Estimating the effect of online consumer reviews: an application of count data models

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Abstract

This study attempts to estimate the effect of online consumers' star ratings on perceived evaluations of consumer reviews such as usefulness and enjoyment. The author suggests the use of count models in analysing secondary data composed of an unstructured format. The data includes 5,090 online reviews of about 45 restaurants located in London and New York respectively. The results reveal curvilinear (U-shaped) relationships between star ratings and usefulness and enjoyment. That is, online consumers perceive extreme ratings (positive or negative) as more useful and enjoyable than moderate ratings. Additionally, the findings of this research indicate the usefulness of the negative binomial model, which allows researchers to manage the features of count data, as well as address the heteroscedasticity in linear regression and the overdispersion problem in the Poisson regression model.

Key words: Online consumer reviews, information evaluation, count data models, and negative binomial model

1. Introduction

The advent of information technology has resulted in the development of a new form of web communication, known as eWOM (electronic word-of-mouth), operated by consumer participation (Tussyadiah & Fesenmaier, 2009). Online consumer reviews have become one of the vital information sources which allow people to gather sufficient and reliable information about products and services (Liu & Park, 2015). In particular, due to the characteristics of tourism products (e.g. intangibility and perishability), online reviews provide substantial benefits to current travellers, enabling them to obtain authentic and indirect consumption experiences through checking the discourse types of comments (Schuckert, Liu, & Law, 2015). In recognising the importance of online reviews in tourism and hospitality, a number of researchers have investigated the effects of consumer reviews, essentially in terms of product sales (Ye, Law, Gu, & Chen, 2011) and the decision-making process (Sparks, Perkins, & Buckley, 2013). These studies conclude that online reviews have positive influences on increasing revenues and assisting with purchase decisions.

Importantly, easily accessible online reviews facilitate consumers in finding plentiful information (low search costs); however, they also make it difficult for people to determine helpful information (high evaluation costs). Overall, the important question of 'what makes online reviews useful?' still has not been sufficiently discussed. Based on an adaptive decision-making strategy (Payne, Bettman, & Johnson, 1992), consumers are likely to focus on heuristic information cues when the size of information to be evaluated is larger than their cognitive abilities. With regard to the context of online consumer reviews, it has been identified that star rating is a key element of heuristic information, which is regarded as an explanatory variable in this current research.

Therefore, the first aim of this chapter is to examine the relationship between star ratings and perceived usefulness and enjoyment on online reviews. In order to address the research question, over 5,000 reviews were collected from Yelp (yelp.com), a well-recognised consumer review website for tourism and hospitality products. This study then employed the negative binomial regression, a type of count model (Allison & Waterman, 2002). Analysing secondary data obtained with an unstructured format commonly violates the assumptions of the ordinary least square (OLS) regression, or general count models such as the Poisson regression (Hox & Boeije, 2005). For instance, there can be skewed distribution of the data, zero inflation problems, and overdispersion (where unconditional variance is larger than the mean) (Gurmu & Trivedi, 1996; Jackman, Kleiber, & Zeileis, 2007). Thus, the second aim of this chapter is to discuss count models and, in particular, provide evidence of the usability of negative binomial models in analysing the online review data.

2. Literature review

2.1 Online consumer reviews in tourism and hospitality

Online travellers like to obtain detailed and up-to-date information and examine indirect experiences of tourism products in order to make a better decision on them (Xiang, Wang, O'Leary, & Fesenmaier, 2015). In this sense, online reviews developed by other consumers have relatively higher reliability and bring about more attention from other consumers. Based on the important role of online reviews in the tourism field, numerous researchers have investigated the effects of online reviews, which can essentially be classified into the three areas of product sales, the decision-making process and evaluation of the information sources (Park & Nicolau, 2015).

