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Satisfaction and tourism expenditure behaviour

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Abstract In the literature, the quantification of the effect of satisfaction on tourists' expenditure behaviour has not been extensively studied. This research aims to fill in this gap, providing additional information about this crucial relation by analysing it from a microdata perspective. In particular, the Fuzzy Double-Hurdle model, a new model which combines the well-known Double-Hurdle model and the fuzzy set theory, is suggested and presented, both technically and by means of a real case study. The proposed model gathers the advantages of the Double-Hurdle model and the fuzzy set theory together producing a suitable model for the analysis of censored observations in presence of imprecise data. Specifically, the Double-Hurdle model allows to efficiently estimate the average values of a non-negative, non-normally distributed variable characterised by high frequency of zero values, as tourists' expenditure can be, considering the two-stages nature of the decision process. On the other end, the inclusion of the fuzzy set theory in the regression model allows to cope with the imprecision of both collected information (i.e. levels of satisfaction) and kind of measurement used (i.e. Liker-type scale). The results will help tourism managers to more accurately evaluate the efficacy of their policies

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and marketing strategies in enhancing tourists' satisfaction and, consequently, in increasing the level of spending at the destination.

Keywords Satisfaction · Expenditures behaviour · Imprecise data · Likert–type scale · Fuzzy numbers · Fuzzy regression · Fuzzy Double-Hurdle

1 Introduction

The level of satisfaction expressed by tourists who visit a destination can be seen as a tool to measure destinations' efforts in planning and marketing tourism products and services (Yoon & Uysal, 2005). Furthermore, tourists' satisfaction is a powerful and critical instrument to destination competitiveness, affecting destination choice, revisit intention and destination loyalty (Yoon & Uysal, 2005; Dolnicar et al., 2015; Alrawadieh et al., 2019). In particular, the more tourists are satisfied with a destination, the more they will recommend the destination to other people creating new tourists for the destination, enhancing destination reputation, increasing acceptance of higher prices and, consequently, producing higher profit for the destination (Anderson et al., 1997; Baker & Crompton, 2000; Kozak & Rimmington, 2000; Homburg et al., 2005; Dmitrović et al., 2009; Munier & Camelis, 2013). Therefore, it is crucial to fully understand both causes and consequences of being a dis/satisfied tourist (Song et al., 2012).

This research focuses on examining the important relationship between level of tourists' satisfaction and expenditure behaviour. The literature devoted to the analysis of this relationship is quite scarce and the call for new researches in this field is clear (Disegna & Osti, 2016; Jurdana & Frleta, 2017). In the tourism literature, to quantify, from a microdata perspective, the relation between level of satisfaction and level of spending, it is common practice to make use of either the standard linear regression model or the Tobit model (or one of its generalisation). In this study we suggest the adoption of the Fuzzy Double-Hurdle model, a new model that combine the Double-Hurdle model (Cragg, 1971) with the fuzzy set theory (Zadeh, 1965). This decision has been driven by two reasons. Firstly, the Double-Hurdle model has the following two main advantages over the standard regression model: 1) it allows to estimate the decision to purchase and the amount of money spent while on holiday (i.e. the two stages of the decision-making process) separately; 2) the standard linear regression model can produce biased and inconsistent estimates due to the high frequency of zero expenditures, the non-normality and non-negative nature of the data. Secondly, satisfaction is a subjective evaluation of a post-experience, or post-use, that depends on prior expectations. Therefore, as any other human feelings, satisfaction is the outcome of a complex individual process that involves a certain degree of uncertainty and imprecision (Lin & Yeh, 2013). To capture and measure these information, it is common practice to make use of the Likert-type scales. Unfortunately, this kind of measurement is itself imprecise and, summing up this imprecision with the imprecision of the information to be collected, we obtain final data that are even more vague (D'Urso et al., 2016). Nevertheless, most of the studies conducted in marketing, tourism, management, and business overlooked this relevant issue assuming that the levels of satisfaction collected through Likert-type scale are precise, or "crisp", data. In this study, the imprecision of both information (level of satisfaction) and measurement (Likert-type scale) is a posteriori corrected by means of fuzzy set theory. More precisely, the levels of satisfaction are recoded into triangular fuzzy numbers before their inclusion into a suitable regression model, i.e. the fuzzy regression model. Hence, the incorporation of the fuzzy regression model into the Double-Hurdle model and the creation of the Fuzzy Double-Hurdle model.

The paper is structured as follows. Section 2 comprises a review of the studies in which the link between tourists' satisfaction and expenditure at the destionation has been analysed and a review of the most common econometric models used for the micro analysis of tourism expenditure is presented. Section 3 introduces the idea of imprecise information and the use of fuzzy set in tourism, describing the approaches behind the fuzzy regression model. Section 4 theoretically describes the Fuzzy Double-Hurdle model while section 5 illustrates how this model works in a real situation drawn from the tourism field. Lastly, Section 6 will draw the conclusions.

2 Satisfaction and expenditures behaviour in tourism

2.1 Satisfaction and tourists' expenditure

The relationship between tourists' satisfaction and expenditure behaviour has not been extensively studied in the tourism literature (Zhang et al., 2010; Kim et al., 2010; Disegna & Osti, 2016; Jurdana & Frleta, 2017). The first study in this field has been conducted by Bigné et al. (2005) who discovered that the overall tourists' satisfaction doesn't affect the Willingness to Pay (WTP) for a Spanish-Mediterranean Theme park. Similarly, Kim et al. (2010) found that the overall tourists' satisfaction doesn't affect the overall WTP to visit festivals but it negatively affects the propensity to spend on a specific expenditure category, i.e. festivals' admission price. In a recent paper, Disegna et al. (2017a) found that the higher the level of the overall satisfaction, the higher the estimated probabilities of spending simultaneously on three expenditure categories (i.e. accommodation, transportation, and other services). Following Kim et al. (2010) study, the overall tourists' satisfaction negatively affects the amount of money tourists spend on accommodation, food and beverages, admission price and total expenditure. In addition, Disegna & Osti (2016) found that the overall tourists' satisfaction negatively affects also the amount of money spent on transportation, meaning that the more tourists are satisfied with the destination, the less they will travel around in search of new or different places. Conversely, Chen & Chang (2012) pointed out that the overall tourists' satisfaction positively affects the level of spending for tourists with mid-range overall expenditures (i.e. 50^{th} and 75^{th} quantiles) while Mortazavi

(2018) found a positive relationship between overall satisfaction and overall expenditure at the destination when a correction for endogeneity is included in the model. Splitting the overall satisfaction into the level of satisfaction with different aspects of the visited destination (such as city, event, festival or exhibition), Zhang et al. (2010) found that the more tourists are satisfied with "hotel, food, and attractions" and "facilities", the higher their overall expenditure at exhibitions. Furthermore, Disegna & Osti (2016) study suggests that the levels of tourists' satisfaction with "landscape" and "price" have a positive effect on the overall tourists' expenditure while the higher the satisfaction with a specific aspect of the destination, the higher the level of spending on that particular category (for instance, the higher the satisfaction with "food and beverages", the higher the tourists' expenditure on food and beverages). Similarly, Jurdana & Frleta (2017) found that tourists who are more satisfied with a particular aspect of the destination, in this case the diversity of facilities, significantly spend more at the destination.

As illustrated, findings are sometimes contradictory. The discrepancies in the results can be caused by different reasons, among which: the use of different Likert-type scales to capture satisfaction levels, the number of attributes used to measure satisfaction, the method applied to *a priori* transform satisfaction variables and/or the method used to analyse the relationship between tourists' expenditure and satisfaction. Table 1 highlights the main characteristics, in terms of satisfaction variables and methods used, of the studies presented in this section. Clearly, tourists' satisfaction has always been treated as a precise information. However, as it will be extensively described in Section 3.1, tourists' satisfaction is a human feeling that is typically imprecisely and vaguely defined (D'Urso et al., 2016). This study represents a first attempt to overcome this major gap in the literature devoted to quantify the relationship between expenditure and satisfaction.

