Cheating in Online Ratings and Restaurant Competition

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Abstract
We investigate fake online ratings which are posted by restaurant on their competitors. As consumers use online ratings to choose where to eat out, restaurants face an incentive to post fake negative ratings on their competitors. This might undermine the credibility of honest ratings and lead to a decrease in consumer welfare. We examine whether restaurants respond to the incentive to cheat on the basis of what drives consumer choices, which would maximise the benefit of cheating. Cheating is measured by exploiting an organisation difference between two popular ratings websites: TripAdvisor and OpenTable. We measure different types of competition by discounting competing restaurants in the same price range or cuisine type according to distance. We find that an increased presence of competitors in the same price range or of similar ranking leads to a statistically significant increase in cheating suffered by restaurants. Restaurants cheat on competitors in the same price range and who are close in the ranking. This suggests that economic incentives factor into the decision to cheat.

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1. Introduction

In recent years, consumers have increasingly been using online ratings websites such as TripAdvisor to make purchasing decisions. Online ratings increase the quality of information available to consumers, which allows them to make better choice and increases their surplus. There is growing empirical evidence that product sales are highly sensitive to changes in average rating (see Anderson and Magruder 2012), which suggests that ratings are an important factor in consumers' decisions. As anyone can easily post a rating, sellers can influence consumers by posting fake ratings which resemble authentic ones. They can either post fake positive ratings of themselves, or fake negative ones of their competitors. Whilst it is not possible to observe cheating directly, there is substantial evidence that it is widespread. In February 2004, a bug on Amazon's website caused the true identities of reviewers to be unintentionally revealed. It appeared that a large proportion of book reviews had been written by the authors themselves[1]. Yelp, a popular ratings website, uses an algorithm to automatically hide suspicious ratings. 16% of its ratings are thereby classified as untrustworthy[2]. Cheating in online ratings is a major problem for two reasons. Firstly, it decreases the quality of the information available to consumers, which distorts their choices and lowers their welfare. Secondly, it might lead consumers to mistrust all ratings, including honest ones.

In this paper, we undertake an empirical analysis of negative cheating, which consists in restaurants posting fake negative ratings of their competitors in order to gain an advantage over them. We investigate what motivates restaurants to cheat on their competitors. If restaurants are rational, they will cheat on the basis of what drives consumer choice, such as location and price range. Restaurants maximise the benefit of

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[1] See by Harmon (2004)

[2] See Luca (2015)

cheating only to the extent that they cheat on restaurants from which they are likely to steal customers. We can therefore establish the economic incentives to cheat from consumers' selection criteria. *Can cheating in online ratings be explained by economic incentives?* It might be the case that some restaurants are simply dishonest and will cheat regardless of whether they stand to gain economically from doing so. We will estimate by OLS the effect on negative cheating of different types of competition which reflect consumer selection criteria.

As fake ratings are designed to resemble authentic ones, we cannot observe directly whether a given rating is fake. To overcome this, our empirical strategy exploits an organisational difference between two popular ratings websites for restaurants: TripAdvisor and OpenTable. Whilst on TripAdvisor, anyone can easily post a rating (including the restaurant owner), OpenTable, requires that users book and attend to be eligible to post a rating. We therefore expect cheating to be more prevalent on TripAdvisor than on OpenTable due to the difference in the cost of cheating across the two websites. We will only be examining numerical ratings, which are on the same 5-star scale for both websites. We derive a measure of negative cheating from the difference in the proportion of 1-star ratings across the two websites, which will be our dependant variable.

We break down competition into categories which reflect the selection criteria of consumers (and will be our independent variables). Location is intuitively an important criteria for consumers, which leads to stronger competition between nearby restaurants. We account for distances in our measures of competition by weighting restaurants according to distance. Consumers also choose where to eat on the basis of other characteristics, such as the price range. We therefore derive a measure of competition by restaurants of the same price range. Our results rely on the identifying assumption that

TripAdvisor and OpenTable users have similar preferences for unobservable characteristics which are correlated with competition intensity.

We find strong evidence that negative cheating is driven by the economic incentives which result from competition on the basis of price range and quality. A one standard deviation in competition by restaurants of the same price range leads to 0.05 standard deviations in cheating. In contrast with previous research, we do not find a significant effect for competition on the basis of cuisine type. Our results contribute to the growing literature on online manipulation, by investigating the effect of competition on the basis of price range and ranking on TripAdvisor.

2. Literature Review

This paper is informed by previous empirical work on cheating in online ratings. Mayzlin, Dover and Chevalier (2014) find that independent hotels are more likely to cheat on their neighbours than hotels which are part of multi-unit chains. They also introduce a methodology which exploits differences in the ratings distribution across websites with differing identify verification policies. A similar approach will be used in this paper. To determine whether two hotels are neighbours, a distance threshold is used. This simple rule does not capture how competition decreases with distance and is highly sensitive to the choice of threshold, which raises the concern of multiple hypothesis testing. Luca and Zervas (2015) find that negative cheating by restaurants on the basis of cuisine type is only significant for independently owned restaurants. They introduce a methodology to weigh restaurants according to distance using kernel functions. This approach will be used in this paper, as it is reasonable to assume smooth discounting of restaurants by consumers according to distance.