Following a statement that the number of consumer reviews written on the social media websites reflects product sales, previous studies have identified a positive relationship between online reviews and revenues in hotels (Xie, Chen, & Wu, 2012) and restaurants (Zhang, Ye, Law, & Li, 2010). For example, Ye et al. (2011) found that a 10% increase in travel review ratings improves the volume of hotel bookings by more than 5%. A study conducted by Ogut and Tas (2012) concluded that a 1% increase in online review ratings leads to increased sales per room by about 2.6%, depending on destinations. Reviews about the quality and service of restaurants, as well as the volume of reviews, also have positive relationships with restaurant popularity (Zhang et al., 2010). Additionally, high ratings of online reviews tend to generate price premiums (Yacouel & Fleischer, 2012; Zhang, Ye, & Law, 2011). Online reviews, potentially representing service quality, lead consumers to have increased confidence in their decisions. This increase in trustworthiness encourages travellers to pay higher prices when purchasing tourism products.

With regard to the online buying process, Leung, Law, van Hoof, and Buhalis (2013) suggested online consumer contents essentially affect entire phases of the travel planning process, including pre-, during- and post-consumption. Specifically, positive reviews with numerical ratings improve attitudes toward travel products, being associated with the formation of consideration sets (Vermeulen & Seegers, 2009) and purchasing intentions (Sparks & Browning, 2011). Filieri and McLeay (2014) attempted to identify the factors that bring about the adoption of online information by consumers with regard to the elaboration likelihood theory, including the central route (e.g. information accuracy, value-added information, information relevance, information timeliness) and the peripheral route (e.g. product ranking).

Interestingly, several tourism and hospitality researchers have explored travellers' responses to online reviews concerning the trustworthiness, helpfulness and usefulness of the reviews (Racherla & Friske, 2012; Wei, Miao, & Huang, 2013). It has been recognised in this research that positive reviews are likely to be more favourable than negative comments, and heuristic cues of online reviews lead readers to enlarge the perceived helpfulness of the reviews. A recent research by Liu and Park (2015) concluded that the messenger characteristics (e.g. disclosed photo, reviewers' expertise) and message characteristics (number of words, star ratings readability) of the online reviews affect the perceived usefulness of online reviews.

When reviewing the literature of online reviews, it was noted that many studies have used a survey method or experimental design approach to estimate the effect of online comments on consumer behaviours (Schuckert et al., 2015). Importantly, however, this study uses data reflecting *actual* user behaviours collected from a real tourism review website. Thus, it is suggested that an alternative method of count models – the negative binomial model – better addresses the research question, as discussed in the following section.

2.2 Count models

Count models deal with specific types of data, which are discrete, using a non-negative integer (e.g. 0, 1, 2 …), which stand for counts rather than rankings. In other words, they represent the number of occurrences of an event within a fixed period. Count models aim to identify factors influencing the average number of occurrences of an event. Since count data is distinct from binary data consisting of two values ('0' or '1'), alternative estimations have been suggested for use, such as the Poisson and negative binomial models (Castéran & Roederer, 2013; Czajkowski, Giergiczny, Kronenberg, & Tryjanowski, 2014; Hellerstein & Mendelsohn, 1993). While the linear least square regression coping with continuous variables is applicable, the estimated results can be inefficient, inconsistent and biased (Cameron & Trivedi, 2013). This is because the response variable is categorical or discrete, which often produces skewed distribution of residential errors, as well as making an ineffective approach of a simple transformation.

2.2.1 *Poisson estimation*

The Poisson model is useful when the outcome is count with which the large count becomes rare occurrences (Kutner, Nachtsheim, Neter, & Li, 2004). The Poisson function predicts the number of occurrences of events (Y = 0, 1, 2 …) during an interval of time. The Poisson distribution can be expressed as follows:

$$p(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}$$

where Y refers to a Poisson distribution with parameter (or intensity) μ

Therefore it can be said that $\mu = \exp(\chi`_i\beta)$

Importantly, one of properties of the Poisson estimation is the equality of mean and variance for $\mu > 0$, known as equidispersion (Cameron & Trivedi, 2013).

$$E(y|\chi) = \mathrm{var}(y|\chi) = \mu$$

Since the mean is equal to the variance, any factor affecting one element of the equation will simultaneously influence the other.

