Effects of official versus online review ratings

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Introduction

The rating systems of tourism and hospitality services are instrumental for both the businesses and consumers. Businesses use them to determine their promotion and pricing strategies, while consumers rely on them to make an informed decision. These systems help stakeholders to reduce uncertainties, because of the informational asymmetry between the service providers and the customers.

The impact of information asymmetry on the market can be illustrated using comparative statics within a supply and demand framework as shown in Figures 1 and 2. According to the well-known Akerlof's (1970) "market for lemons" model, if maintaining high-quality standards is costly, businesses with high quality could be crowded out by the low-quality businesses, because consumers are unable to distinguish between these two categories ex-ante, which will result in a suboptimal equilibrium. Government agencies or independent bodies therefore have to intervene by introducing rating systems through official inspections to reveal essential private information about the services e.g. health and safety, hoping to achieve an efficient separating equilibrium.

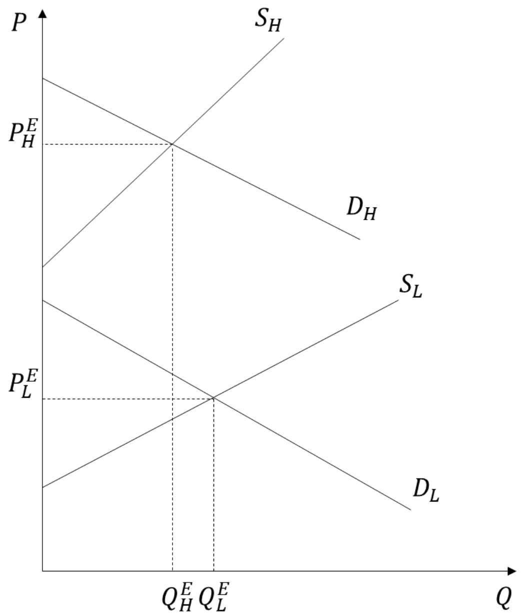

Figure 1. Separating equilibrium on the market for high- and low-hygiene restaurants.

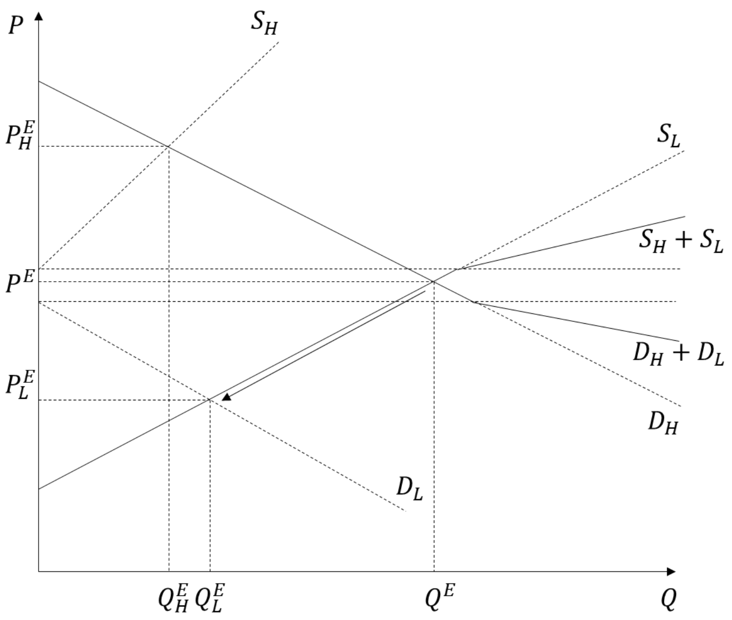

Figure 2. "Crowding-out" of high-hygiene restaurants in the presence of information asymmetry.

