Spill-over Effects of Online Consumer Reviews in the Hotel Industry

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Abstract

The purpose of this research is to investigate and estimate the spill-over effects of online consumer reviews as a proxy to reflect hotel performance, focusing on 689 hotels located in London, UK. This study used a series of data mining approach to collect estimated variables from a travel search engine website (i.e., Kayak.com) and made the first attempt to apply spatial econometric modelling at the firm level in the tourism and hospitality field. The findings of this research identified a complementary effect of consumer rating between neighbouring hotels, and showed the spatial dependency of room prices across hotels at the destination. Furthermore, a local estimation using geographically weighted regression approach allows researchers to understand the spatial variations of the spatial effects. Important implications for tourism and hospitality managers to develop regional marketing and promotions are provided.

Keywords: Data mining; spill-over effect; online consumer reviews; spatial economic modelling

1 Introduction

There have been a number of studies identifying factors that affect hotel performance/satisfaction, such as hotel attributes (e.g., rooms, facilities, service quality, etc.), pricing, location, and security (Zhou, Ye, Pearce, & Wu, 2014). The main focus of extant studies about hotel management is on their internal strategy; however, this research highlights the importance of spill-over effects associated with a specific type of spatial interaction among hotels within a certain place. That is, since the different accommodations located in the same place interact with each other (Ritchie et al., 2013), the operational strategy (e.g., pricing) as well as guest experiences (i.e., online consumer reviews) may drive the gross demand for the tourism place and, in turn, influence the performance, not only of a given hotel but also other hotels in the region. Analysing spill-over effects has largely been considered in the tourism field in terms of understanding tourist flow, and assessing the effects of the external environment (e.g., oil prices and recession) and mega events on tourism demand (Gooroochurn & Hanley, 2005). In addition, some hospitality studies have examined spill-over effects to explain the influence of co-branding and foreign direct investment (Mao & Yang, 2016).

The advancement of information technology enhances consumer empowerment, as people can share their experiences of hotel consumption with other consumers at any time and from any place (Liu & Park, 2015). In this sense, managers in the tourism and hospitality industry largely concern the consumer ratings which have been regarded as a proxy to reflect the firm performance (Ye, Law, & Gu, 2009). In this sense, information system scholars recently demonstrated the existence of spill-over effects in the context of online reviews, where an online comment from one customer affects the reactions of other consumers to leave online reviews regarding their consumption (see Chae, Stephen, Bart, & Yao, 2015; Janze, 2016).

In particular, current travellers can easily compare room prices through various online booking channels (e.g., Kayak, Booking.com, etc.). This comprehensive information enables people to estimate 'value for money' in regard to opportunity cost against the choice of another given hotel, recognizing the specific room rate. Consumers are likely to present a satisfaction behaviour rather than an optimising behaviour when evaluating travel products (Clemons & Gao, 2008). Therefore, the aim of this research is to estimate the spill-over effects between hotels in the context of online consumer reviews with considering room prices.

2 Literature Review

Spill-over effects have gained significant attention from tourism scholars, particularly in understanding tourist flow (Gooroochurn & Hanley, 2005), as well as in assessing foreign direct investment and productivity in the accommodation industry (Yang & Mao, 2015). From the economics perspective, the spill-over effect can refer to both positive and negative externalities derived from the economic activities or processes which influence any elements not directly linked with the activity (Yang & Wong, 2012). With regard to tourist flow, it is identified that a city surrounded by an area with a thriving tourism industry can receive the positive spill-over effects in tourist flows (Yang & Wong, 2012). In other words, travel destinations can receive distinctive benefits connected with proximity or spatial groups that improve attractiveness to tourists who plan multi-destination trips (Yang & Fik, 2014). It is suggested that cities, particularly those which are less developed places for travel, could obtain mutual benefits with neighbouring cities to support local tourism development with regard to a cross-city spill-over effect. It also can be argued that the spill-over effect would be widespread in the hotel industry, where a region's hotel industry exerts influence on gross number of guest visits to hotels in other regions and/or those accommodations located in the same region. In other words, a hotel in a specific region can be influenced by the strategy of adjacent hotels in terms of either positive or negative spill-over effects.