While the Poisson model is nonlinear, the maximum likelihood estimation facilitates evaluation of the model as a typical count model. Due to the computational convenience of the estimation, a number of researchers in tourism and hospitality have used the Poisson model to understand travel behaviours, including length of stay (Alegre, Mateo, & Pou, 2011), visit frequency to a destination (Castéran & Roederer, 2013) and museums (Bridaa, Meleddub, & Pulinac, 2012), and travel cost analysis (Chae, Wattage, & Pascoe, 2012). However, there is an important limitation in the Poisson model, which may bring about biased and incorrect estimated results (Gurmu & Trivedi, 1996; Zeileis, Kleiber, & Jackman, 2008), denoting overdispersion. The assumption of the Poisson model is the equality of mean and variance. In the context of count data, the conditional variance frequently exceeds the mean. It refers to overdispersion relative to the Poisson model. When the conditional variance is less than the mean, it represents underdispersion. These two cases of over- and underdispersion inhibit the suitability of the Poisson model, resulting from unobserved heterogeneity. In order to manage the restrictions of the Poisson model, this study uses an alternative count model, the negative binomial model, as a type of generalized linear model (Cameron & Trivedi, 2013).

2.2.2 Negative binomial estimation

The negative binomial model is a form of Poisson regression that contains a random component considering the uncertainty about the true values at which events occur for individual cases (Gardner, Mulvey, & Shaw, 1995). In other words, this model addresses the issue of overdispersion by including a dispersion parameter to accommodate the unobserved heterogeneity in the count data. The additional parameter allows the variance to exceed the mean. Hence, the negative binomial estimator can manage 'incidental parameter' bias, and is generally superior to the Poisson estimator (Allison & Waterman, 2002).

The negative binomial model can be written as

$$P(y_t) = \frac{\Gamma(\alpha^{-1} + y_t)}{\Gamma(\alpha^{-1})\Gamma(y_t + 1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + e^{\sum_{k=1}^{K} \beta_k x_{tk}}} \right)^{\alpha^{-1}} \left(\frac{e^{\sum_{k=1}^{K} \beta_k x_{tk}}}{\alpha^{-1} + e^{\sum_{k=1}^{K} \beta_k x_{tk}}} \right)^{y_t} \quad \forall y_t = \{0,1,2,...\}$$

Where Γ represents the gamma function, x_{tk} the characteristic k of online review t and β_k the parameter which indicates the effect of x_{tk} on $P(y_t)$.

The parameter α covers the dispersion of the observations, in such a way that

$$E(y_t) = e^{\sum_{k=1}^{K}\beta_k x_{tk}} = \lambda_t$$

and

$$V(y_t) = e^{\sum_{k=1}^{K}\beta_k x_{tk}} + \alpha \cdot e^{2\sum_{k=1}^{K}\beta_k x_{tk}} = \lambda_t + \alpha \cdot \lambda_t^2$$

One way of verifying the validity of the negative binomial model against the Poisson model is to test the null hypothesis α=0. Note that its acceptance would imply that $E(y_t)=V(y_t)$, so that the Poisson model is a particular case of the negative binomial when α=0 (Gurmu & Trivedi, 1996).

Due to the benefits of the negative binomial model in managing the restriction of the Poisson model, several tourism scholars have used the estimation in order to understand self-drive trips using the contingency behaviour model (Mahadevan, 2014) to calculate the number of days cars are hired for (Palmer-Tous, Riera-Font, & Rosselló-Nadal, 2007); the length of stays for senior tourists (Alén, Nicolau, Losada, & Domínguez, 2014) and youth travellers (Thrane, 2016); numbers of visitations to a destination (Czajkowski, Giergiczny, Kronenberg, & Tryjanowski, 2014); and number of hotel rooms rented (Yang & Cai, 2016). Thus, this research assesses the appropriateness of models between the Poisson and negative binomial models in understanding the features of the data distribution. Then the effect of online star ratings on information evaluations in terms of perceived consumer usefulness and enjoyment is discussed.