We are also informed by literature on the economic incentives to post ratings. Wang (2010) studies reviewers' incentives to contribute across websites with different social features. He finds that reviewers are more productive and give less extreme ratings when they are given a public profile page by the website (as opposed to being anonymous). This suggests that ratings should be more extreme on OpenTable than on TripAdvisor, since reviews are anonymous only on the former. As the more extreme ratings are found on TripAdvisor, this study reinforces our assumption that this is due to the presence of fake ratings. Li and Hitt (2008) investigate selection issues in reviewing. They find that the distribution of ratings for many products tends to be bimodal, with ratings tending toward extreme value. They argue that this can be explained by self-selection of reviewers who had an extreme experience. We will discuss the possibility that selection into posting ratings differs across websites. Gao et al. (2015) finds a strong correlation between doctors' online ratings and an offline measure of quality, which suggests that online ratings approximate to underlying consumer opinion (at least in some settings). This finding reinforces our methodology for measuring cheating, which relies on the assumption that ratings would be similar across websites in the absence of cheating.

Anderson and Magruder (2012) estimate the relationship between ratings on Yelp.com and restaurant reservation availability. They exploit the fact that ratings are rounded up to half units to implement a regression discontinuity design. A half-unit increase in the average rating is found to cause restaurants to sell out nineteen percent more frequently, implying that restaurants face a strong incentive to cheat. However, no evidence of cheating is found through robustness checks. This is likely to be due to the low power of the methodology used. In Appendix A, we show that cheating is discontinuous around such rounding thresholds. We will contribute to the existing literature by investigating the effect of competition on the basis of a wider range of consumer selection criteria.

3. Data

TripAdvisor and OpenTable are two highly popular ratings websites for restaurants. Every month, TripAdvisor receives 350 million visitors and 450,000 new ratings are posted on OpenTable. As well as offering a platform for ratings, OpenTable allows users to book restaurants with whom they have a business relationship. TripAdvisor operates a more open platform in which anyone can create a listing, and features just about every existing restaurant. Therefore, the restaurants on OpenTable are a close subset of those on TripAdvisor. As we would like data from both websites for every restaurant in our sample, we first sample all of those on OpenTable in a given city and then find matching observations on TripAdvisor (we will address the potential issue of sampling bias). We identified 7 large cities which likely feature strong restaurants competition and a high density of ratings website users. We collect data on 6071 restaurants in those cities, the largest being London with 2152 observations and the smallest Houston with 268 observations.[3] The data was 'scraped' from the two websites in March 2016, which consists in downloading a set of webpages and extracting information at high speed[4]. This paper therefore contributes to the growing economics literature which uses scraped data (see Edelman 2012 for an overview). As well as the number of ratings in each star category for both websites, our dataset includes a set of restaurants characteristics such as cuisine type, price category and location coordinates.

Table 1 provides summary statistics for ratings characteristics across websites. On average, there are 679 ratings on OpenTable and 258 on TripAdvisor (there are 4.1 million ratings in total). The mean average rating is 4.25 and 4.12 on TripAdvisor and OpenTable respectively. Users are moderately more critical on TripAdvisor than on OpenTable. In contrast, Mayzlin et al. (2014) finds a gap of 0.43 in average rating for a

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[3] Also included are Chicago, San Francisco, Los Angeles, Miami and New York.

[4] A technical description of the system used to collect data is in Appendix C.

Table 1: Summary statistics of ratings across wesbsites

	OpenTable		TripAdvisor	
	Mean	Standard deviation	Mean	Standard deviation
Number of ratings	679.66	973.12	258.21	402.03
Average rating	4.25	0.60	4.12	0.30
Proportion of 1-star ratings	0.029	0.028	0.037	0.038