Table 1 Description of satisfaction attributes and some methods used in the literature.

Reference	**Satisfaction dimensions**	**Likert-type scale**	**Transformation**	**Method**
Bigné et al. (2005)	5	5-point	PCA	SEM
Zhang et al. (2010)	21	5-point	PCA	OLS
Kim et al. (2010)	1	7-point	Categorisation	Logit, OLS, Tobit
Chen & Chang (2012)	1	5-point	None	Quantile, OLS
Disegna & Osti (2016)	10	10-point	None	Double-Hurdle
Disegna et al. (2017a)	10	10-point	Average	Copula Logit
Jurdana & Frleta (2017)	22	5-point	PCA	OLS
Mortazavi (2018)	3	10-point	Log	OLS, IV

Notes: PCA – Principal Component Analysis; SEM – Structural Equation Modelling; OLS – Ordinary Least Squared; IV – Instrumental Variable

2.2 Modeling expenditure in tourism

The literature studying tourists' expenditure behaviour and its determinants is vast but the empirical studies can be usually distinguished between macro- and micro-level. Micro-level studies constitute the biggest category and the approaches adopted to model tourists' expenditure behaviour and quantify the effect of expenditures' determinants are several. Table 2 summarises the econometric models adopted in some recent microdata studies. The OLS method and the Tobit model (Tobin, 1958), or one of its generalisation, are clearly the most popular methods adopted in this field but alternative approaches (such as the quantile regression or Switching model) are emerging. The use of alternative models has increased over the years because OLS estimates of parameters can be biased and inconsistent when the dependent variable is non-negative (i.e. continuous over strictly positive values) and it takes zero values (i.e. respondents decide not to spend on a particular good or service) with positive probability (Amemiya, 1984). The well-known Tobit model has been the first censored model introduced in the late 50s to deal with the problem of zero values. After that, the Double-Hurdle model has been formulated by Cragg (1971) to allow the possibility to model the propensity to spend and the amount of money spent (i.e. the two stages of the decision-making process) using two separate regressions. Successively, Heckman (1976) introduced a two-step estimation procedure more flexible then the one suggested by Cragg. In particular, while in Cragg's procedure the bivariate normal distribution between the error terms of the two stages is imposed, in Heckman's procedure only the normality of the error term at the first stage (i.e. the propensity to spend) is required. The drawback of the Heckman's procedure is that only the sub-sample of positive observations are used in the second stage. To overcome this problem, one can adopt the procedure suggested by Heien & Wessells (1990) that allows to consider the whole sample in each regression, producing more efficient estimates.

Table 2 Microdata studies on tourists' expenditure behaviour.

Reference	Models
Downward & Lumsdon (2000, 2003, 2004); Wang et al. (2006); Apostolakis & Jaffry (2009); Kim et al. (2010); Saayman & Saayman (2012); Belenkiy & Riker (2013); Akca et al. (2016); Jingwen & Mingzhu (2018)	OLS
Lee (2001); Ham et al. (2004); Kim et al. (2008); Downward et al. (2009); Kim et al. (2010); Zheng & Zhang (2013); Barquet et al. (2011); Kim et al. (2010)	Tobit
Weagley & Huh (2004); Jang & Ham (2009); Brandolini & Disegna (2012); Alegre et al. (2013); Brida et al. (2013a,b,c); Bernini & Cracolici (2015, 2016); Bernini et al. (2017); Disegna & Osti (2016);	Double-Hurdle
Lew & Ng (2012); Hung et al. (2012); Chen & Chang (2012); Marrocu et al. (2015); Almeida & Garrod (2017)	Quantile
Alegre et al. (2011)	Ordered Logit
Alegre & Cladera (2010)	Switching
Gómez-Déniz et al. (2019)	Fractional

3 Satisfaction, imprecise information and fuzzy regression analysis

3.1 Satisfaction and imprecise information

Following the Expectancy-Disconfirmation Paradigm, introduced by Oliver in the early 80s (Oliver, 1980), satisfaction can be defined as a subjective evaluation, vague by definition, of a specific product or service. This individual evaluation is the outcome of a comparison process in which prior expectations are compared against post-use perceptions of the evaluated item. In tourism literature, both qualitative scales, such as Likert–type scales, and qualitative interviews have been adopted to measure tourists' satisfaction (for an explanation of the two approaches, see Oliveri et al., 2018). Since Likert-type scales are user-friendly, easy-to-develop and easy-to-administer, this kind of measurements is commonly adopted, in both academia and industry, to investigate human feelings (Coppi et al., 2012; Benítez et al., 2007; Li et al., 2013; Disegna et al., 2018). Furthermore, even if Likert–type scales consist of a set of linguistic expressions (such as "satisfied" or "dissatisfied, "important" or "not important", "agree" or "disagree"), it is common practice to convert each expression into a natural number to obtain an apparently quantitative scale, making subsequent quantitative analysis easier. For some examples of quantitative applications of Likert-type scales, see Table 1. However, this kind of measurement doesn't produce accurate data mainly because: respondents subjectively interpret each linguistic expression (or its related natural number), attaching to it specific meanings that depend on their personal background (Davidov et al., 2014; Dolnicar, 2019); differences between consecutive linguistic expressions (or natural numbers) is not always clear (Disegna et al., 2018); respondents are forced to convert their feelings and opinions into specific linguistic expressions (usually coded into natural numbers) often producing inaccurate information (Hsu & Lin, 2006; Benítez et al., 2007; D'Urso, 2007).

As underlined by Chou et al. (2008), it is generally difficult to manage imprecise data through traditional methods. To partially overcome the drawbacks that characterise the Likert–type scale and to more precisely capture human feelings/thinking, the simple visual analogue scale or the fuzzy rating scale can be adopted instead of the traditional Likert-type scale (Gil & González-Rodríguez, 2012; De la Rosa de Sàa et al., 2015). However, as discussed in Disegna et al. (2018), these advanced kind of measurements are not yet adopted in tourism and marketing research. Therefore, an *a posteriori* correction has to be adopted in order to limit the imprecision and vagueness inherent to both Likert-type variables and human thinking. To this end, a suitable tool is represented by the fuzzy sets theory, firstly introduced by Zadeh (1965). In particular, Likert-type variables can be recoded into fuzzy variables by associating a range of possible values to each individual score/expression (Pérez-Gladish et al., 2010; Zhang & Lipkin, 2013; Wang et al., 2014). As suggested by Hu et al. (2010), this kind of recoding not only reduce the imprecise of the collected data but it is also allows to obtain more reliable and effective analysis. Furthermore, fuzzy numbers have a very intuitive meaning, which can be easily grasped by potential users, and it is more comprehensive than other methods (Sohrabi et al., 2012). Therefore, we recommend to formalise Likert-type scale variables into fuzzy variables before the adoption of any advanced analysis.