3 Methods

3.1 Data collection

This research collected data on online consumer reviews from Yelp, which constitutes the majority of consumer feedback on restaurants and is regarded as an important travel activity (Park & Fesenmaier, 2014)[1]. Consumer reviews were collected relating to restaurants located in two main tourism destinations: London and New York. This approach allowed the researcher to reduce the potential of confounding effects on the estimations with regard to a specific feature of a destination. Other than controlling the location of the restaurants, the researcher took into account the prices and brand familiarity of the restaurants which may affect information search and evaluation (Gursoy & McCleary, 2004). The restaurants were selected according to the classification of price groups and excluding national and local chains. Racherla and Friske (2012) found that a restaurant's position on the website has an influence on users' perception as more attention is drawn to businesses listed in the top places among the reviews. Thus, this study used the collection process in a random manner instead of selecting them in either rankings or alphabetical order. As a result, 45 restaurants in London with 2,500 reviews and 10 restaurants in New York with 2,590 reviews were chosen for data analysis.

3.2 Model estimations

This study applied a method to assess the effect of heuristic online reviews (particularly star ratings) on the usefulness of the reviews and the enjoyment of the consumer. The data reflecting the number of votes awarded to individual reviews included features of count data which are nonnegative and occur in integer quantities. According to the integral nature of online review votes, the estimated results using continuous models (e.g., linear regression) that restricts managing censoring (e.g. zeros) brings about biased estimations. Thus, this research used count data models (Hellerstein & Mendelsohn, 1993).

[1] The study uses the same data set as Park and Nicolau's (2015) paper published in the *Annals of Tourism Research*. Detailed descriptions of the data collection and measurements can be found in the article.

The most well-known approximation is derived from the Poisson distribution $P(\lambda)$, where λ is the average of the random variable, which, in this research, is the number of 'useful' or 'enjoyment' votes awarded to the review in a certain period of time. As discussed above, however, the Poisson model is developed based on the assumption of average-variance equality. It is too restrictive to represent individual behaviours, as it is not able to cope with the heterogeneity of these individuals and creates what is known as the 'problem of overdispersion' (Gurmu & Trivedi, 1996). Hence, in order to address the restrictions of the Poisson modelling, this study applied an alternative count model based on a negative binomial distribution (Cameron & Trivedi, 2013).

One way of verifying the validity of the negative binomial model as opposed to the Poisson model is testing the null hypothesis (i.e. dispersion parameter = 0 denoting α at the equation discussed in the literature review), reflecting equality of mean and variance $E(y_t)=V(y_t)$. When this hypothesis is rejected (i.e. $\alpha \neq 0$), it can be said that the negative binomial is a more appropriate approach than the Poisson model as it addresses the overdispersion problem (Gurmu & Trivedi, 1996). Furthermore, this approximation copes with the bias problems of regression analysis arising from the discrete character of the dependent variable (Hellerstein & Mendelsohn, 1993).

3.3 Measurements

This research assessed an independent variable – star ratings – that indicates the perceived quality of products and services using five star levels (Chevalier & Mayzlin, 2006; Mudambi & Schuff, 2010; Racherla & Friske, 2012). Given the raw data of the star rating variable, a series of data manipulations were applied. Firstly the data was divided into two categorized variables (i.e. positive and negative reviews) with positive reviews consisting of four and five stars and negative reviews consisting of one and two stars; secondly dummies were given for each star rating. This approach enabled the researcher to investigate the relative influences of reviews on two types of consumer responses (i.e. perceived usefulness and enjoyment) with the medium rating ('3') as a reference group. Additionally, these three alternative ways to approach the inclusion of the star rating variable into the model allowed for the identification of the intricacies of different particular effects, as well as confirming robustness in cases where the scores of this variable are highly skewed (mean: 4.28; standard deviation: 0.88). Therefore, examining the variable itself could lead to misleading results, as the mean value could not reflect the whole range of its effect.