In addition to the official ratings, e.g. AAA Diamond Ratings for hotels (Nalley, Park, & Bufquin, 2019) and the UK Food Hygiene Ratings for restaurants, today's consumers increasingly use ratings from online customer reviews in websites such as Google Reviews, Yelp and TripAdvisor, while businesses are closely monitoring the changes in the online review ratings (Xu, Zhang, Nicolau, & Liu, 2020), because a change in the rating could significantly influence their business (Nalley et al., 2019). This study aims to compare the effectiveness of two types of ratings, based on all available restaurants located in Newcastle upon Tyne, UK that had a UK Food Hygiene and Google review ratings.

Data and methods

We collected: 1) the official UK Food Hygiene Ratings from the latest inspection (from 0 to 5, where 0 = requiring urgent improvement and 5 = very good hygiene standard); 2) current Google rating from Google Maps; 3) the number of Google reviews to date; 4) price category (ranging from 1 to 4, collected from Google Maps or qualitatively assessed via content analysis of the menus); 5) the cuisine of the restaurant; 6) social media coverage (proxied by the number of web pages found using the Google search query "«name of the restaurant» Newcastle") and 7) the geographic location (obtained from converting the location postcode into latitude and longitude coordinates) for the sampled restaurants. Data was collected in March 2019 and all restaurants available in Newcastle that have been rated in both the UK Food Hygiene and Google Review were included in the sample.

Consistent with previous studies (Öğüt & Onur Taş, 2012; Ye, Law, Gu, & Chen, 2011), we use the number of Google reviews to proxy the clientele as the dependent variable. Assuming that a similar proportion of visitors submit a Google review for each restaurant, this constitutes a measure that is tightly correlated with the unobservable "true" size of the restaurant's clientele. This can be justified, because previous empirical evidence suggests that that the number of online reviews is correlated with the number of customers, restaurant popularity, and even sales (Liu & Park, 2015; Park & Nicolau, 2015). Compared to other proxies of clientele, such as sales figures that could be underreported by restaurants due to tax reasons, the number of online review is considered to be more reliable.

Additionally, unlike the official food hygiene ratings, which are frequently updated to reflect the changes in food safety condition of a restaurant, Google ratings are backwards-looking and naturally sticky to the extent they might take into account outdated reviews. Therefore, the research design could be biased *in favour* of the official rating.

Two approaches are adopted to account for the geographic location's impact. First, the geodesic distances from the restaurant to several key places in Newcastle (Central station, Grey's Monument, Tyne Bridge and the campuses of Northumbria University and Newcastle University) are calculated using longitudes and latitudes. Second, a measure of "peer effect" or "location effect" is computed for every restaurant, using clienteles of other restaurants inversely weighted by distance between restaurants, applying the following formula:

$$Location_i = \frac{1}{330} \sum_{j=1, j \neq i}^{330} \frac{Clientele_j}{Distance_{ij}}$$

This approach allows to implicitly account for multiple latent variables, including heterogeneities in local demand, competition, network effects, and spill-over effects. Table 1 presents the descriptive statistics for the sample.

Table 1. Descriptive statistics

Parameter	**Number of observations**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
Clientele, reviews	330	198.14	297.18	3	2451
Hygiene rating	330	4.28	1.14	0	5
Google rating	330	4.15	0.47	1.5	4.9
Price category	330	1.55	0.55	1	4
Coverage, webpages	330	81876	243317	7	1680000
Location effect, adjusted reviews	330	266.99	205.91	26.05	679.39
Distance to the city centre, km	330	1.30	0.63	0.31	2.73

To control for consumer's preferences, the sampled restaurants are divided into ten broad categories: American, Asian (including, among others, Thai, Bangladeshi and Pan-Asian restaurants), British, Chinese, Indian, Italian (excluding fast-food pizza deliveries and takeaways), Japanese, Mexican, Middle Eastern (including Lebanese, Turkish and Persian restaurants) and Other (covering all restaurants that do not belong to any particular group mentioned above). Table 2 presents the descriptive statistics.