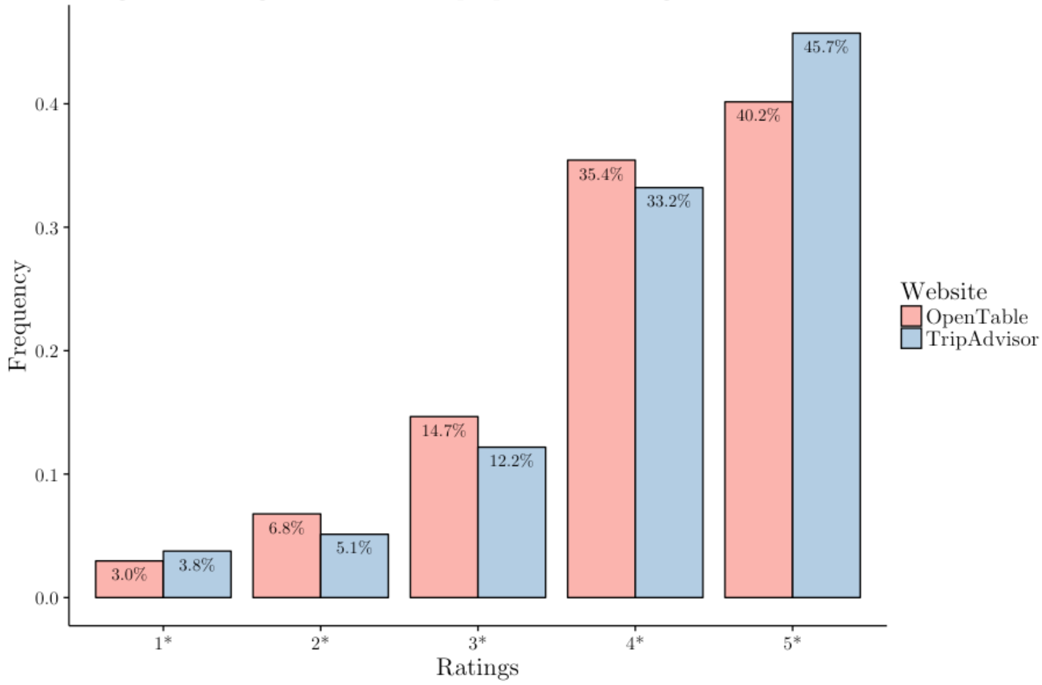
Note: These statistics are for 4,391 restaurants which are used in this paper after dropping observations.

sample of hotels between Expedia and TripAdvisor. The standard deviation are 0.60 and 0.30 respectively for OpenTable and TripAdvisor. This large gap can be explained by the fact that a large proportion of listing on TripAdvisor have very few ratings, so the mean rating is very sensitive to individual ratings.

To derive our measure of negative cheating, we will be comparing the distribution of ratings across websites. Figure 1 is a histogram of the proportion of ratings in each rating category in both websites. We can see that ratings are more extreme on TripAdvisor, with a higher proportion of 1-star ratings. We perform a two-sample t-tests on proportion of 1-star ratings across websites for the entire sample and we find that the difference in proportion is significant at the 1% level. It is likely that differences in taste between users across websites plays a large role, which we discuss in the next section.

Our dataset is only a small subset of the restaurants in the cities from which we sampled. To construct measures of competition, we need to account for every restaurant in the given city so we cannot rely on the dataset hereby described. We have a separate dataset which includes every restaurant on TripAdvisor for the cities in our sample. The variables are the same as discussed previously.

Figure 1: Histogram of the mean proportion of rating accross websites.



The main limitation of our dataset is that it does not include the ownership characteristics of restaurants. It has been shown in the previous literature that independent businesses cheat more relative to those which are part of multi-unit chains.

4. Empirical Strategy

We now derive the parametric assumptions which are needed to construct our measures of negative cheating and of competition. We do so by considering how the incentives to post ratings differ across the two websites, for both consumers and restaurants. Our approach will therefore be to let the data speak, which reduces the problem of multiple hypothesis testing.

We exploit the fact that on TripAdvisor anyone can easily post a rating, whereas OpenTable requires that users book and attend to be eligible to post a rating. The cost of rating fraud on OpenTable is the opportunity cost of the time and money spent attending a restaurant. In addition, there is a cost associated with the possibility of getting caught. On TripAdvisor, it is far less costly to cheat. There also exists a market for fake TripAdvisor ratings, as individuals on online marketplace 'Fiverr' offer cheating services for as little as $5[5]. TripAdvisor also received more traffic than OpenTable, so the benefit of rating fraud is higher on TripAdvisor, as well as being less costly.

We construct a measure of negative cheating on TripAdvisor from the difference in the distribution of ratings across websites. We focus on 1-star ratings, as it is likely that an individual who cheats will post an extreme rating. Mayzlin (2014) uses the difference in the proportion of 1* ratings across websites to obtain the proportion of fake ratings on TripAdvisor. As we are interested in the absolute number of fake negative ratings, the proportion will underestimate the number of fake ratings for restaurants with few ratings and overestimate it for restaurants with many ratings. This would lead to an upward bias in our estimates as the number of ratings is positively correlated with the level of competition. We therefore scale the proportion by the average number of ratings across websites for the given restaurant and control for the number of ratings in our estimation.