There are two dependent variables measured by counting the number of online users who voted that the reviews were useful or pleasurable (Ghose & Ipeirotis, 2011; van der Heijden, 2003). This research then considered a number of control variables, including identity disclosure (the presence of real names and photos) (Forman, Ghose, & Wiesenfeld, 2008), level of reviewer expertise (the number of previous reviews written by a reviewer) (Chen, Dhanasobhon, & Smith, 2008) and reputation (the number of times that each reviewer achieved the 'elite' title) (Gruen, Osmonbekov, & Czaplewski, 2006), review elaborateness (the number of words in each review content) (Shelat & Egger, 2002), and readability[2] (Korfiatis, Garcia-Bariocanal, & Sanchez-Alonso, 2012). These control variables were decided based on the findings of previous studies arguing that the characteristics of messengers and messages affect the perceived evaluations of online consumer reviews. Additionally, the location of the restaurants were added as another control variable so as to test the potential confounding effect on the results (1 = London and 0 = New York).

[2] Readability was examined by automated readability index (ARI) (Zakaluk & Samuels, 1988). This index takes into account the number of words and characters to evaluate the comprehensibility of a text. The estimated value of ARI indicates the educational level required to understand the textual information.

4 Results

4.1 Analysis of OLS regression model

Table 1 presents the results of a linear regression with normally distributed errors. The variables estimated explain 16% for usefulness and 15% for enjoyment. In both models, the variable of star rating shows negative relationships while the squared term of star ratings have positive influences on the outcomes. This model, however, is problematic: the main issue is that the data violates the assumption that the variances of the residuals are the same for the original response variable in the regression model (Fox, 1984). To evaluate this property, an approach to testing heteroscedasticity using the White method (Cameron & Trivedi, 2013) was employed. It was identified that the model possesses heteroscedasticity, which potentially results in misrepresenting the estimated variances of the coefficients compared with relevant true variances. Considering count data in which the absolute values of the residuals generally correlate with the explanatory variables, the estimated standard errors of the coefficients are likely to be smaller than their true values (Gardner et al., 1995). The t-test results corresponding to the coefficient estimations can be inflated accordingly.

Table 1. The results of OLS regression

	LR[1] Usefulness	**LR[1] Enjoyment**
Star ratings	-1.642***	-0.561***
	(0.229)	(0.176)
Squared Star ratings	0.232***	0.100***
	(0.229)	(0.023)
Exposure name	-0.015	0.047
	(0.164)	(0.126)
Exposure photo	0.268***	0.168***
	(0.081)	(0.062)
Reviewer's expertise	0.002***	0.001***
	(0.001)	(0.001)
Reviewer's reputation	0.097***	0.097***
	(0.020)	(0.020)
Information elaborateness	0.155***	0.003***
	(0.136)	(0.001)

Readability (ARI)	0.014	0.001
	(0.009)	(0.001)
Location	-0.028	0.008
	(0.068)	(0.052)
Constant	2.457***	0.316***
	(0.442)	(0.341)
R-squared	0.160	0.152
Adjusted R-squared	0.159	0.150
Log likelihood	-11606.26	-10274.5
AIC	4.566	4.043
SIC	4.578	4.056

Note: 1 refers to linear regression; *p < 0.05; **p<0.01; ***p<0.001; numbers in parenthesis refer to standard errors

A conventional alternative to responding to heteroscedasticity is transforming the data in order to remove the correlation between the expected counts and residuals. However, the simple transformation approach would not be able to cope with the features of count data generally including many 'zeros' (King, 1988). More importantly, the counting numbers are the natural and meaningful values as counts, and thus, the analysis should retain these merits. Therefore, it can be suggested to use certain models dealing with count data.