3.2 Applications of fuzzy theory in tourism

Despite ample research regarding fuzzy sets was conducted in the past, less attention was paid to its applications in tourism. As underlined by Ngai & Wat (2003) and Sohrabi et al. (2012), until 2003 applications of fuzzy sets in the tourism field was almost absent while recent study, as discussed below, increasingly adopt this theory thanks to its inherent advantages. In the study of Ngai & Wat (2003), the Hotel Advisory System (HAS), a fuzzy expert system, has been developed and presented as a useful and effectively tool to assist tourists in the hotel selection process. The Fuzzy Multi-Criteria approach to measure tourists' perceived risk of travel has been adopted by Hsu & Lin (2006). To analyse the quality of service of three hotels in Gran Canaria island, Benítez et al. (2007) suggested to fuzzify the linguistic information ("poor", "fair", "good", and "very good") into triangular fuzzy numbers. Different conservation projects aiming to increase cultural and tourism competitiveness of an archaeological site, have been evaluated through a ranking procedure based on both qualitative and quantitative variables expressed as fuzzy numbers by Sanna et al. (2008). The Fuzzy Multi-Criteria Decision Making model has been implemented by Chou et al. (2008) to select hotels location by international tourists. To identify the factors influencing tourists' choices and preferences at a destination, Hsu et al. (2009) applied the TOPSIS method on information originally collected through linguistic terms and converted into triangular fuzzy numbers. The fuzzy number construction approach proposed by Cheng (1991) has been adopted by Wu et al. (2010) to identify the sustainable indicators that characterize and distinguish urban ecotourism concept from urban tourism and ecotourism concepts. The Fuzzy Quality Function Deployment method, applied on triangular fuzzy numbers, has been implemented by Lin et al. (2011) to evaluate the performance of tourists' services offered by hospitality firms. Chiang (2011) combined the fuzzy $C-$means clustering method with a decision tree algorithm to segment the air transport passenger market and to create fuzzy decision rules. Similarly, fuzzy $C-$means was adopted to segment passengers' travel behaviour before and after the use of the intercity High-speed rail from Beijing to Tianjin (Jian & Ning, 2012). The Fuzzy Rasch model, which combines the Rasch model with the fuzzy theory, has been suggested by Huang & Peng (2012) to analyse the Tourism Destination Competitiveness (TDC) of nine Asian countries. In order to select the most appropriate indicators that influence tourists to choose a hotel, Sohrabi et al. (2012) suggested to conduct a factor analysis to obtain the main hotel selection factors followed by the definition of a set of fuzzy membership functions for the final factors. Using a fuzzy logic approach and parameter weighting matrices, Rangel-Buitrago et al. (2013) provided a scenic assessment of 135 sites long the Colombian Caribbean coast. Lin & Yeh (2013) introduced the use of Choquet Integral to more accurately model the Multiple-Criteria Decision-Making process that helps travellers to select the best hotel. D'Urso et al. (2013, 2015) proposed the use of a fuzzy version of the Bagged Clustering algorithm introduced by Leisch (1999), to segment tourists based on their motivation to visit two different cultural attractions. A novel matching-clustering procedure, based on fuzzy numbers and fuzzy clustering, has been suggested by Disegna et al. (2018) to make comparison between cross-sectional samples while two innovative fuzzy clustering algorithms have been recently introduced to model spatial-temporal information (Disegna et al., 2017b; D'Urso et al., 2019). In DUrso et al. (2019), the fuzzy C-means and fuzzy C-medoids for fuzzy data, and their extensions in the bagged framework, are presented both technically and empirically in the tourism field. Finally, a fuzzy multi-criteria decision-making model has been adopted by Martin et al. (2019) to determine tourist satisfaction.

To the best of our knowledge, fuzzy regression model is yet to be adopted in the tourism literature.

3.3 Fuzzy regression analysis

Standard linear regression model is the most widely used method to evaluate the causal relation between a dependent variable and a set of independent variables, or covariates. When one or more variables (dependent and/or independent) are imprecisely defined and/or measured, the standard linear regression model is unable to capture the relationship between dependent and independent variables and its extension in the fuzzy framework, i.e. the fuzzy regression model (Chang & Ayyub, 2001; Coppi & D'Urso, 2003; D'Urso, 2003; D'Urso & Massari, 2013), has to be adopted. The fuzzy regression model can be adopted to evaluate the relationship between either a fuzzy or a crisp dependent variable and a set of independent variables made up by fuzzy and/or crisp variables. This approach is particularly useful when additional information are necessary, but unavailable, to cope with data imprecision, as it is often the case when one is dealing with secondary data.

Different approaches have been developed in the literature to estimate a fuzzy regression model. Based on the pioneering works of Tanaka et al. (1982); Celmiņš (1987); Diamond (1988), these approaches can be split into the following two main categories (see D'Urso, 2003):

– the *possibilistic approaches*: in this framework, the fuzzy regression coefficients are estimated by minimizing the fuzziness of the predicted dependent variable, conditionally on obtaining fuzzy predicted values which contain (to a certain possibility degree) the observed fuzzy dependent values. Since its introduction (Tanaka et al., 1982; Tanaka & Watada, 1988), this approach have been widely adopted in the literature (see, for instance, Kim et al., 1996; Diamond & Tanaka, 1998; Chang & Ayyub, 2001).

– the *least squares approaches*: these approaches are suitable extensions for fuzzy data of the well-known least squares criterion. Their aim is to find the linear model which "best approximates" the observed data in a given metric space. The least squares criterion is then used with respect to the chosen metric. This methodology has been adopted by many researchers in the last two decades (see for instance, Celmiņš, 1987; Diamond, 1988; Chang & Lee, 1996; Ming et al., 1997; D'Urso & Gastaldi, 2000, 2002; Coppi & D'Urso, 2003; D'Urso, 2003; Wu, 2003; D'Urso & Santoro, 2006; D'Urso & Massari, 2013). However, the approaches suggested in the literature within this framework are very heterogeneous. The main features distinguishing them involved both the definition of the linear regression model and the specific metric space used for the application of the least squares criterion (Coppi et al., 2006).

4 A Fuzzy Double-Hurdle model

As we already discussed in Section 2.2, the Tobit model, or one of its generalizations, is one of the best micro econometric model to adopt when the aim is to analyse a non-negative variable which takes zero values with substantially high frequency. In this study the Double-Hurdle model (Cragg, 1971) is adopted in order to model separately the decision to purchase (first stage or selection stage) and the decision on how much money to spend on a particular purchase (second stage or outcome stage). The first stage of the Double-Hurdle model is estimated using a Probit model such as:

$$P(y_{1i} = 1) = \Phi\left(\frac{\mathbf{x}_{1i}\boldsymbol{\alpha}_1}{\sigma_1}\right), \quad i = 1, \ldots, n \tag{1}$$

where y_{1i} takes value 1 when the i-th respondent decide to purchase something and 0 otherwise; $\mathbf{x}_{1i}$ is a $(1 + K_1)$ vector of K_1, $(k_1 = 1, \ldots, K_1)$, independent variables plus the intercept; $\boldsymbol{\alpha}_1$ is the $(1 + K_1)$ vector of coefficients to be estimated; σ_1 is the constant variance of the error term; and $\Phi(\cdot)$ is the standard normal cumulative distribution.

Traditionally, the second stage of the Double-Hurdle model is modelled using the standard linear regression model where only the sub-sample of respondents who declared a positive expenditure are used. In order to avoid the problem of sample selection, defined by Heckman (1976) as an omitted variable problem, the estimator proposed by Heien and Wessells in the early 90s is adopted in this study (Heien & Wessells, 1990). This estimator is called inverse Mill's ratio (λ) and it is calculated for each observation through the estimates obtained at the first stage as follows:

$$\lambda_i = \begin{cases} \frac{\phi(z_i)}{1-\Phi(z_i)}, & \text{if } y_{1i} = 1 \quad (i = 1, \ldots, n) \\ \frac{\phi(z_i)}{\Phi(z_i)}, & \text{otherwise} \end{cases} \tag{2}$$

where $\phi(\cdot)$ is the density function for a standard normal variable, and $z_i = \frac{\mathbf{x}_{1i}\boldsymbol{\alpha}_1}{\sigma_1}$, $(i = 1, \ldots, n)$.