Following the development of information technology, online travellers can easily share their hotel experiences via social media websites. These comments play a key role in affecting future travellers' hotel choices because travellers perceive that online comments are more reliable and/or trustworthy than information provided by hotel marketers. As such, online consumer ratings have been regarded as one of the determinants of product sales and price premiums (Öğüt & Onur Taş, 2012). A study conducted by Park and Nicolau (2015) identified that directional reviews (i.e., extremely positive or extremely negative ratings) that allow travellers to understand the expected advantages and disadvantages derived from the hotel consumptions are much more helpful than ambiguous information. Indeed, in terms of a decision net model, it is a fact that travellers are likely to make a destination decision first and then consider accommodation as a secondary decision (Park, Nicolau, & Fesenmaier, 2012). This implies that, given a destination at the initial stage of travel planning, the online consumer ratings of a hotel affect not only the demand for that hotel, but also the demand for other hotels located in the same region.

In this vein, there are several studies that demonstrate the spill-over effects in the context of online consumer reviews (e.g., Chae et al., 2015; Janze, 2016) based upon the statement that spill-over effects indicate the extent to which "existing information and perceptions influence beliefs that are not directly addressed by or related to the original information source or perception object" (Janakiraman, Sismeiro, & Dutta, 2009; page 2). Janze (2016) identified cross-organizational spill-over effects in user-generated online service reviews. Specifically, the study examined how the perception of consumers of a service provider expressed in online reviews is affected by interdependent service providers, for instance, airports and flights. That is, increased (decreased) overall ratings of a service node (i.e., airports) are linked with increase (decrease) of consumer ratings on those things following the service node (i.e., flights). This phenomenon was explained by a concept of treatment-by-association (TBA) closely related to guilt-by-association (GBA). TBA refers to the perceptual attribution of positive and negative features to units (or entities) due to the units they associate with and incorporate implicit memory (Janze, 2016). In other words, TBA is associated with the psychological concept of priming, that is, a process by which an experience (or perception) of a unit (event, item, person, or object) leads to an increase in the approachability of related material or behaviours (Baumeister & Vohs, 2007). For example, when someone experiences a very pleasant flight, their openness to positive feelings and emotions will be increased when using the airport of arrival. Accordingly, based upon the assumption that hotels in a travel area are interdependent service nodes, the notion of TBA is appropriate to account for the spill-over effects in online hotel reviews.

Chae, et al. (2016) proposed three typologies of online spill-over effects (focal product spill-overs, brand spill-overs, and category spill-overs) to understand online word-of-mouth (WOM) effects at the brand and category levels. Among them, category spill-overs are particularly relevant to the hospitality industry, defined as WOM generated by general consumers about products from the same category as the focal product. The study by Chae et al. (2016), sheds light on (1) spill-over effects with respect to online WOM of the same brand’s products in other categories and/or competing products, and (2) spill-over effects of online WOM on other brands’ products in the same category. Apart from brand/category-based spill-over effects, Chae et al. (2016) also identified the spill-over effects of online WOM across different segments, corresponding to the two-step flow of the communication model (e.g., Katz & Lazarsfeld, 1955). Specifically, online consumer reviews provided by specialists or experts in a certain product influence the behaviours of online reviews by other segments, such as generalist or less experienced consumers. Interestingly, the results show the positive and negative spill-over effects in the context of online WOM.

Thus, the authors of this research argue that the online consumer ratings of hotels in a certain region involve spill-over effects which influence the performance of other hotels. In addition, there is a substantial literature stating that room pricing is one of key determinants for travellers in choosing a hotel, and a main driver in generating the largest proportion of hotel performance (Oh, 2003). Current travellers can easily obtain sufficient information about room rates and compare them across different hotels by accessing booking channels. This comprehensive information enables travellers to assess 'value for money' with regard to opportunity cost against the choice of another given hotel, recognizing the specific room rate. The concept of value for money had been regarded as an important attribute for hotel satisfaction (Choi & Chu, 2001). In this sense, the perceived value for money obtained by the comparison shows spill-over effects on other hotels' guest experiences. Consumers are likely to present a satisfaction rather than an optimizing behaviour when evaluating travel products (Clemons & Gao, 2008). Therefore, it can be hypothesized that:

Hypothesis 1: The increase in online consumer ratings of hotels in a city is significantly associated with the increase in online consumer ratings of other hotels in the same city.

Hypothesis 2: The increase in online consumer ratings of hotels in a city is significantly associated with the increase in room prices of neighbouring hotels in the same city.