We define our measure of the negative cheating suffered $\mathrm{F1*}_i^{\mathrm{TA}}$ as follows:

[5] See Shaffer (2013)

$$F1*_i^{TA} = \left(\frac{1*_i^{TA}}{Total_i^{TA}} - \frac{1*_i^{OT}}{Total_i^{OT}} \right) \times \frac{Total_i^{TA} + Total_i^{OT}}{2} \tag{1}$$

where 'TA' and 'OT' are shorthand for TripAdvisor and OpenTable respectively. $1*_i^{TA}$ is the number of 1-star ratings on TripAdvisor and $Total_i^{TA}$ is the total number of ratings on TripAdvisor. The letter F refers to the word 'fake' and symbolises cheating (whereas C is used for 'competition'). Whereas this formulation provides us with an accurate measure of cheating, it is not possible to interpret directly. Therefore, we normalise it and interpret it in terms of standard deviations. As this measure is highly sensitive to small changes in the number of 1-star ratings on either website we restrict our sample to restaurants with a minimum of 30 ratings on both websites.[6] This does not lead to sampling bias, as the number of ratings is found to be uncorrelated with restaurant competition.[7]

We now derive measures of competition (which we will refer to as 'competition indices' from now on). As location is an important criteria for consumers, competition intensity between two restaurants largely depends on the distance which separates them. We account for the relationship between distance and competition intensity by weighting competitors by distance with kernel functions (as proposed by Luca 2015). We define the 'general' competition index C_i^G, which accounts for every competing restaurant, as follows:

$$C_i^G = \sum_{j \neq i} K\left(\frac{d_{ij}}{h} \right) \tag{2}$$

[6] The sample size drops from 6071 to 4391 observations.

[7] The correlation with the general competition index (defined below) is -0.06.

where d_{ij} is the distance between restaurants i and j in km.[8] K() is a kernel weighting function[9] and h is its bandwidth. The sum is taken over all of restaurants in the restaurant's city. The functional form imposes parametric assumptions on how competition intensity decreases with distance. The choice of kernel reflects the relative weight that is given to competitors with different distances, whilst the bandwidth defines how quickly the absolute weight decreases with distance. We consider how consumers are likely to discount restaurants according to distance. We define an exponential kernel as follows:

$$K\left(\frac{d_{ij}}{h}\right) = e^{-\frac{d_{ij}}{h}} \tag{3}$$

As it is equal to its derivative, a change in the distance of a competitor will lead to a change in the index which is proportionate to the competitor's contribution to the index. As it declines relatively slowly, we give some weight to a wide range of restaurants. We select a bandwidth of 1, for which a restaurant 400m away contributes approximately 0.8 times as much as a restaurant 200m away.

Location is not the only factor which drives consumer choices. The price range of a restaurant is also important for consumers, which creates an incentive for restaurants to cheat on competing restaurants in the same price range. We derive a measure of competition by restaurants of the same price range (which we will refer to as the price index). To determine if two restaurants are of the same price range, we use TripAdvisor's price range categorisation, which consists in a number of '$' symbols. We define the price index as follows:

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[8] The distance between two restaurants is computed using the haversine formula.

[9] The word kernel is usually normalised but his is inconsequential as we will normalise the index values.

$$C_i^P = \sum_{j \neq i} K\left(\frac{d_{ij}}{h}\right) \times 1\left[\text{same price category}_{ij}\right] \tag{4}$$

where [same price category$_{ij}$] is a dummy variable equal to one if restaurants i and j are of the same price category. We thereby restrict the location-based competition outlined previously to restaurant in the same price range. Similarly, we construct the measure of competition by restaurants of the same cuisine type, using TripAdvisor's categorisation of food types.[10] We define the cuisine index as follows:

$$C_i^T = \sum_{j \neq i} K\left(\frac{d_{ij}}{h}\right) \times 1\left[\text{same cuisine}_{ij}\right] \tag{5}$$

Likewise, we define the measure of competition by restaurants of a different cuisine type.

$$C_i^{\bar{T}} = \sum_{j \neq i} K\left(\frac{d_{ij}}{h}\right) \times 1\left[\text{different cuisine}_{ij}\right] \tag{6}$$

Finally, we derive a measure of competition on the basis of TripAdvisor ranking. As TripAdvisor users are likely to compare restaurants on the basis of their relative rankings, we will use the absolute difference in ranking to capture how restaurants compare in terms of quality (the underlying mean ratings is unobserved). We define our measure of competition on the basis of ranking as follows:

$$C_i^Q = \sum_{j \neq i} K\left(\frac{d_{ij}}{h_1}\right) \times K\left(\frac{\left| R_i - R_j \right|}{h_2}\right) \tag{7}$$

where R_i is the ranking of restaurant i and h_2 is the kernel bandwidth for the differences in ranking. We select a bandwidth h_1 of 2, as we expect consumers to consider restaurants

[10] Details of how the cuisine categories are defined are in Appendix D.

which are further away if their criteria is food quality. To allow for a wide range of restaurants to be included in the index, we select a bandwidth h_2 of 500.

Table 2 presents the correlation matrix of our indices. We will consider the correlations when we address the issue of multicollinearity in our regressions.