The inverse Mill's ratio variable is then included among the independent variables used in the standard regression model at the second stage playing the fundamental role of linking the two stages. It is important to note that if the coefficient of the variable λ is not significantly different from zero, then the two stages are independent and the sample selection problem is unimportant; that is, the sample selection rule ensures that all potential observations are sampled, so that the Tobit model can be used instead of the Double-Hurdle model.

In this study, we suggest the use of a new version of the Double-Hurdle model, i.e. the Fuzzy Double-Hurdle model, where the standard linear regression model, traditionally used to estimate the second stage of the model, is replaced by the fuzzy regression model. This suggestion is motivated by the necessity to deal with imprecise data used in the regression model as dependent and/or independent variable. Here we assume that the dependent variable of the second stage of the model, i.e. the amount of money respondents spend, is crisp (non imprecise) and the set of independent variables includes both fuzzy (imprecise) and crisp variables.

Hence, in order to formalise the imprecision, we consider a fuzzy approach in which a general class of fuzzy data, called LR (Left and Right) fuzzy data, can be defined in a matrix form as follows (Dubois & Prade, 1988):

$$\widetilde{\mathbf{X}} \equiv \{\tilde{x}_{ip} = (m_{1ip}, m_{2ip}, l_{ip}, r_{ip})_{LR} : \; i = 1, \ldots, n; \; p = 1, \ldots, P\}, \tag{3}$$

where $\tilde{x}_{ip} = (m_{1ip}, m_{2ip}, l_{ip}, r_{ip})_{LR}$ is the p-th LR fuzzy variable observed on the i-th unit; m_{1ip} and m_{2ip} (with $m_{2ip} > m_{1ip}$) are respectively the left and right centres and the interval $[m_{1ip}, m_{2ip}]$ is usually called the "core" of the fuzzy number; l_{ip} and r_{ip} represent the left and right spreads, i.e. the vagueness of the observations. Any LR fuzzy variable is defined by a continuous and monotonically increasing membership function that maps an interval $[a, b]$ to $[0, 1]$ (Zimmermann, 1996). A common LR fuzzy variable is the triangular one that is characterised by the following membership function (i.e. $m_{ip} \equiv m_{1ip} = m_{2ip}$) is defined:

$$\mu_{\tilde{x}_{ip}}(u_{ip}) = \begin{cases} 1 - \frac{m_{ip} - u_{ip}}{l_{ip}} & u_{ip} \leq m_{ip} \, (l_{ip} > 0) \\ 1 - \frac{u_{ip} - m_{ip}}{r_{ip}} & u_{ip} > m_{ip} \, (r_{ip} > 0) \end{cases} \tag{4}$$

In our analysis, the set of independent variables of the fuzzy regression model has P triangular fuzzy independent variables $(p = 1, \ldots, P)$, J crisp independent variables $(j = 1, \ldots, J)$ and λ, which is a crisp variable obtained from the estimation of the first stage regression. Therefore, the following fuzzy linear regression model (D'Urso, 2003; D'Urso & Massari, 2013) is suggested:

$$
\begin{aligned}
\mathbf{y}_2 &= \hat{\mathbf{y}}_2 + \boldsymbol{\varepsilon} \\
\hat{\mathbf{y}}_2 &= \tilde{\mathbf{X}}_2\tilde{\boldsymbol{\alpha}}_2 + \mathbf{X}_2\boldsymbol{\alpha}_2 + \beta\lambda \qquad (5)\\
&= \mathbf{M}\boldsymbol{\alpha}_m + \mathbf{L}\boldsymbol{\alpha}_l + \mathbf{R}\boldsymbol{\alpha}_r + \mathbf{X}_2\boldsymbol{\alpha}_2 + \beta\lambda \qquad (6)\\
&= \mathbf{W}\boldsymbol{\alpha}_w + \mathbf{L}\boldsymbol{\alpha}_l + \mathbf{R}\boldsymbol{\alpha}_r
\end{aligned}
$$

where $\mathbf{y}_2$ is a column n vector which represents the amount of money respondents spend while on holiday; $\boldsymbol{\varepsilon}$ is a column n vector of error terms; $\widetilde{\mathbf{X}}_2$ is the $(n \times (3 + 3P))$ matrix of P fuzzy variables (i.e. triangular) plus the intercept, thus $\mathbf{M}, \mathbf{L}$ and $\mathbf{R}$ are $(n \times (1 + P))$ matrices of the centres, left and right spreads, respectively; $\tilde{\boldsymbol{\alpha}}_2$ is the $(3 + 3P)$ vector of P fuzzy coefficient to be estimated, thus $\boldsymbol{\alpha}_m, \boldsymbol{\alpha}_l$ and $\boldsymbol{\alpha}_r$ are $(1 + P)$ vectors of the coefficients to be estimated for the centres, left and right spreads, respectively; $\mathbf{X}_2$ is the $(n \times J)$ matrix of crisp independent variables; $\boldsymbol{\alpha}_2$ is a column J vector of coefficients to be estimated for the crisp independent variables; β is the unknown coefficient of λ, which is a column n vector of inverse Mill's ratio values; $\mathbf{W}$ is a $(n \times (1 + K_2))$ matrix obtained by juxtaposing $\mathbf{M}$, $\mathbf{X}_2$ and λ, where $K_2 = (P+J+1)$ is the total number of independent variables (crisp and fuzzy) included in the model; $\boldsymbol{\alpha}_w$ is a column $(1 + K_2)$ vector of coefficients obtained by combining $\boldsymbol{\alpha}_m$, $\boldsymbol{\alpha}_2$ and β.

The proposed fuzzy linear regression model consists of modelling the crisp dependent variable by means of a multiple regression model on both the LR and the crisp independent variables. To obtain the estimates of the fuzzy regression model parameters, the Least-Squares (LS) criterion is adopted (D'Urso & Gastaldi, 2000; Coppi & D'Urso, 2003; D'Urso, 2003; D'Urso & Giordani, 2003; Coppi et al., 2006; D'Urso et al., 2011) and the iterative LS estimates for the model (5) are computed as followed (D'Urso & Massari, 2013):

$$
\begin{aligned}
\hat{\boldsymbol{\alpha}}_w &= (\mathbf{W}'\mathbf{W})^{-1}\mathbf{W}'(\mathbf{y}_2 - \mathbf{L}\boldsymbol{\alpha}_l - \mathbf{R}\boldsymbol{\alpha}_r) \\
\hat{\boldsymbol{\alpha}}_l &= (\mathbf{L}'\mathbf{L})^{-1}\mathbf{L}'(\mathbf{y}_2 - \mathbf{W}\boldsymbol{\alpha}_w - \mathbf{R}\boldsymbol{\alpha}_r) \qquad (7)\\
\hat{\boldsymbol{\alpha}}_r &= (\mathbf{R}'\mathbf{R})^{-1}\mathbf{R}'(\mathbf{y}_2 - \mathbf{W}\boldsymbol{\alpha}_w - \mathbf{L}\boldsymbol{\alpha}_l).
\end{aligned}
$$

Finally, the linear model that "best approximates" the observed data is selected as the final model.

5 Satisfaction and tourism expenditure behaviour: an empirical study

5.1 Questionnaire and data description

This study focuses on the 507 international visitors who spent their holidays in any municipality located in the South–Tyrol region (Northern Italy) in 2014.

