal distances in travel intention-behavior. *Annals of Tourism Research, 57*, 160–175.
Kastenholz, E. (2004). "Management of demand" as a tool in sustainable tourist destination development. *Journal of Sustainable Tourism, 12*(5), 388–408.
Kim, H. B., Park, J. H., Lee, S. K., & Jang, S. S. (2012). Do expectations of future wealth increase outbound tourism? Evidence from Korea. *Tourism Management, 33*(5), 1141–1147.
Laurino, A., & Beria, P. (2014). Low-cost carriers and secondary airports: Three experiences from Italy. *Journal of Destination Marketing and Management, 3*(3), 180–191.
Li, H., Song, H., & Li, L. (2017). A dynamic panel data analysis of climate and tourism demand: Additional evidence. *Journal of Travel Research, 56*(2), 158–171.
Markowitz, H. (1952). Portfolio selection. *Journal of Finance, 7*, 77–91.
McKercher, B., & Lew, A. A. (2003). Distance decay and the impact of effective tourism exclusion zones on international travel flows. *Journal of Travel Research, 42*(2), 159–165.
McKercher, B., & Mak, B. (2019). The impact of distance on international tourism demand. *Tourism Management Perspectives, 31*, 340–347.
Melenberg, B., & Van Soest, A. (1996). Parametric and semi-parametric modelling of vacation expenditures. *Journal of Applied Econometrics, 11*(1), 59–76.
Morley, C., Rosselló, J., & Santana-Gallego, M. (2014). Gravity models for tourism demand: Theory and use. *Annals of Tourism Research, 48*, 1–10.
Neuts, B., Romao, J., Nijkamp, P., & Shikida, A. (2016). Market segmentation and their potential economic impacts in an ecotourism destination: An applied modelling study on Hokkaido, Japan. *Tourism Economics, 22*(4), 793–808.
Nicolau, J. L. (2008). Characterizing tourist sensitivity to distance. *Journal of Travel Research, 47*, 43–52.
Nicolau, J. L., & Más, F. J. (2005). Stochastic modelling. A three-stage tourist choice process. *Annals of Tourism Research, 32*, 49–69.
Nicolau, J. L., & Más, F. J. (2008). Sequential choice behavior: Going on vacation and type of destination. *Journal of Travel Research, 29*(5), 1023–1034.
Núñez-Sánchez, R. (2015). Regional public support to airlines and airports: An unsolved puzzle. *Transportation Research Part E: Logistics and Transportation Review, 76*, 93–107.
Oliveira, A. V. M. (2008). An empirical model of low-cost carrier entry. *Transportation Research Part A: Policy and Practice, 42*(4), 673–695.
Perdue, R. R. (1996). Target market selection and marketing strategy: The Colorado downhill skiing industry. *Journal of Travel Research, 34*(4), 39–46.
Rakotondramaro, H., & Botti, L. (2017). Optimizing tourist demands with utility efficient frontier. *Tourism Economics, 24*(2), 157–166.
Ramos-Pérez, D. (2016). State aid to airlines in Spain: An assessment of regional and local government support from 1996 to 2014. *Transport Policy, 49*, 137–147.
Seetanah, B., Sannassee, R. V., Teeroovengadum, V., & Nunkoo, R. (2019). Air access liberalization, marketing promotion and tourism development. *International Journal of Tourism Research, 21*(1), 76–86.
Shang, H. L. (2012). Point and interval forecasts of age-specific fertility rates: A comparison of functional principal component methods. *Journal of Population Research, 29*, 249–267.
Smeral, E. (2012). International tourism demand and the business cycle. *Annals of Tourism Research, 39*(1), 379–400.
Song, H., Qiu, R. T. R., & Park, J. (2019). A review of research on tourism demand forecasting: Launching the annals of tourism research curated collection on tourism demand forecasting. *Annals of Tourism Research, 75*, 338–362.
Sönmez, S. F., & Graefe, A. R. (1998). Influence of terrorism risk on foreign tourism decisions. *Annals of Tourism Research, 25*(1), 112–144.
Sun, Y. Y., & Lin, P. C. (2019). How far will we travel? A global distance pattern of international travel from both demand and supply perspectives. *Tourism Economics, 25*(8), 1200–1223.
Train, K. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge: Cambridge University Press.
Van Soest, A., & Kooreman, P. (1987). A microeconometric analysis of vacation behaviour. *Journal of Applied Econometrics, 2*, 215–226.
Weaver, A. (2015). Target markets as working archetypes: Classifying consumers at tourism New Zealand. *Journal of Vacation Marketing, 21*(2), 163–174.
Wilson, T., & Rees, P. (2005). Recent developments in population projection methodology: A review. *Population, Space and Place, 11*(5), 337–360.
Yang, Y., Liu, H., & Li, X. (2019). The world is flatter? Examining the relationship between cultural distance and international tourists flows. *Journal of Travel Research, 58*(2), 224–240.

Juan L. Eugenio-Martin is Senior Lecturer at Universidad de Las Palmas de Gran Canaria. His research interests are tourism demand modelling and the economic assessment of tourism impacts.

José M. Cazorla-Artiles is PhD student at Universidad de Las Palmas de Gran Canaria. His research interests are tourism demand modelling and quantitative data analysis.