Table 2: Correlation Matrix of Competition Indices

	C_i^G	C_i^P	C_i^T	$C_i^{\overline{T}}$	C_i^R
C_i^G	1	0.727	0.839	0.973	0.746
C_i^P	0.727	1	0.618	0.722	0.534
C_i^T	0.839	0.618	1	0.773	0.616
$C_i^{\overline{T}}$	0.973	0.722	0.773	1	0.703
C_i^R	0.746	0.534	0.616	0.703	1

5. Estimation and Results

We regress cheating on the five competition indices to determine on what basis restaurants cheat on each other. We estimate by OLS the following model:

$$\begin{aligned} F1^{*TA}_{i} = \alpha + \beta_{G} C_{i}^{G} + \beta_{P} C_{i}^{P} + \beta_{T} C_{i}^{T} + \beta_{\bar{T}} C_{i}^{\bar{T}} + \beta_{R} C_{i}^{R} \\ + \beta_{1} Q_{i}^{TA} + \beta_{3} \log\left(R_{i}^{TA}\right) + \beta_{5} X_{i} + \varepsilon_{i} \end{aligned} \quad (8)$$

X_i controls for restaurant characteristics (the price category P_i^{TA} and dummies for cuisine types) which should matter to the extent that TripAdvisor and Expedia users value them differently. We thereby allow for the possibility that OpenTable users have a preference for high-end dining. The inclusion of the general competition index C_i^G is important, as a change in any other competition index is exogenous only if we hold constant the competition by all other restaurants. We control for the logarithm of the number of TripAdvisor ratings R_i^{TA}, as our dependant variable is likely to be correlated with it due to its functional form. We control for the average TripAdvisor rating Q_i^{TA}, as it is correlated with both competition and the proportion of 1-star ratings on TripAdvisor. We achieve identification on the basis that competition is unlikely to be correlated with any other variables which are related to the measure of cheating. Such variables in the error term include unobservable restaurant characteristics, which represents the main potential source of endogeneity in our specification. Users on TipAdvisor and OpenTable are likely to have different preferences for unobserved restaurant characteristics, such as the quality of service. If OpenTable users have a stronger preference for quality of service than TripAdvisor users, then the measure of cheating will be correlated with the quality of service (as OpenTable users will post less negative ratings). This only creates omitted variable bias if the quality of service is correlated with competition intensity. Whereas we expect there to be important differences in preferences of users across websites, we do not expect these to be correlated with competition. Therefore, we make the identifying assumption that TripAdvisor and OpenTable users value restaurants facing different competition intensities in a similar way. In the robustness section, we further investigate the possibility of such selection on unobservable characteristics.

Since OpenTable users are required to both book and attend their booking in order to be eligible to post a rating, they bear a higher transaction costs to attend a restaurant. Therefore, they might be more careful in choosing restaurants which suit their preferences than TripAdvisor users. There could be an upward bias on our estimates if transaction costs is correlated with competition. We expect this to be true only for some restaurants which are so popular that they are difficult to book. As cheating is conducted by competitors and not by the restaurant itself, we do observe cheating by individual restaurants. However, if an increased presence of restaurants with certain characteristics (holding everything else constant) leads to a significant increase in cheating, we attribute the cheating to restaurants with those characteristics. We can therefore estimate the extent of cheating on the basis of these characteristics.

Table 3 presents the results of the OLS estimation for equation (8), as well as intermediate regressions to assess the robustness of estimated coefficients to small changes in specification. Heteroskedasticity robust standard errors are used. Interpretation is conducted in terms of standard deviation changes, such that we can compare the effects of different types of competition in the same unit of measure (we are unable to evaluate the economic significance of the magnitude of the effects). We find that a one standard deviation increase in the price index leads to 0.060 ($p < 0.01$) standard deviation increase in negative cheating. The coefficient is robust to small changes in the specification. This effect is estimated holding constant the competition of restaurants in all price ranges (captured by C_i^G), which precludes the possibility that it is due to a general increase in competition. This means that restaurants respond to the economic incentive to cheat on

Table 3: Estimation Results for Equation (8)

	Dependent variable: $F1^{*}{}_{i}^{TA}$		
	(1)	(2)	(3)
C_i^G (General Index)	-0.123***		0.007
	(0.026)		(0.085)
C_i^P (Price Index)	0.058***	0.060***	0.060***
	(0.018)	(0.018)	(0.018)
C_i^T (Cuisine Type Index)		-0.035	-0.036
		(0.043)	(0.044)
$C_i^{\overline{T}}$ (Different Type Index)		-0.095**	-0.101
		(0.040)	(0.080)
C_i^R (Ranking Index)	0.081***	0.077***	0.077***
	(0.022)	(0.021)	(0.022)
Q_i^{TA}	-0.269***	-0.270***	-0.270***
	(0.021)	(0.021)	(0.021)
$\log(R_i^{TA})$	0.099***	0.101***	0.101***
	(0.021)	(0.021)	(0.022)
$\text{PriceCategory}_i^{OT}$	0.121***	0.122***	0.122***
Cusine type dummies?	YES	YES	YES
Constant	0.176	0.171	0.171
	(0.116)	(0.118)	(0.118)
Observations	4,391	4,391	4,391
R^2	0.089	0.090	0.090

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

the basis of price range.