Data have been collected by Bank of Italy (Banca dItalia) through the "International Tourism in Italy" survey. This survey is annually conducted to determine the tourism balance of payments and monitore both travel expenditures and length of stay of inbound and outbound visitors from/to Italy. The stratified sampling method is applied (using different types of stratified variables per each type of frontier) and face–to–face interviews are carried out at national borders (including highways, railway, airports and harbours). Sampling is done independently at each type of frontier. Tourists are interviewed at the end of the trip, when they are returning to their place of habitual residence. Interviews are conducted at different times of the day, during both working days and holidays, and month by month, with a fixed number of interviews per each period of survey. The questionnaires are anonymous and are offered in 14 languages.

Socio–demographic characteristics of the interviewee (such as age, occupation and country of origin), information on the trip (such as travel group size), level of satisfaction with different aspects of the destination as well as information on travel expenditures are collected.

In particular, interviewees were requested to report their level of overall satisfaction with the destination and their satisfaction with the following specific aspects of the visited place: hospitality and friendliness of local people (*Friendliness*); landscape and natural environment (*Landscape*); hotels and other accommodation (*Accommodation*); *Food and beverages*; prices and cost of living, (*Prices*); quality and variety of products offered in stores (*Shopping*); information and tourist services (*Information*); *Safety.* A 10–point Likert–type scale was used, where [1] was "Very unsatisfied" to [10] "Very satisfied". Figure 1 displays the percentage distribution of the level of satisfaction per each observed item. The percentage of visitors who attributed a value lower than 6 to the different aspects of the trip is sharply low, with the exception of *Prices.* As already discussed in Section 3.1, human feelings (such as level of satisfaction) collected through Likert-type scale are always imprecise and vague information. Therefore, in order to *a posteriori* handle the imprecision that characterise this kind of data, each variable is recoded into a triangular fuzzy variable. Figure 2 shows the adopted fuzzy recoding from the 10–point Likert–type scale to the fuzzy numbers. For instance, to the value 1 in the Likert–type scale corresponds a fuzzy number in the range [1, 2]. It is important to underline that the degree of vagueness, i.e. the right and left spread, of the extreme linguistic terms, i.e. 1 and 10, is higher than the degree of vagueness of the other linguistic terms and that the degree of vagueness decreases more and more approaching to the central values, i.e. 5 and 6. In fact, it is common to think that a value below 5 indicates a negative evaluation while a value above 6 expresses a positive judgement. Therefore, respondents well know the difference between values 5 and 6, i.e. these values are little vague, but it is more difficult for them to understand/appreciate the difference between 1 and 2, or between 9 and 10, i.e. these values incorporate a higher degree of uncertainty.

Travel expenditures include total purchases in both goods and services split in the following five different categories: "Accommodation" (hotel, apartment

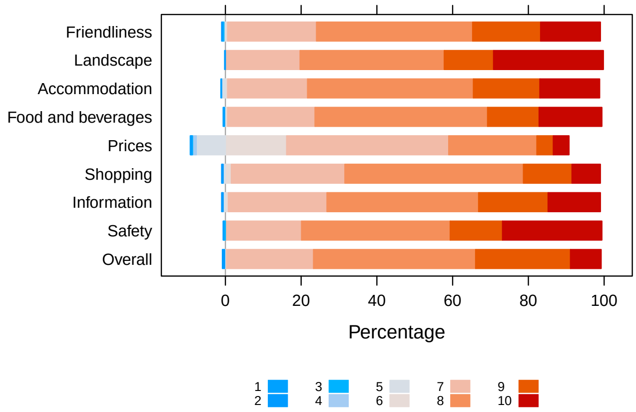

Fig. 1 Percentage distribution of the level of satisfaction for each item.

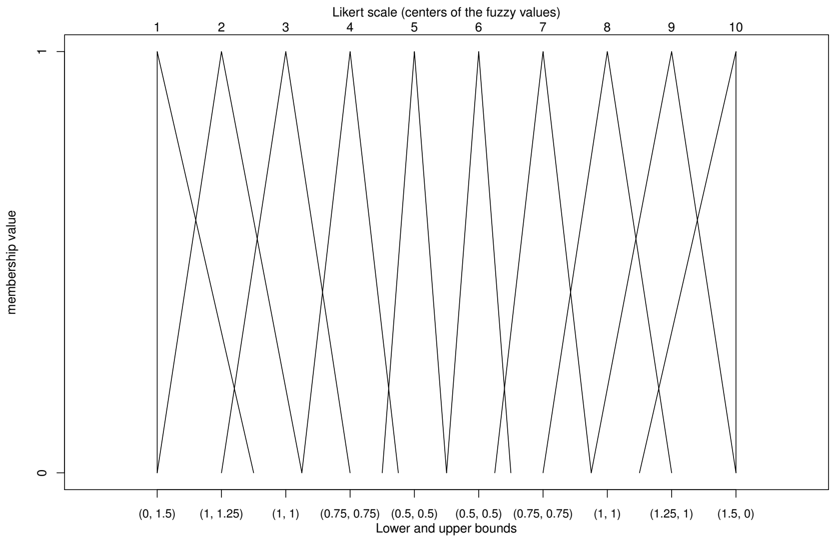

Fig. 2 Linguistic satisfaction terms in the form of fuzzy numbers.

for rent, campsite, etc), which also includes expenditure on food and beverage on the accommodation premises; "Food & beverages" consumed outside the accommodation premises; "Transportation" in the visited destination, including purchase of fuel; "Shopping", including souvenirs, gifts, clothes, food and beverages, etc, purchased only for personal use; "Other services", like museums, shows, entertainment, guided excursions, language courses and so on. As reported in table 3, more then half of the sample doesn't spend any money on either "Transportation" or "Other services" while the majority of respondents declared to have purchased something on the remaining expenditure categories (i.e. "Accommodation", "Food & Beverages" and "Shopping") with an average expenditure (excluding zeros) that span between €59 ("Accommodation") and €11 ("Transportation").

Table 3 Description of travel expenditures.

	% zero	Mean (€, excluding zeros)
Accommodation	19.72	59.43
Transportation	62.33	10.85
Food & Beverages	18.15	27.44
Shopping	39.25	21.20
Other services	67.06	21.86
Total travel expenditure	4.34	98.73

5.2 Empirical results and discussion

The Fuzzy Double-Hurdle model has been adopted to estimate how respondents' socio-demographic characteristics, trip characteristics and respondents' levels of satisfaction affect tourists' expenditure behaviour. In particular, five separate models, one for each expenditure category (i.e. "Accommodation", "Food & Beverages", "Shopping", "Transportation" and "Other services"), have been estimated. For comparison purposes, the traditional Double-Hurdle model has been estimated as well for each expenditure category. The unrestricted models (i.e. no variable selection procedures have been adopted) are presented to allow for direct comparison between the Fuzzy Double-Hurdle models and the Double-Hurdle models. Respondents' levels of satisfaction have been included among the independent variables of the regressions at the second stage solely, assuming that these variables barely affect the propensity to spend. Tourists' expenditures are per person per night and they have been log-transformed in order to account for non-linear relationships.

The propensity to spend, i.e. the first stage of the Double-Hurdle model, is estimated using the Probit regression model regardless the version (fuzzy or traditional) of the Double-Hurdle model adopted. Table 1 in the Appendix reports the estimate coefficients of the propensity to spend for each tourists' expenditure category. In terms of goodness of the models (see the McKelvey & Zavoina's R^2 values), we can observe that the "Accommodation" and the "Food & Beverages" models are the best.

It is important to note that the higher the overall travel expenditure, the higher the propensity to spend in each spending category considered, indicating the existence of strong dependences among expenditures, as described in Disegna et al. (2017a). Country of origin seems to be the most important determinant of the propensity to spend in all the categories considered but

"Food & Beverages". In particular, tourists coming from a country other than Germany and Austria tend to be more willing to spend while on holiday. Furthermore, being over 65 years old and travel alone negatively affect only the propensity to spend on "Transportation", indicating that older and/or lone tourists tend to remain in the selected municipality.