4.2 Analysis of count models

As discussed in the literature review, the Poisson regression is a more reasonable model to analyse count data than the linear regression model. First, the nature of counts include nonnegative numbers. The Poisson distribution allocates probabilities only to the nonnegative integers of the outcome variable. Second, the variance of the dependent variable increases as a function of mean, referring to equidispersion. Thus, it can be said that the Poisson model has greater validity than the linear regression model (Gardner et al., 1995). Checking the goodness of fit between models such as LL (log-likelihood), AIC (Akaike information criterion) and SIC (Schwarz criterion or Bayesian information criterion), all of the values for the Poisson model (see Table 3); LL = -8513.1 for PI U and -6480.4 for PI E, AIC = 2.799 and 2.551, and SIC = 2.813 and 2.565) are better than for linear regression (see Table 1); LL = -11606.26 and -10274.5, AIC = 4.566 and 4.043, and SIC = 4.578 and 4.056 for usefulness and enjoyment in linear regression, respectively).

It is, however, important to consider a critical limitation of the Poisson model, such as over- or underdispersion. When comparing the unconditional mean and variance of the dependent variables (see Table 2), the results do not show equidispersion. That is, the unconditional variances of the outcome variables are much higher than their mean values (variance = 6.68 and 3.92; mean = 1.22 and 0.76 for usefulness and enjoyment respectively). This result provides an indication of an overdispersion problem.

Table 2. The summary of dependent variables

	Observations	Mean	Variance	Min.	Max.
Usefulness	5,090	1.22	6.68	0	65
Enjoyment	5,089	0.76	3.92	0	55

Following the initial assessment, the researcher tested the overdispersion parameter α by applying the negative binomial model. As shown in Table 3, particularly for the models of NB U1 and NB E1, the parameter α is larger than 0 and statistically significant ($p<0.001$). Furthermore, the models including categorical variables of star ratings (e.g. NB U2, U3, E2 and E3) consistently show the invalidation of the property of mean-variance equality of the Poisson models (Cameron & Trivedi, 1998). This implies the existence of heterogeneity of travel behaviours, which in turn suggests the adoption of a model that manages the variations in order to avoid possible biases in the estimations (Gurmu & Trivedi, 1996). Furthermore, the goodness of fit indexes including AIC and SIC are compared with the Poisson and negative binomial models. It can be confirmed that the indicators related to the negative binomial model are better than the ones associated with the Poisson model. In terms of the

Table 3. The results of Poisson and Negative Binomial models

	Usefulness				Enjoyment			
	PI[1] U	**NB[2] U[3]1**	**NB U2**	**NB U3**	**PI E[4]**	**NB E1**	**NB E2**	**NB[2] E3**
Star ratings	-1.277***	-1.134***			-0.780***	-0.497**		
	(0.075)	(0.140)			(0.123)	(0.196)		
Squared Star ratings	0.180***	0.161***			0.134***	0.100***		
	(0.010)	(0.019)			(0.016)	(0.026)		
Positive reviews (4 & 5)			0.081				0.474***	
			(0.071)				(0.095)	
Negative reviews (1 & 2)			0.400***				0.126	
			(0.111)				(0.154)	
Positive review (5)				0.225***				0.635***
				(0.073)				(0.097)
Positive review (4)				-0.146†				0.228*
				(0.076)				(0.100)
Negative review (2)				0.273*				0.167
				(0.123)				(0.166)
Negative review (1)				0.733***				0.020
				(0.178)				(0.285)
Real name	0.116	0.125	0.095	0.114	0.305	0.258	0.269†	0.254
	(0.081)	(0.116)	(0.115)	(0.116)	(0.126)	(0.160)	(0.160)	(0.160)
Real Photo	0.379***	0.348***	0.350***	0.351***	0.482***	0.480***	0.481***	0.480***
	(0.038)	(0.054)	(0.054)	(0.054)	(0.052)	(0.070)	(0.070)	(0.070)
Reviewer’s Expertise	0.358***	0.302***	0.300***	0.316***	0.390***	0.363***	0.355***	0.370***
	(0.003)	(0.0722)	(0.073)	(0.073)	(0.030)	(0.088)	(0.089)	(0.088)
Reviewer’s reputation	0.113***	0.127***	0.121***	0.126***	0.168***	0.186***	0.181***	0.183***
	(0.008)	(0.014)	(0.015)	(0.014)	(0.009)	(0.017)	(0.017)	(0.017)
Review elaborateness	0.003***	0.003***	0.003***	0.003***	0.002***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Readability (ARI)	0.015***	0.012*	0.012*	0.012*	0.004***	0.001	0.001	0.002
	(0.003)	(0.005)	(0.001)	(0.005)	(0.004)	(0.007)	(0.007)	(0.007)
Location	0.010	0.081	0.053	0.083	0.048	0.131*	0.096	0.134*
	(0.026)	(0.043)	(0.043)	(0.043)	(0.033)	(0.054)	(0.054)	(0.054)
Constant	0.950***	0.630*	-1.181***	-1.217***	-1.089***	-1.741***	-2.348***	-2.362***
	(0.145)	(0.266)	(0.136)	(0.136)	(0.252)	(0.387)	(0.1856)	(0.187)
α		0.155***	0.191***	0.152***		0.521***	0.555***	0.518***
		(0.043)	(0.0422)	(0.042)		(0.050)	(0.049)	(0.050)