Increased competition by restaurants of the same cuisine type does not have a significant impact on negative cheating. This is surprising, as we expect that cuisine type is an important criteria for consumers. A possible explanation is that consumers are attracted by clusters of restaurants of the same cuisine type (such as Chinatown districts) from which restaurants benefit. Another explanation is the omission of ownership characteristics (whether a restaurant is independently owned or is part of a multi-unit chain). It is reasonable to believe that independent restaurants face more incentives to cheat than those which are owned by a corporation. Luca et al. (2015) finds that increased competition by same-type independent restaurants increases negative cheating whereas increased competition by same-type chain restaurants decreases negative cheating. As our sample of competitors constitutes a mix of both ownership categories, it is likely that the two effects cancel out.

The coefficient on the index for different cuisine type is not significant for the specification in column (3). Due to the strong correlation with the general index, there is multicollinearity which explains the large standard deviation on the estimate. In column (2), the general index is omitted and the estimate for different cuisine is almost unchanged. However, the standard deviation decreases from 0.080 to 0.040 and the estimate becomes significant at the 5% significance level. We therefore interpret the coefficient estimates as being significant. This suggests that restaurants cheat less on restaurants of different food type. Luca (2015) finds that increased competition by different cuisine type restaurants only leads to a decrease in negative cheating for chain restaurants. We can therefore hypothesise that chain restaurants are driving our results.

A one standard deviation increase in our measure of competition by restaurants in similar ranking leads to a 0.077 ($p < 0.01$) standard deviation increase in the measure of negative cheating. The effect is robust to small changes in specification and suggests that

restaurants cheat on competitors with similar ranking. This is not surprising, as rankings are displayed prominently by TripAdvisor and are likely to have a strong influence on consumers. It is likely that restaurants cheat with the aim of moving up the ranking.
With regard to restaurant characteristics, estimated coefficient for the price category is positive, which is likely due to a stronger preference for high-end restaurant by OpenTable users.
Overall, we find strong and statistically significant effects on ratings fraud of competition on the basis of price and ranking. This suggests that restaurants cheat on competitors which are in the same price range or are close to them in the ranking.

6. Robustness Checks

We investigate the potential for selection on unobservables, which is the main concern with our results. We investigate OpenTable and TripAdvisor users differ in their taste for unobserved restaurant characteristics which are correlated with competition intensity. We re-estimate the model without these controls for observable characteristics (the price range and the cuisine type) and examine the extent to which the coefficients change. The effect on the coefficients can be seen as similar to adding more control variables, as unobservable variables are similar to the controls that we have (see Altonji, Elder and Taber 2005 for a formal argument). The results are shown in table 4, with column 1 being

Table 4: Robustness Specification with No Controls

	Dependent variable: $F1{*}_i^{TA}$	
	(1)	(2)
C_i^G (General Index)	-0.098*	0.007
	(0.058)	(0.085)
C_i^P (Price Index)	0.058***	0.060***
	(0.018)	(0.018)
C_i^T (Cuisine Type Index)	-0.019	-0.036
	(0.030)	(0.044)
$C_i^{\overline{T}}$ (Different Type Index)	0.010	-0.101
	(0.051)	(0.080)
C_i^R (Ranking Index)	0.073***	0.077***
	(0.022)	(0.022)
Observations	4,391	4,391
R^2	0.078	0.090

Note: Heteroskedasticity robust standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

without controls and 2 with controls. We do not display coefficients for cuisine type dummies in the interest of clarity.

The coefficient on the ranking index increases from 0.073 to 0.077, whilst the coefficient on price index increases from 0.058 to 0.060. These small changes can largely be explained by the removal of the price range control variable, so we no longer account for a stronger preference for high-end dining by OpenTable users. We therefore conclude that selection on unobservables is not likely to be a major explanation for our results.

To assess the robustness of our results to the choice bandwidth, we estimate model (8) with a bandwidth of 0.5 and 1.5 (for the ranking index we set it at 1 and 3). We also assess robustness to the choice of kernel, by estimating the model using a gaussian kernel used by Luca (2015) which we define as follows:

$$K^{G}\left(\frac{d_{ij}}{h}\right) = e^{-\frac{1}{2}\left(\frac{d_{ij}}{h}\right)^{2}} \tag{9}$$

The results are presented in table 5. We find that the estimate for the price index is robust to changes in bandwidth, whilst the estimate on the ranking index is not. Both estimates are robust to changes in the kernel function.

Table 5: Robustness to kernel bandwidth and kernel functions.