3 Research Methods

3.1 Spatial Autoregressive Model

The spill-over effects can be conceptualised as that values observed at hotel i depend on the values of neighbouring hotels at nearby locations. The longer the distance from hotel i, the weaker such dependence would be. In order to identify and capture the spill-over effects of hotel performance and other explanatory variables, this study applies a spatial Durbin model (SDM) with inclusion of the spatially lagged terms of both dependant variable and independent variables. The SDM is a general form of spatial autoregressive models (SAR) in which spatial dependence across observations is accounted for by the spatially lagged terms. With the inclusion of the spatially lagged dependent variable, estimation biases caused by omitted variables may be reduced (LeSage & Pace, 2009). Given the above conceptual and statistical reasons, this study specifies a SDM in the following vector form:

$$Y = \rho WY + X\beta + WX\theta + \varepsilon, \tag{1}$$

where Y is an $N \times 1$ vector of online consumer ratings of overall experience in a sample of N hotels; X is an $N \times 3$ matrix of explanatory variables including the hotel star rating X_1, median room price X_2, and online user rating of service quality X_3; W represents the row standardized ($N \times N$) spatial weight matrix, which conceptualises the spatial relationship; β, ρ, and θ are the vectors of spatial parameters to be estimated; and ε is the error term. Since the coefficients in the model gauge the effects averaged across all the observations, Equation (1) is referred to as a global model. The parameters are estimated with a maximum likelihood method provided in the R (R Core Team, 2016) package *spdep* (Bivand & Piras, 2015), where ρ is estimated by numerical optimisation first, and β and θ parameters by generalized least squares subsequently.

3.2 Local Estimation

In the tourism literature, it has been found that the effects of tourism activities present spatial heterogeneity across geographic regions (Li, Chen, Li, & Goh, 2016; Yang & Fik, 2014). Spatial heterogeneity refers to the situation when the regression coefficients of spatial lags vary across observations or regions. In this case, a local estimation where coefficients are allowed to vary from hotel to hotel would be beneficial for understanding the spatial variations of the spatial effects. This study applies the geographically weighted regression (GWR) approach (Páez, Uchida, & Miyamoto, 2002) to locally estimating the spill-over effects.

Based on the global model described by Equation (1), a local model can be specified for hotel i in the sample:

$$U(i)Y = \rho_0 U(i)WY + U(i)X\beta_0 + U(i)WX\theta_0 + U(i)\varepsilon_0, \tag{2}$$

where $U(i)$ denotes an $N \times N$ diagonal spatial weight matrix for hotel i. Note that the vectors β_0, ρ_0, and θ_0 are now sub-indexed to denote local parameters that vary from hotel to hotel.

Based on a chosen kernel function and a bandwidth, it assigns weights to the m nearest neighbours (within the bandwidth) of hotel i, and zero to the other hotels in the sample (Ertur, Gallo, & LeSage, 2007). This essentially extracts a sub-sample for each local model. The models can then be estimated recursively (Pace & LeSage, 2004). Due to the smaller sub-sample, local estimates could be very sensitive to local model specifications, Páez et al. (2011) recommend a minimum sample size of 160 for a GWR.

3.3 Data and Variables

The data are gathered from the online metasearch engine KAYAK in mid-August 2016 by applying an automatic crawling method in R. The sample consists of 1832 hotels in London. In line with Equation (1), the data are collected for all the variables including the overall user rating Y, star rating X_1, median room price X_2, and the user rating of service quality X_3 for each hotel. The median prices across various online providers are collected for one room (2 guests) on the last night of each month spanning from August 2016 to February 2017. A median price across the seven-month period is then calculated for each hotel. To generate the spatial weight matrix W, the latitude and longitude coordinates of each hotel are also collected. Rental apartments are excluded from the sample to ensure the consistency in the hotel star rating. Due to the variations in the hotel availability and missing values across the seven-month period, the sample size is reduced to 689 eventually.

4 Results and Discussions

4.1 Global Estimation

To empirically test whether there is spatial dependence in the variables, this study first estimates a regression model with the ordinary least squares (OLS) method. The spatial autocorrelation in the residuals can be examined. Then the proposed SDM is fitted with the inclusion of spatially lagged terms.