R-squared	0.224	0.214	0.196	0.216	0.190	0.173	0.153	0.175
LR Index	0.162	0.300	0.297	0.301	0.175	0.316	0.313	0.315
LR statistic	3294.8***	6103.4***	6040.9***	6108.0***	2750.5***	4960.4***	4913.5***	4962.1***
Log likelihood	-8513.1	-7108.8	-7140.1	-7106.5	-6480.4	-5375.4	-5398.9	-5374.6
AIC	3.350	2.799	2.811	2.799	2.551	2.118	2.127	2.118
SIC	3.363	2.813	2.825	2.815	2.565	2.132	2.141	2.135

Note: 1 refers to the Poisson model; 2 refers to the Negative Binomial model; 3 refers to usefulness; 4 refers to enjoyment; *p<0.05; **P<0.01; ***p<0.001;

explanatory power of the model, statistical evidence including significant likelihood ratio, LR index over 30% and R-square over 15% supports the acceptable ability of the negative binomial models to assess the proposed relationships (Hensher & Johnson, 1981; Train, 2009) (see Table 3).Thus, this research uses the negative binomial model as a main data analysis.

4.3 Assessing the effect of star ratings on review evaluations

The variables of star ratings show a negative linear relationship and a positive curvilinear (U-shaped) relationship with both usefulness ($b = -1.134$ & 0.161, $p < 0.001$) and enjoyment ($b = -0.497$ & 0.100, $p < 0.01$) (see Table 3). The models containing two categorical variables (i.e. positive and negative ratings with a neutral value as a reference) were analysed in order to estimate the relative influences with directional online reviews (see NB U2 and NB E2). Interestingly, only negative reviews are significant in explaining usefulness (NB U2; $b = 0.400$, $p < 0.001$) whereas, in the case of enjoyment, the positive reviews were positively significant (NB E2; $b = 0.474$, $p < 0.001$). This finding implies that online travellers are more likely to read either positive or negative reviews that enhance the completeness of information, rather than balanced ratings (Cheung et al., 2009).

As a way to unravel the asymmetric effects of star ratings on different consumer responses, a more sophisticated analysis composed of binary variables that represent individual star ratings was conducted (see NB U3 and NB E3). In the model estimating usefulness, given middle point as a reference, all variables of each star rating except for ‘positive review (4)’ are statistically significant at p-value below 5%. When comparing the relative coefficient values (see NB U3), it was identified that the negative reviews ($b = 0.733$ for rating 1 and 0.273 for rating 2, $p < 0.05$) have higher impacts on review usefulness than positive reviews ($b = 0.225$ for rating 5, $p < 0.001$) (Chevalier & Mayzlin, 2006).