The estimated coefficients of the second stage of the Double-Hurdle models are reported in Tables 2-6 in the Appendix. In terms of goodness of the models (see the adjusted R^2 values), we can observe that the "Accommodation", the "Food & Beverages" and the "Shopping" models are able to explain the relationships between dependent and independent variables better than the other two models (i.e. "Transportations" and "Other services"). To highlight similarity/differences between the traditional and the fuzzy regression models, Table 4 reports the significant estimated average effects of each independent variable on the dependent variable. Regardless the regression model adopted (i.e. standard linear regression model or fuzzy regression model), crisp estimated coefficient can be directly interpreted as the average change in the dependent variable due to a unitary change in the independent variable, holding all the other independent variables constant. As expected, the results obtained through the traditional and the fuzzy regression models regarding the set of crisp independent variables are very similar, especially for the regression on "Accommodation", "Other services" and "Food & Beverages" It is important to note that the estimated coefficient of the MR variable is significantly different from zero in all model considered, justifying the use of the Double-Hurdle model for each of these analyses. Furthermore, the higher the overall tourists' expenditure, the higher the level of spending in all tourist expenditure categories considered. Thanks to the adoption of the log-log transformation, the estimated coefficient of these independent variables can be directly read as the value of the elasticity. Therefore, we can observe that the estimated percentage change in the dependent variable is less than the percentage change in the overall travel expenditure for each model and the level of spending on "Accommodation" is the more reactive to a percentage change in the overall tourists' expenditure. Interestingly, the estimated elasticities obtained through the traditional and the fuzzy regression model are very similar for each expenditure category.

When it comes to interpret the effect of a fuzzy independent variable on the dependent variable, it is necessary to describe three different coefficients, i.e. one for the center and two for the vagueness related to the independent variable (left and right spreads). Following eq. (5), the estimated average effect of a fuzzy independent variable will be the sum of the estimated coefficients of the center and the two spreads. When an estimated coefficient (related to either the center or the spread) is not significant (i.e. not significantly different from zero) than we can consider, as usual, that its effect is null. For instance, when the estimated coefficient of one (or both) spread is not significantly different from zero, while the estimated coefficient of the center is significant, then we can conclude that the vagueness of the fuzzy independent variable will not affect the estimated average expenditure on a particular category. On the contrary, when the estimated coefficient of the center is not significantly different from zero while one (or both) estimated coefficient of the spread is significant, we can conclude that the fuzzy independent variable is centered in zero and that only the vagueness around this value significantly affect the estimated average expenditure on a particular category. For instance, looking at Table 4, a unitary change in the level of satisfaction with the item *Information*, accompanied by a 10% change in the vagueness around the central value (it will be unrealistic to assume a unitary change in the spreads), will produce an average estimated change in the level of spending on "Shopping" equals to $-1.255 \times 1 + 5.787 \times 0.1 + 0.295 \times 0.1 = -0.647$. Looking at Table 2, a unitary change in the level of satisfaction with the item *Prices*, accompanied by a 10% change in the vagueness around the central value, will produce an average estimated change in the level of spending on "Accommodation" equals to $0 \times 1 + 0 \times 0.1 + 0.284 \times 0.1 = 0.028$ because the estimated coefficients for both the center and the left spread are not significantly different from zero.

As we can observe, the traditional and the fuzzy regression models produce quite different results regarding the estimated average effects of the levels of tourists satisfaction on expenditures and fuzzy regression models seem to produce more meaningful and accurate results. For instance, the level of spending on "Accommodation" is positively affected not only by the level of *Safety* a tourist feels in a destination but also by the perceived level of satisfaction with prices and cost of living (*Prices*). The higher the satisfaction with landscape and natural environment (*Landscape*), the lower the level of spending on "Shopping", indicating that tourists who enjoy to be outside spend less time inside shops, while, as expected, the higher the satisfaction with quality and variety of products offered in stores (*Shopping*), the higher the level of spending on "Shopping". Finally, the more the tourists are overall satisfied with the destination (*Overall*), the higher the level of spending on "Other services", indicating that tourists will enjoy more the entertainments (i.e. museums, theaters, guided tours, etc) offered by the destination.

6 Conclusions

In response to calls for tourism researchers (e.g. Disegna & Osti, 2016; Jurdana & Frleta, 2017) to clearly identify the consequences of being a dis/satisfied tourist on the expenditure behaviour while on holiday, the main objective of this study is to present a new econometric model, the Fuzzy Double-Hurdle model, to quantify the effect of satisfaction on the level of spending. While an ample body of the tourism literature unanimously agree that satisfaction leads to several favourable behavioural intentions (see for instance Munier & Camelis, 2013; Dolnicar et al., 2015), only few researches have been devoted to the analysis of the effects of being dis/satisfied tourists on expenditure behaviour and the findings are oftentimes contradictory. Nonetheless, these studies are similar for the measurement used to obtain information on the level of satisfaction, i.e. Likert-type scales, and for completely ignoring the imprecision

Table 4 Significant estimated average effects on the dependent variable at the second stage of the traditional and the fuzzy regression models.

Independent variables	Accommodation		Food & Beverages		Shopping		Transportation		Other services	
	Traditional	Fuzzy	Traditional	Fuzzy	Traditional	Fuzzy	Traditional	Fuzzy	Traditional	Fuzzy
Intercept	-0.603	-3.725	1.862	0.206		-13.335		1.287		0.805
Inverse Mill Ratio	-1.896	-1.888	-1.755	-1.764	-2.582	-2.545	0.373	0.372	0.976	1.007
ln overal travel expenditure	0.814	0.814	0.575	0.586	0.598	0.601	0.192	0.196	0.232	0.219
More than 65 years old								-0.503		
Employee								-0.433		
Self–employed	0.217	0.221						-0.280		
Austria			0.289	0.258					-0.396	-0.395
Germany	0.182	0.192						-0.387	-0.496	-0.517
Visit alone				0.186						
Landscape						-0.040			-0.143	0.038
Friendliness				0.418						
Food and beverages				-0.028						
Prices		0.028								-0.050
Information						-0.647			-0.136	-0.050
Safety	0.103	0.151	-0.086					-0.331		
Shopping	–	–	–	–	–	0.746			–	–
Overall										0.054

Notes: – variable not included in the regression.

of both data (i.e. satisfaction) and instrument (i.e. Likert-type scale). Specifically, in this niche literature, so far satisfaction has been treated as a precise, or "crisp", information even if it is well-known that, as other human feelings, it derives from a subjective and complex evaluation process that leads, by definition, to imprecise information (Lin & Yeh, 2013). Similarly, Likert-type scale has been considered as a precise measurement to capture emotions and human feelings even if its different sources of imprecision have been widely discussed in the literature (Hsu & Lin, 2006; Benítez et al., 2007; D'Urso, 2007; Davidov et al., 2014; Disegna et al., 2018). Hence, the main motivation in suggesting the Fuzzy Double-Hurdle model in this research is driven by the necessity to take into consideration and correctly deal with imprecise data such as satisfaction. In particular, the Fuzzy Double-Hurdle model is a censored model ables to cope with the presence of imprecise data since it is developed in the fuzzy framework. Like in the traditional Double-Hurdle model, the suggested model separately estimate the propensity to spend (first stage) and the amount of money spent (second stage). The Probit model and the Fuzzy regression model are used to estimate the first and second stage of the Fuzzy Double-Hurdle model respectively. The model has been adopted to quantify the effect on tourists' expenditure behaviour of being dis/satisfied tourists in South–Tyrol (Northern Italy). In particular, five separate models, one per each expenditure category (i.e. "Accommodation", "Food and Beverages", "Shopping", "Transportation" and "Other services"), have been estimated. In each model the dependent variable is crisp (tourism expenditure) while the set of independent variables includes both crisp (respondents socio-demographic characteristics and trip characteristics) and fuzzy variables (satisfaction). The findings of the Fuzzy Double-Hurdle models have been compared with the findings of the traditional Double-Hurdle models and they mainly differ in terms of average estimated effects of the fuzzy variables (i.e. satisfaction). Some interesting results emerge from the analysis, such as the positive relationships between satisfaction on *Prices* and expenditure on "Accommodation" and between satisfaction on *Shopping* and expenditure on "Shopping". The findings highlight the necessity to consider and adequately treat the issue of imprecise information to avoid the possibility to not capture important information and relations between variables and hence producing more accurate results. This is vital especially when the effect of satisfaction on expenditure is relevant in the definition of future planning and marketing strategies for the destination.