Table 2. Newcastle restaurants – breakdown by cuisine

Cuisine	Number of restaurants	% of restaurants	Hygiene rating	Google rating	Clientele
American	45	13.64%	4.67	3.80	251.73
Asian	10	3.03%	4.20	4.33	222.70
British	62	18.79%	4.55	4.21	308.58
Chinese	31	9.39%	3.68	4.12	65.10
Indian	28	8.48%	3.64	4.25	105.54
Italian	42	12.73%	4.05	4.25	184.36
Japanese	6	1.82%	4.67	4.47	248.67
Mexican	8	2.42%	5.00	4.38	336.25
Middle East	11	3.33%	4.00	4.43	165.55
Other	87	26.36%	4.38	4.13	160.68
Total	*330*	*100.00%*	*4.28*	*4.15*	*198.14*

The study's framework can be expressed using the following econometric equations:

$$\mathrm{Log}(Clientele_i) = \alpha + \beta_1 Hygiene_i + \varepsilon_i \tag{1}$$

$$\log(Clientele_i) = \alpha + \beta_2 Google_i + \varepsilon_i \tag{2}$$

$$\log(Clientele_i) = \alpha + \beta_1 Hygiene_i + \beta_2 Google_i + \varepsilon_i \tag{3}$$

$$\log(Clientele_i) = \alpha + \beta_1 Hygiene_i + \beta_2 Google_i + \beta_3 Price_i + \varepsilon_i \tag{4}$$

$$\log(Clientele_i) = \alpha + \beta_1 Hygiene_i + \beta_2 Google_i + \beta_3 Price_i + \beta_4 \log\,(Coverage_i) + \varepsilon_i \tag{5}$$

$$\log(Clientele_i) = \alpha + \beta_1 Hygiene_i + \beta_2 Google_i + \beta_3 Price_i + \beta_4 \log(Coverage_i) + \beta_5 \log(Location_i) + \varepsilon_i \tag{6}$$

$$\log(Clientele_i) = \alpha + \beta_1 Hygiene_i + \beta_2 Google_i + \beta_3 Price_i + \beta_4 \log(Coverage_i) + \beta_5 \log(Location_i) + \gamma_j Cuisine_{ij} + \varepsilon_i \tag{7}$$

$$\log(Clientele_i) = \alpha + \beta_1 Hygiene_i + \beta_2 Google_i + \beta_3 Price_i + \beta_4 \log(Coverage_i) + \beta_5 \log(Location_i) + {} + \beta_6 \log^2(Location_i) + \gamma_j Cuisine_{ij} + \varepsilon_i \tag{8}$$

Equation 7 serves as the main model for the study and includes all the regressors from Equation 6 and a set of cuisine-specific dummy variables. As a robustness check, Equation 8 further includes all the regressors from Equation 7 and a squared log location term to account for nonlinearities in peer effect, allowing it to potentially form an inverted U-shaped relationship, reflecting the interaction of network and local competition effects.

Results

Table 3 presents the estimation results for Equations 1-7. In simple single-factor regression models (Equations 1-2), both Food Hygiene Ratings and Google ratings are positively associated with restaurants' clientele ($p<0.01$). Equation 3 shows that neither estimators decrease much in comparison to the previous models, suggesting that the two measures are covering orthogonal characteristics of the restaurants, supporting the claim that Food Hygiene Ratings do not measure food quality but can promptly reflect the changes in food safety conditions (Draper & Draper, 2016).