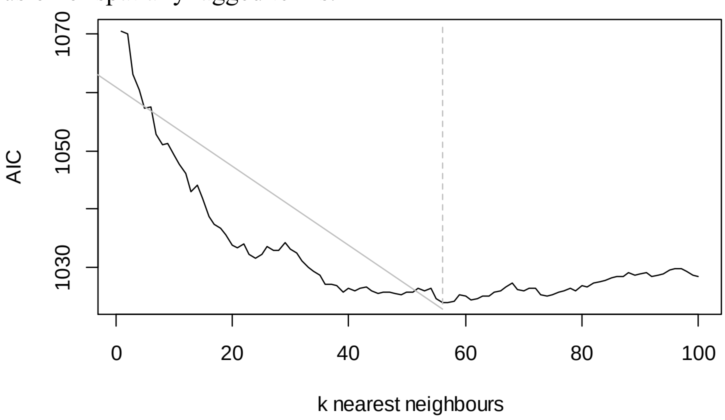

Fig. 1. AIC against adaptive distance band where k is the number of neighbours

The estimation of a spatial model is sensitive to the specification of weight matrix (W in Equation 1). As such, an automated routine is developed to choose the weigh matrix specification that generates the lowest Akaike information criterion (AIC) value resulted from various alternatives. As a result, a Gaussian form function is chosen, combining with an adaptive distance band (the maximum distance to the k-nearest neighbours), as the weight matrix. The weighting scheme is adaptive because the distance band for each observation may vary depending on the number of neighbouring observations. This is useful especially when the density of hotels varies across the city. Fig. 1 illustrates the process of determining the number of nearest neighbours, where k = 56 is chosen. The weight for a point at distance d from the focal observation is $e^{-\frac{d^2}{2h^2}}$, where h denotes the adaptive distance band which is the maximum distance to the k = 56 nearest neighbours. The distances between hotels are measured by the Great Circle distance based on their longitudes and latitudes. Once the weight matrix is generated, it is then row-normalized with a row sum of one.

Table 1. Global model estimation

Variable	OLS	SDM			
		Estimate	Direct effect	Indirect effect	Total effect
Constant	1.952*** (0.179)	-2.057** (1.032)			
Star	0.423*** (0.033)	0.343*** (0.032)	0.347***	0.715***	1.062***

Price	0.001***	0.003***	0.003***	-0.009***	-0.006***
	(0.000)	(0.000)			
Service	0.486***	0.467***	0.469***	0.559**	1.028***
	(0.021)	(0.020)			
*W**Star		0.249			
		(0.169)			
*W**Price		-0.006***			
		(0.001)			
*W**Service		0.107			
		(0.160)			
*W***Y*		0.442***			
		(0.129)			
σ^2		0.251			
N	689	689			
Log likelihood		-502.915			
AIC	1096.6	1023.8			
LM		0.502			
Wald		11.806***			
Moran I	0.179***				

Notes: *** denotes significance at the 0.01 level, ** at the 0.05 level, and * at the 0.10 level. The values in parentheses are standard errors. σ^2 denotes the variance of residuals. LM refers to the LM test statistics for residual autocorrelation. Wald refers to the Wald test statistics on *W***Y*. Moran I refers to the Moran I test statistics for spatial autocorrelation.

Table 1 presents the model estimation results. A highly significant Moran I test statistics indicates a strong spatial autocorrelation. When the spatial lag terms are introduced in the model, the spatial dependence is removed from the residuals as suggested by the insignificant LM test statistics. In the meanwhile, the AIC for SDM is lower than the OLS model, which suggests that the spatial specification improves the model fit.

Of most importance, the Wald test statistics and the *p*-value for *W***Y* indicate that the spatial autoregressive term is significant. The positive sign of *W***Y* implies a complementary effect of consumer rating between neighbouring hotels. This result supports the hypothesis that there is a positive spill-over effect on hotels' performance over neighbouring hotels in a city. When the spatially weighted average of consumer ratings of neighbouring hotels increases by one point, the consumer rating of a given hotel tends to increase by 0.442 points. The potential reason is that the online consumer reviews for a hotel generate WOM effects not only on 'my' hotel, but on the hotels located in the surrounding area as well.

In both the OLS and the SDM models, the median room price significantly contributes to the overall user rating of a hotel. This finding is consistent with the expectation that when the price level of a hotel increases, more funds are likely to be invested in facilities and human resources which eventually improve the consumer experience. While the star rating and the rating of service quality are traditionally regarded as good indicators of a hotel's performance, this study further confirms this finding. However, as a spatial dependence is detected, it is necessary to capture the spatial spill-over effects of these variables. The lagged terms in the SDM suggest that the interdependence of room price is statistically significant while the spatial effects of star rating and service rating are non-significant. The negative sign of *W**Price indicates a competition effect on room price between hotels. This finding derives an interesting dilemma that increasing room price would improve the consumer experience of a hotel (as illustrated by relationship *a* in Fig. 2), yet on the other hand decrease neighbouring hotels' consumer rating (relationship b) and eventually decrease this particular hotel's performance through the feedback loop (loop *c* in Fig. 2).