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Conflict of interest

The authors declare that they have no conflict of interest.

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Appendix

Table 1 Estimated coefficients of the first stage models (Probit regression).

Independent variables	Accommodation[a]	Food & Beverages[b]	Shopping[c]	Transportation[d]	Other services[e]
ln overall travel expenditure	0.046** (0.021)	0.085*** (0.025)	0.124*** (0.019)	0.091*** (0.019)	0.130*** (0.022)
34-44 years old	−0.033 (0.033)	−0.075 (0.054)	0.007 (0.075)	−0.105 (0.08)	0.055 (0.073)
45-64 years old	−0.011 (0.024)	0.004 (0.039)	0.069 (0.065)	−0.086 (0.071)	0.066 (0.063)
More than 65 years old	−0.019 (0.037)	−0.103 (0.074)	0.106 (0.08)	−0.251*** (0.087)	−0.048 (0.077)
Employee	0.024 (0.033)	−0.036 (0.031)	0.006 (0.076)	−0.024 (0.079)	−0.060 (0.076)
Self–employed	0.017 (0.02)	−0.059 (0.066)	−0.069 (0.09)	−0.008 (0.088)	0.042 (0.083)
Austria	−0.266** (0.117)	0.008 (0.036)	−0.131* (0.074)	−0.305*** (0.056)	−0.148*** (0.043)
Germany	−0.008 (0.02)	−0.009 (0.03)	0.028 (0.058)	−0.177*** (0.057)	−0.104* (0.054)
Visit alone	−0.008 (0.02)	−0.019 (0.041)	−0.049 (0.068)	−0.166** (0.074)	0.026 (0.065)

Notes: ***Significant at $p \leqslant 0.01$, **Significant at $p \leqslant 0.05$, *Significant at $p \leqslant 0.1$. Robust standard errors in brackets.
[a]No. of observ. = 507; Wald $\chi^2(9) = 151.85$; Prob $> \chi^2 = 0$; Log pseudolikelihood= -156.62987; McKelvey & Zavoina's R^2=0.505.
[b]No. of observ. = 507; Wald $\chi^2(9) = 110.18$; Prob $> \chi^2 = 0$; Log pseudolikelihood= -183.53811; McKelvey & Zavoina's R^2=0.352.
[c]No. of observ. = 507; Wald $\chi^2(9) = 79.83$; Prob $> \chi^2 = 0$; Log pseudolikelihood= -299.59336; McKelvey & Zavoina's R^2=0.239.
[d]No. of observ. = 507; Wald $\chi^2(9) = 72.88$; Prob $> \chi^2 = 0$; Log pseudolikelihood= -294.23347; McKelvey & Zavoina's R^2=0.267.
[e]No. of observ.= 507; Wald $\chi^2(9) = 74.24$; Prob $> \chi^2 = 0$; Log pseudolikelihood= -280.54565; McKelvey & Zavoina's R^2=0.239.

Table 2 Expenditure on accommodation: estimated coefficients of the second stage.

Independent variables	OLS[a]	Fuzzy LS[b]		
		Center	Left spread	Right spread
Intercept	−0.603* (0.354)	−4.079** (1.721)	1.895** (0.902)	1.648*** (0.110)
Inverse Mill Ratio	−1.896*** (0.068)	−1.888*** (0.071)		
ln overal travel expenditure	0.814*** (0.022)	0.814*** (0.022)		
34-44 years old	0.134 (0.108)	0.128 (0.117)		
45-64 years old	−0.002 (0.076)	−0.018 (0.085)		
More than 65 years old	0.175 (0.133)	0.192 (0.136)		
Employee	0.138 (0.121)	0.169 (0.124)		
Self–employed	0.217* (0.129)	0.221* (0.134)		
Austria	−0.106 (0.119)	−0.103 (0.113)		
Germany	0.182*** (0.054)	0.192*** (0.054)		
Visit alone	−0.128 (0.103)	−0.119 (0.100)		
Landscape	−0.047 (0.041)	−0.199 (0.298)	0.412 (1.221)	−0.049 (0.110)
Friendliness	−0.047 (0.029)	−0.120 (0.135)	0.334 (0.570)	0.100 (0.121)
Food and beverages	0.022 (0.041)	0.247 (0.58)	−0.842 (2.332)	0.06 (0.111)
Prices	0.022 (0.023)	−0.047 (0.053)	0.326 (0.261)	0.284*** (0.110)
Information	−0.008 (0.038)	−0.011 (0.371)	−0.170 (1.494)	−0.120 (0.105)
Safety	0.103*** (0.030)	0.151** (0.076)	−0.222 (0.365)	0.001 (0.126)
Accomodation	0.023 (0.036)	−0.049 (0.234)	0.229 (1.034)	−0.169 (0.108)
Overall	0.025 (0.052)	0.046 (0.216)	0.236 (0.873)	0.161 (0.149)

Notes: ***Significant at $p \leqslant 0.01$, **Significant at $p \leqslant 0.05$, *Significant at $p \leqslant 0.1$.
No. of observ. = 507 in each model.
[a]Robust standard errors in brackets; F(18, 488) = 213.6; Prob > F = < 0.001; Adjusted $R^2 = 0.848$.
[b]Bootstraped standard errors in brackets.

Table 3 Expenditure on food and beverages: estimated coefficients of the second stage.

Independent variables	OLS[a]	Fuzzy LS[b]		
		Center	Left spread	Right spread
Intercept	1.862*** (0.383)	2.254 (3.442)	0.565 (1.689)	2.062*** (0.120)
Inverse Mill Ratio	−1.755*** (0.055)	−1.764*** (0.048)		
ln overal travel expenditure	0.575*** (0.023)	0.586*** (0.024)		
34-44 years old	0.093 (0.110)	0.064 (0.110)		
45-64 years old	0.019 (0.083)	0.024 (0.089)		
More than 65 years old	0.083 (0.128)	0.068 (0.125)		
Employee	0.032 (0.103)	0.017 (0.095)		
Self–employed	−0.01 (0.121)	−0.057 (0.112)		
Austria	0.289*** (0.108)	0.258** (0.109)		
Germany	0.064 (0.085)	0.057 (0.084)		
Visit alone	0.152 (0.096)	0.186** (0.094)		
Landscape	−0.078 (0.050)	0.056 (0.811)	−0.481 (3.216)	0.013 (0.137)
Friendliness	0.021 (0.043)	0.725* (0.378)	−3.077** (1.547)	−0.065 (0.114)
Food and beverages	0.004 (0.038)	−1.282 (1.021)	4.848 (4.092)	−0.280*** (0.103)
Prices	−0.032 (0.023)	−0.011 (0.052)	−0.165 (0.258)	−0.126 (0.109)
Information	−0.019 (0.035)	0.030 (0.442)	−0.198 (1.813)	0.081 (0.110)
Safety	−0.086** (0.034)	−0.127 (0.153)	0.145 (0.723)	−0.114 (0.127)
Overall	0.035 (0.068)	−0.063 (0.755)	0.458 (3.00)	−0.047 (0.130)

Notes: ***Significant at $p \leqslant 0.01$, **Significant at $p \leqslant 0.05$, *Significant at $p \leqslant 0.1$.
No. of observ. = 507 in each model.
[a]Robust standard errors in brackets; F(17, 489) = 138.35; Prob > F = < 0.001; Adjusted $R^2 = 0.782$.
[b]Bootstraped standard errors in brackets.