Table 3. Estimation results

Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	3.4007*	1.8973*	0.9729	0.9305	-0.5233	-1.798*	-1.6102	0.2727
	15.9682	*3.4279*	*1.8269*	*1.7120*	*-0.8919*	*-2.8572*	*-2.5109*	*0.1069*
Hygiene rating	0.2731*		0.2564*	0.2357	0.1184	0.0747	0.0544	0.0524
	5.4012		*5.3562*	*4.8049*	*2.4857*	*1.5979*	*1.2299*	*1.1858*
Google rating		0.6437*	0.6019*	0.4413*	0.5651*	0.5594*	0.5467*	0.5578*
		4.8982	*4.7150*	*3.2304*	*4.1006*	*3.9066*	*3.8550*	*3.9318*
Price category				0.5153*	0.5500	0.4251*	0.4478	0.4542*
				4.3854	*4.7129*	*3.8873*	*3.7514*	*3.8232*
Coverage					0.1547*	0.1238*	0.0944*	0.0951*
					4.9538	*3.8974*	*3.0866*	*3.1267*
Location effect						0.3768*	0.3788*	-0.4035
						5.6851	*5.7215*	*-0.4013*
(Location effect)^2								0.0764
								0.7895
R^2	0.0645	0.0611	0.1177	0.1666	0.2393	0.3149	0.3506	0.3522

Notes: Estimation results of Equations 1-7. T-statistics are calculated using Huber-White-Hinkley heteroscedasticity-consistent standard errors and are reported *in italics.* Estimators significant at 1% have * sign on them.

The inclusion of further control variables in Equations 4-5 drastically reduces the significance and magnitude of the official hygiene rating, with the estimator decreasing more than two-fold in presence of highly statistically significant price and social media coverage factors, implying that the separating equilibrium of the market exists, with high-quality restaurants being able to simultaneously attract more customers and charge higher prices. Furthermore, this result arguably reveals that price can be a successful signalling mechanism, contrary to the findings of the "market for lemons" model.

With the inclusion of location effect and cuisine dummies, the official hygiene rating ceases to be significant, while the changes in the Google rating factor are marginal, supporting the superior robustness of the Google rating measure despite the research design being favourable towards the official hygiene rating. Instead of the "location effect", we also perform an estimation with distances to key places in Newcastle. The results were very similar quantitatively and qualitatively to those reported. Finally, Equation 8, regressing log clientele on the set of cuisine dummies, location effect and location effect squared, finds no nonlinearities in the "peer effect", suggesting that the positive clientele spill-overs and network effects from successful neighbouring restaurants outweigh the drawback from increased competition.

Table 4 shows that regardless of the number of fitted terms (1-5), the F-statistics produced are insignificant, confirming the proper specification and reliability of Equation 7, i.e. the impact of online review rating is higher and more robust even after controlling for price, location, social media coverage, and cuisine. One counterargument to the claim that Google ratings are superior in explaining variations in clientele is the observation that Food Hygiene Ratings are more volatile (a standard deviation of 1.14 versus 0.47 on a similar 0 to 5 or 1 to 5 scale). Nevertheless, even accounting for this difference, one standard deviation increase in Food Hygiene Ratings would increase clientele from 5.97% to 31.13%, depending on the estimation, and a similar increase in Google rating would result in a more robust 20.74% to 28.29% increase.

Table 4. Ramsey RESET-test

Number of fitted terms	Ramsey RESET p-value
1	0.6579
2	0.5139
3	0.6834
4	0.8215
5	0.7811

Conclusion

This study suggests that online review ratings play an increasingly influential role in consumer patronage, while that of official ratings is decreasing. Nevertheless, official ratings are necessary, as those schemes focus on inspecting the private aspects of the services such as health and safety. The information asymmetry problem cannot be resolved by customer review rating only, because customers are not inspectors, they are not equipped with the specialist skills or tools required to perform the inspection nor do they have legal access to a restaurant's "private" space (e.g. kitchen) or food handling staff (e.g. chefs). Our findings further reveal that in Newcastle, the separating equilibrium of the market exists, which suggests that restaurants that strive improve their services in such a market are able to simultaneously charge a higher price and attract more customers. This study is limited to the restaurant industry in one city, future research could examine data in other tourism sectors, e.g. tourist attractions, hotels, and online travel agencies in different cities.

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