Due to the existence this spatial feedback loop, LeSage and Pace (2009) propose measures to gauge the direct, indirect and total effects. The direct effect captures the average influence of changing an explanatory variable on the dependent variable, including the feedback effects through neighbours and back to the focal observation. The indirect effect can be interpreted as either the average impact of changing an explanatory variable of the focal observation on the dependent variable of all the other observations, or the impact from the change of an explanatory variable of other observations on the dependent variable of the focal observation. The total effect is the sum of direct and indirect effects, measuring the impact of changing an explanatory variable of the focal observation on the dependent variable of all the observations in the sample.

Accounting for this feedback effect, the ultimate direct effect of price is significant and positive (as shown in Table 1), which implies that the positive contribution of price (as denoted by relationship *a* and loop *c* in Fig. 2) eventually outweighs the negative spill-over effect (relationship *b* through loop *c* in Fig. 2). On the other hand, when a price rise takes place at neighbouring hotels, the negative spill-over effect (relationship *d* and loop *c* in Fig. 2) appears to be stronger than the positive feedback effect (relationship *e* through loop *c*), which results in a negative indirect effect. The price rise at neighbouring hotels can be effectively regarded as a price drop at the focal hotel, which has the same effect as lowering the room price of a hotel. This finding suggests that travellers tend to consider the relative room price as an indicator reflecting their experience staying in a hotel. Combining both the direct and indirect effects, the total effect of room price is significant and negative.

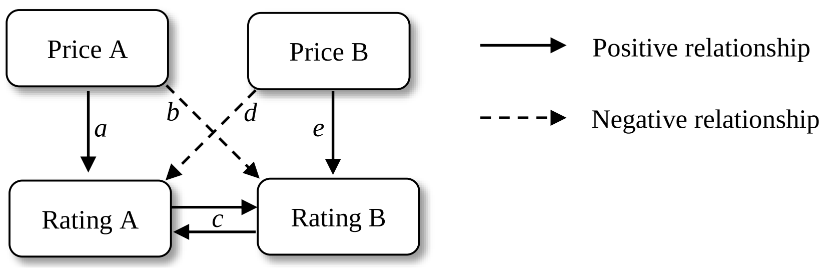

Fig. 2. Relationships between room price and consumer rating of hotels A and B

As shown in the last three columns of Table 1, although the coefficients of star rating (*W**Star) and service rating (*W**Service) are non-significant, both explanatory variables have significant spatial effects. This finding suggests that the overall consumer rating of a hotel is significantly and positively associated to its own star rating and service rating, and also significantly and positively associated with the star rating and service rating of neighbouring hotels.

As far as the consumer rating is concerned, it can be concluded from the above findings that on average, there appears to be a competitive effect in terms of the room price. In the meanwhile, the performance of hotels in London are complimentary on consumer rating, star rating and service rating. Hotels tend to be spatially clustered with a similar score of user ratings, and mutually influential by the performance of neighbouring hotels through the spill-over of WOM effects. Accounting for the feedback loops, the star rating, room price and service quality of a hotel all significantly and positively contribute to its own overall consumer rating. Their indirect spatial effects are all significant as well, but the room price has a negative effect on neighbouring hotels' consumer rating. It is also found that the relative room price of a hotel is associated with the perceived hotel performance.

4.2 Local Estimation

The global estimation above outlines the average effects across all the observations in the sample. However, it would be useful to provide diagnostic information for the industry to pinpoint the local effects for a given hotel. A set of coefficients are estimated for each of the hotels in the sample, which can be used to device competitive strategy for a given hotel. This section demonstrates such a process.

The key to the local estimation is the specification of the local spatial weight matrix $U(i)$, which involves the selection of kernel function and bandwidth. The kernel function controls the shape of the distance delay effect, and the bandwidth controls the smoothness of the delay. A bandwidth that is too narrow may result in large or even unrealistic variations in parameter estimates. While a very wide bandwidth may generate estimates with little variations, it does not represent the local conditions. Therefore, it is essentially a trade-off between variance and bias. Based on the AIC, a Gaussian kernel function with an adaptive bandwidth is chosen for the GWR. The local estimation is a process to estimate Equation (2) for each of the hotels in the sample, which generates 689 sets of coefficients in total. The minimum, quartiles, and the maximum values of each coefficient across 689 hotels are summarised in Table 2.