Table 4 Expenditure on shopping: estimated coefficients of the second stage.

Independent variables	OLS[a]	Fuzzy LS[b]		
		Center	Left spread	Right spread
Intercept	−0.047 (0.446)	−14.282*** (5.511)	7.727*** (2.794)	1.741*** (0.167)
Inverse Mill Ratio	−2.582*** (0.155)	−2.545*** (0.154)		
ln overal travel expenditure	0.598*** (0.033)	0.601*** (0.033)		
34-44 years old	0.038 (0.157)	0.067 (0.175)		
45-64 years old	0.096 (0.132)	0.113 (0.145)		
More than 65 years old	0.173 (0.182)	0.223 (0.184)		
Employee	−0.039 (0.159)	−0.05 (0.151)		
Self–employed	−0.013 (0.182)	−0.052 (0.184)		
Austria	0.143 (0.160)	0.126 (0.163)		
Germany	0.003 (0.105)	−0.015 (0.109)		
Visit alone	−0.175 (0.160)	−0.186 (0.163)		
Landscape	0.045 (0.071)	−0.157 (0.972)	0.242 (3.929)	−0.399** (0.197)
Friendliness	−0.066 (0.049)	−0.616 (0.529)	2.218 (2.167)	−0.131 (0.167)
Food and beverages	−0.044 (0.059)	2.381 (1.652)	−9.785 (6.632)	0.006 (0.156)
Prices	0.018 (0.036)	−0.043 (0.080)	0.342 (0.386)	0.081 (0.162)
Information	0.071 (0.055)	−1.255** (0.537)	5.787*** (2.240)	0.295** (0.150)
Safety	0.027 (0.051)	0.223 (0.197)	−1.24 (0.830)	−0.163 (0.160)
Shopping	0.052 (0.056)	0.746* (0.408)	−2.763 (1.692)	0.02 (0.195)
Overall	< 0.001 (0.073)	0.092 (0.896)	−0.129 (3.603)	0.248 (0.207)

Notes: ***Significant at $p \leqslant 0.01$, **Significant at $p \leqslant 0.05$, *Significant at $p \leqslant 0.1$.
No. of observ. = 507 in each model.
[a]Robust standard errors in brackets; F(18, 488) = 29.73; Prob > F = < 0.001; Adjusted $R^2 = 0.572$.
[b]Bootstraped standard errors in brackets.

Table 5 Expenditure on transportation: estimated coefficients of the second stage.

Independent variables	OLS[a]	Fuzzy LS[b]		
		Center	Left spread	Right spread
Intercept	−1.474 (0.527)	−2.774 (6.024)	0.496 (3.055)	2.574*** (0.249)
Inverse Mill Ratio	0.373*** (0.159)	0.372** (0.145)		
ln overal travel expenditure	0.192*** (0.038)	0.196*** (0.040)		
34-44 years old	−0.280 (0.175)	−0.203 (0.181)		
45-64 years old	−0.150 (0.162)	−0.069 (0.155)		
More than 65 years old	−0.528 (0.199)	−0.503** (0.207)		
Employee	−0.367 (0.153)	−0.433*** (0.159)		
Self–employed	−0.248 (0.161)	−0.280* (0.169)		
Austria	−0.235 (0.151)	−0.203 (0.156)		
Germany	−0.434 (0.131)	−0.387*** (0.138)		
Visit alone	0.087 (0.123)	0.107 (0.135)		
Landscape	0.344 (0.084)	0.706 (1.423)	−1.886 (5.702)	−0.156 (0.199)
Friendliness	0.053 (0.063)	−0.131 (0.631)	0.995 (2.513)	0.100 (0.185)
Food and beverages	−0.008 (0.070)	−0.163 (1.842)	0.862 (7.357)	−0.170 (0.188)
Prices	0.024 (0.042)	−0.049 (0.076)	0.430 (0.376)	−0.168 (0.272)
Information	0.038 (0.071)	−0.194 (0.788)	1.265 (3.211)	0.246 (0.202)
Safety	−0.227 (0.067)	−0.489** (0.203)	1.579* (0.952)	0.168 (0.206)
Shopping	−0.056 (0.070)	0.090 (0.653)	−0.586 (2.636)	−0.066 (0.195)
Overall	0.059 (0.064)	0.025 (1.362)	−0.731 (5.372)	−0.344 (0.240)

Notes: ***Significant at $p \leqslant 0.01$, **Significant at $p \leqslant 0.05$, *Significant at $p \leqslant 0.1$.
No. of observ. = 507 in each model.
[a]Robust standard errors in brackets; F(18, 488) = 10.42; Prob > F = < 0.001; Adjusted $R^2 = 0.263$.
[b]Bootstraped standard errors in brackets.

Table 6 Expenditure on other services: estimated coefficients of the second stage.

Independent variables	OLS[a]	Fuzzy LS[b]		
		Center	Left spread	Right spread
Intercept	0.107 (0.539)	4.379 (10.620)	−2.13 (5.284)	1.610*** (0.252)
Inverse Mill Ratio	0.976*** (0.175)	1.007*** (0.173)		
ln overal travel expenditure	0.232*** (0.050)	0.219*** (0.052)		
34-44 years old	0.119 (0.203)	0.148 (0.233)		
45-64 years old	0.173 (0.176)	0.207 (0.195)		
More than 65 years old	−0.145 (0.214)	−0.123 (0.204)		
Employee	−0.091 (0.177)	−0.061 (0.169)		
Self–employed	0.103 (0.210)	0.111 (0.199)		
Austria	−0.396** (0.187)	−0.395** (0.177)		
Germany	−0.496*** (0.170)	−0.517*** (0.163)		
Visit alone	0.177 (0.167)	0.155 (0.154)		
Landscape	−0.143* (0.086)	−0.140 (2.001)	0.546 (7.974)	0.376* (0.205)
Friendliness	0.062 (0.067)	0.448 (0.968)	−1.657 (3.938)	−0.155 (0.172)
Food and beverages	0.005 (0.073)	−2.672 (3.314)	10.542 (13.304)	0.054 (0.204)
Prices	0.029 (0.042)	0.058 (0.093)	0.071 (0.504)	−0.500** (0.233)
Information	−0.136* (0.072)	0.847 (1.204)	−4.238 (4.846)	−0.496** (0.202)
Safety	0.041 (0.067)	0.338 (0.252)	−1.526 (1.135)	0.014 (0.194)
Overall	0.083 (0.082)	0.094 (1.783)	0.414 (7.105)	0.540** (0.250)

Notes: ***Significant at $p \leqslant 0.01$, **Significant at $p \leqslant 0.05$, *Significant at $p \leqslant 0.1$.
No. of observ. = 507 in each model.
[a]Robust standard errors in brackets; F(17, 489) = 10.99; Prob > F = < 0.001; Adjusted R^2 = 0.227.
[b]Bootstraped standard errors in brackets.