	Dependent variable: $F1*_i^{TA}$		
	(1)	(2)	(3)
	h = 0.5	h = 1.5	Gaussian Kernel
C_i^G (General Index)	-0.029	0.031	-0.044
	(0.084)	(0.085)	(0.095)
C_i^P (Price Index)	0.055***	0.060***	0.060***
	(0.018)	(0.018)	(0.018)
C_i^T (Cuisine Type Index)	-0.024	-0.040	0.003
	(0.044)	(0.043)	(0.004)
$C_i^{\overline{T}}$ (Different Type Index)	-0.040	-0.133*	-0.075
	(0.078)	(0.080)	(0.090)
C_i^R (Ranking Index)	0.044*	0.083***	0.073***
	(0.023)	(0.022)	(0.024)
Observations	4,391	4,391	4,391
R^2	0.087	0.091	0.089

Note: Heteroskedasticity robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

7. Limitations and Potential Extensions

The biggest limitation to our work is that we do not have data on the ownership characteristics of restaurants. Mayzlin et al. (2014) shows that independently owned hotels cheat more than counterpart who belong to multi-unit chains. Therefore, we might obtain different results if we distinguished effect for independent and chain competitors. We expect that we would obtain a positive and significant estimate for competition by independent restaurants of the same cuisine. Whereas it is difficult to find data on ownership, it might be possible to predicted the ownership status of restaurants through textual analysis of restaurant names. If some words such as 'Chipotle' appear repeatedly in the list of restaurant names, they can be identified as being part of multi-unit chains.

Another possible extension would be to use panel data. The inclusion of restaurant fixed effects would allow us to strip out time-invariant unobservable characteristics and therefore address the issue of selection on unobservables. There are two ways in which we could implement this. We could simply scrape the same restaurants at some time in the future and use a first-differences estimator. Or, we could exploit the fact that these websites include the date of individual ratings. This would allow us to re-create what the ratings were at any point in time by restricting the set of ratings to those until a certain date. We could then use a within estimator to eliminate fixed effects.

8. Conclusion

We investigate negative cheating in online ratings, which consists in restaurants posting fake negative ratings on their competitors. Restaurants face an incentive to cheat on competitors with similar characteristics (such as price range) as doing so maximises the benefit of cheating. We analyse the extent to which restaurants respond to these incentives by estimating the effect of increased competition by restaurants of similar characteristics on a measure of cheating. Cheating is measured by examining the difference in rating distribution between TripAdvisor and OpenTable, which have different identity verification policies. Measures of competition on the basis of different characteristics are derived by discounting competing restaurants according to distance. We find that an increased competition by restaurants in the same price range or of similar ranking leads to a statistically significant increase in cheating suffered by restaurants. No evidence of cheating on the basis of cuisine type is found, which is likely to be due to the omission of ownership characteristics. These results show that to a certain extent, restaurants cheat on the basis of what drives consumer choices and that economic incentives factor into the decision to cheat.

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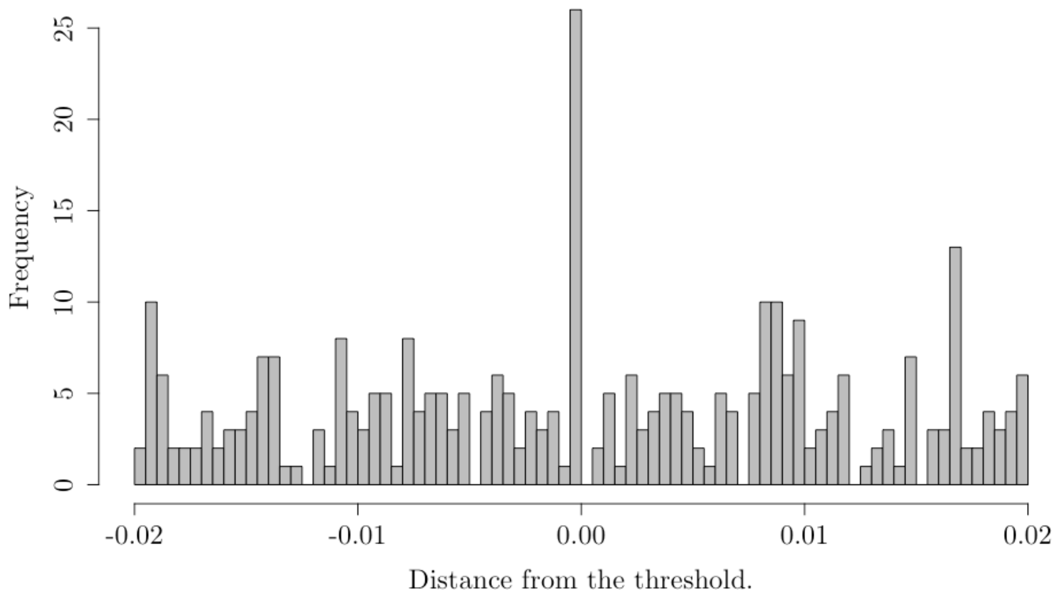
10. Appendix