Corresponding to NB E2, the findings of NB E3 present the significant effects of positive reviews on enjoyment ($b = 0.635$ for rating 5 and 0.228 for rating 4, $p < 0.05$), but an insignificant result with negative reviews ($b = 0.167$ for rating 2 and 0.273 for rating 1, $p > 0.05$) (Fischer et al., 2008).

For the control variables, the potential effect of the locations of restaurants (London and New York) was tested with outcome variables (usefulness and enjoyment). Based on the consistent results across OLS regression, the Poisson and the negative binomial models, it is apparent that the variances of dependent variables explained by the different locations are limited. The disclosure of reviewers' information (e.g. photo) and the features of reviewers (e.g. expertise, reputation), as well as the characteristics of the message (e.g. elaborateness), have positive influences on usefulness and enjoyment. Interestingly, review readability seems to be just significant in the aspect of usefulness.

5 Conclusions

Online reviews have become an important and reliable information source to current travellers, which enable them to evaluate the quality of products/services and to have indirect experiences (Liu & Park, 2015). Within the e-WOM strategy, review ratings represent an attempt to quantify service quality perceptions, which is one of the important information elements used by consumers in making a purchasing decision (Ye, Li, Wang, & Law, 2014). This chapter examined potential asymmetries in the effect of online reviews on usefulness and enjoyment, and suggested the use of the negative binomial model as an appropriate method to cope with count data. It was identified that online consumers perceive extreme ratings (positive or negative) as more useful and enjoyable than moderate ratings, illustrating a U-shaped relationship. More specifically, while negative reviews are more useful than positive ones, positive reviews are associated with higher enjoyment. The findings in which the ability to view a real photo, higher levels of reviewer's expertise and reputation, and the review's elaborateness and readability have positive influences on usefulness and/or enjoyment provide important implications. The location of the restaurants has restricted influence on the results, which evidence a limited confounding effect on the estimation.

While there are a number of studies that assess the effect of online reviews on both consumer purchasing behaviours and product sales, the way to address a crucial question of what makes online reviews useful and enjoyable has been restricted. Along with the theory of information diagnosticity, which refers to the extent to which a consumer believes the product information is helpful to understand and evaluate purchase alternatives (Filieri, 2015), online consumers pay greater attention to directional reviews (i.e. positive and negative ratings) to understand the expected advantages and disadvantages derived from the consumption of the product/service.

Specifically, online consumers tend to focus on negative reviews in order to increase the utility of their decisions by reducing the risk of loss (Kahneman & Tversky, 1979). This strongly supports the notion of negativity bias, arguing that rational consumers recognise the purchasing bias, and they compensate for this bias by considering negative reviews more seriously than positive reviews (Hu, Pavlou, & Zhang, 2007). From the enjoyment aspect, the characteristics of tourism products, which refer to experiential (or hedonic) products, suggest that consumers tend to take into account the elements of excitement and pleasure when searching for travel information (Vogt & Fesenmaier, 1998). This could explain the findings of a higher influence of positive reviews on inducing perceived enjoyment than negative reviews. Thus, this chapter elucidated the asymmetric effects of online review as an important information cue on different aspects of information evaluation.

Utilising secondary data collected from a website with an unstructured format frequently invalidates the properties of using OLS regression or general count models, due to non-normal distribution of data (Hox & Boeije, 2005). In particular, considering count data that is discrete, and nonnegative integers, it is important to adopt an alternative method that is suitable for managing the specific features of data (i.e. overdispersion). In this vein, this chapter used the negative binomial model, which allows for addressing those restrictions. Specifically, this research presents a set of procedures to test the appropriateness of the model, including descriptive and analytical estimations, so as to verify the existence of heterogeneity of tourist preferences. Accordingly, it is identified that the negative binomial model not only shows better goodness of fit for the estimated models, but also brings about higher R-square values than the OLS regression and the Poisson model. Thus, the findings obtained from the negative binomial model can avoid possible biases in the estimations.

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