It can be found from the results that the spatial dependence does exhibit various degrees of variations across hotels. In particular, the own coefficients of star rating, room price and service rating have a positive sign across all the hotels in the sample. While the spill-over effects (W*Star, W*Price, W*Service, and $W*Y$) all span from the negative region to the positive side of the spectrum, the range of local R^2 indicates a good model fit across the hotels.

Table 2. Summary of local estimates

Variable	Minimum	1st quartile	Median	3rd quartile	Maximum
Intercept	-14.160	-3.801	-2.253	1.258	34.160
Star	0.094	0.225	0.302	0.342	0.482
Price	0.001	0.003	0.003	0.004	0.009

Service	0.320	0.422	0.473	0.502	0.593
*W**Star	-0.539	-0.044	0.139	2.569	10.940
*W**Price	-0.023	-0.007	-0.006	-0.004	0.002
*W**Service	-1.381	0.164	0.462	2.034	8.948
*W***Y*	-12.580	-3.289	0.197	0.521	1.279
Local R^2	0.699	0.786	0.802	0.826	0.863

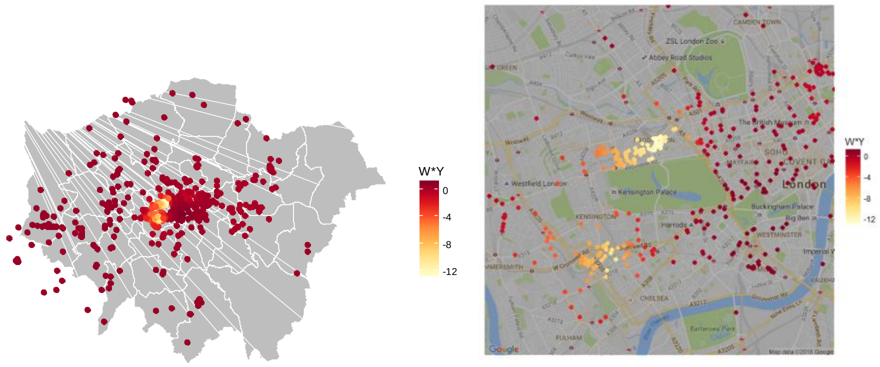

Fig. 3. Local spill-over coefficient of consumer ratings

As a diagnostic tool, the visual presentation of the local estimation would be most intuitive. Fig. 3 maps the spatial variations of the spill-over coefficient of overall user rating (*W***Y*) across the observed hotels in London. It appears that the spill-over effects are mostly positive which is consistent with the global estimation. However, the areas to the north and southwest of Hyde Park displays a negative pattern. Local knowledge suggests that the hotels in the areas are mainly budget hotels. A competitive effect seems dominant among those hotels while the luxury hotels are more likely to benefit from a complementary effect. Due to the space limit, the results for other variables are available upon request from the authors.

5 Conclusion

This paper provides important contributions to theoretical and practical aspects. This research makes the first attempt to apply the spatial econometric modelling at organizational level in the tourism and hospitality context. It allows researchers to identify and estimate the significance of spill-over effects in hotel performance (or guest experiences) with consideration of online word-of-mouth and room prices. More importantly, the findings from the spatial relationships suggest that hotel managers need to fully recognise the positive and negative spill-over effects from neighbouring hotels when understanding their performance. That is, it stresses the importance of regional marketing that collaborate the promotion strategy closely with complementary hotels based upon geographical proximity.

Furthermore, considering a large sample analysed in this study, the local estimation provides useful diagnostic information for the industry to formulate the competitive strategy. That is, the findings about spatial variations of the spill-over effects would enable the hotel managers to recognise the range of geographical zones for recognising the strategic responses to the changes of online reviews in own hotel.

While this study employs a comprehensive approach, there are some limitations. For example, while the local estimation is based on a trade-off between the sub-sample size and parameter variability, the local results should be interpreted as variations around the global level with reference to the global estimation (Wheeler & Tiefelsdorf, 2005). Accordingly, it is recommended for future research to conduct spatiotemporal models which can be used to capture the temporal effects in addition to the spatial ones as well as to understand the dynamic process of the spill-over effects,

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