A. Evidence of cheating at discontinuities

Instead of displaying the precise average rating, TripAdvisor displays the average rating rounded to the nearest half star. For instance, one restaurant with a mean rating of 3.76 will be rounded to 4 stars, whilst one with a mean rating of 3.74 will be rounded to 3.5 stars. This creates an incentive for restaurants who are below the threshold to post fake 5-star ratings to pass the rounding threshold. If cheating does occur at the discontinuity, we would expect the average ratings to pile up at the discontinuity. At every threshold, we restrict our sample to observations with average rating within a symmetric of 0.04. We normalise the average ratings by the value of the threshold (observations at the threshold equal 0). In figure 3, we plot a histogram of the transformed average ratings.

Figure 3: Histogram of average rating around the rounding threshold.



We can see a spike in restaurants at the threshold, which suggests that restaurants pile up at the threshold. Our finding is robust to reasonable changes in the number of breaks in the histogram. This finding is significant as it invalidates the regression discontinuity design of Anderson et al. (2012), which assumes random assignment of restaurants around the threshold. One possible extension to this work would be to implement the bunching estimator introduced by Saez (2010).

B. Variables Description

Variable	Description
OTCity	City of restaurant
OTName	Name of restaurant on OpenTable
OTReviewCount	Number of OpenTable ratings
OTPrice	Price category on OpenTable
OTLongitude	Longitude displayed on OpenTable
OTLatitude	Latitude displayed on OpenTable
OTX	Number of OpenTable ratings of X stars
TAName	Name of restaurant on TripAdvisor
TAReviewCount	Number of TripAdvisor ratings
TAPrice	Price category on TripAdvisor
TALongitude	Longitude displayed on TripAdvisor
TALatitude	Latitude displayed on TripAdvisor
TARanking	Ranking on TripAdvisor
TAX	Number of TripAdvisor ratings of X stars
OTMean	Mean OpenTable rating
TAMean	Mean TripAdvisor rating
OTP1	Proportion of 1-star ratings on OpenTable
TAP1	Proportion of 1-star ratings on TripAdvisor
cheat1	Normalised measure of cheating on TripAdvisor
CuisineN	Cuisine type classification on TripAdvisor

C. Data Collection Methodology

The data was scraped using the programming language Python (the code is available in the data folder). PhantomJS was used as a headless browser, with Selenium for automation and BeautifulSoup for parsing. Openpyxl was used to interact with excel files. We first download assemble a dataset containing all OpenTable restaurants in a given city. The first step is to download all of the restaurant links in the city (which is done by the OTLinks.py script). Then, the restaurant webpages themselves are downloaded and parsed using the OTData.py script, which loops through the links and stores the data in a csv file. The process is repeated for TripAdvisor using the TALinks.py and TAData.py scripts. The final dataset contains listings from both datasets, so there is a final matching process (the OTTAMap.py script). To find matches, a number of features are compared, including phone number, location coordinates and address. A remote server was rented from Amazon Cloud Services (an EC2 Instance) for increased speed and to avoid IP address blocking.

D. Definition of Cuisine Categories

TripAdvisor has a fine-grained categorisation of food types, with 95 categories found in our sample. Many of these appear to be close substitutes, such as ‘Central American’ and ‘Salvadoran’. Therefore, we group these categories into 7 larger geographic areas. The cuisine categories are Asian, Middle Eastern, European, Italian, Anglo-Saxon, Latin American and other. The classification of categories is represented in the table below.

Category	**TripAdvisor Categorisation**
Asia	Asian, Chinese, Vietnamese, Thai, Polynesian, Japanese, Pacific Rim, Indian, Sushi, Bangladeshi, Korean, Malaysian, Nepalese, Philippine, Filipino, Nepali
Middle East and Africa	African, Turkish, Middle Eastern, Moroccan, Lebanese, Halal, Moroccan, Afghani, Pakistani, Persian
Europe	Austrian, Belgian, European, German, Spanish, Russian, French, Portuguese, Greek, Mediterranean, Polish, Dutch, Eastern European, Hungarian, Israeli, Kosher, Swedish, Armenian
Italy	Italian, Pizza
Anglo-Saxon	American, British, Steakhouse, Barbecue, Grill, Australian, Brew Pub, New Zealand, Southwestern, Irish, Swiss, Fast Food, Hawaiian, Scottish
Latin-American	Caribbean, South American, Brazilian, Mexican, Cajun & Creole, Jamaican, Argentinian, Peruvian, Central American, Salvadoran, Venezuelan, Cuban, Argentinean, Guatemalan, Latin, Chilean
Other	Bar, Cafe, Diner, Contemporary, Fast food, Fusion, Gastropub, Gluten Free, International, Healthy, Soups, Wine Bar, Seafood, Pub, Vegetarian, Canadian, Delicatessen, Street Food, Vegan