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Restaurants' motivations to solicit fake reviews: A competition perspective

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ABSTRACT

As restaurants increasingly solicit fake reviews on online word-of-mouth (WOM) platforms, the authenticity and credibility of online reviews have been compromised. This study investigates restaurants' motivations to solicit positive fake reviews from a competition perspective. Our results show that a higher number of positive fake reviews by competitors can more strongly motivate a restaurant to solicit positive fake reviews, whereas a market advantage over competitors (based on review valence) significantly reduces a restaurant's motivation to solicit positive fake reviews. Furthermore, the extent of the above two effects is moderated by the degree of prospective popularity; no significant difference was observed between chain and independently owned restaurants. Theoretical and practical implications of these findings are also discussed.

1. Introduction

As customers increasingly rely on online reviews to make purchase decisions (Nielsen, 2015), many businesses in the hospitality industry, such as restaurants, are becoming adept at using online word-of-mouth (WOM) platforms to boost their online reputation. Many restaurants pursue a better reputation by soliciting positive fake reviews (Costa et al., 2019); a strong online reputation leads to greater purchase potential (Petrescu et al., 2018) and higher profits (Dellarocas, 2006). For example, an extra half-star rating leads restaurants to sell out 19% more frequently (Anderson and Magruder, 2012). Limited publication of positive fake reviews can greatly affect businesses' online visibility and increases the likelihood that customers will choose to patronize certain establishments (Lappas et al., 2016). Restaurants may therefore opt to solicit positive fake reviews for financial benefits (Wu et al., 2020).

Restaurants often solicit positive fake reviews by hiring promulgators online (Zhuang et al., 2018) or by providing discounts to customers (Thakur et al., 2018), resulting in an influx of fake reviews on online WOM platforms. Even as early as 2012, approximately 10.3% of online products featured fake reviews (Hu et al., 2012). Belton (2015) estimated the percentage of fake reviews to be roughly 10–30%. The Economist reported that Amazon had sued the operators of four websites peddling fake reviews and more than 1000 users who were illegally hawking customer reviews (Five-star fakes, 2015). Although scholars in computer science have proposed methods to identify fake reviews (Adelani et al., 2020; Kumar et al., 2019), fraudulent reviews persist: clever promulgators seek to disguise fake reviews as truthful and thus evade detection (Wu et al., 2020).

To efficiently reduce fake reviews, it is important to explore their antecedents. Most research on the antecedents of fake reviews has revolved around firms' characteristics, such as ownership, affiliation, and reputation (Luca and Zervas, 2016; Mayzlin et al., 2014; Siering and Janze, 2019). For instance, Mayzlin et al. (2014) discovered that compared with large hotels, independently owned hotels and those with small management companies were more inclined to solicit fake reviews. Luca and Zervas (2016) further noted that restaurants with a poor reputation were more likely to solicit fake reviews, whereas chain restaurants were less likely to experience review fraud. Siering and Janze (2019) found that the number of fake reviews of poorly-graded restaurants increased after critical health inspections. Besides firms, competitors play crucial roles in restaurants' decisions to amass fake reviews; a firm's positioning in comparison to industry competitors informs customers' decisions. Cao (2020) noted that if firms were free to choose whether to manipulate online reviews, both firms would always choose to manipulate online reviews. Competition can lead firms to engage in manipulation to maintain their online reputation (Gössling et al., 2019). However, the effects of competitors on positive fake review solicitation have been overlooked in the literature.

For restaurants, soliciting positive fake reviews on their behalf is a more effective and less risky strategy to improve their online reputation than soliciting negative fake reviews for competitors. The UK's Competition and Markets Authority (CMA) study revealed that positive

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fake reviews are indeed more common than negative fake reviews in the online context (CMA, 2015). Therefore, we examine how competitors' review manipulation and restaurants' market advantage (compared with the competitors' market) influence restaurants' motivations to solicit positive fake reviews. We also evaluate the moderating effects of prospective popularity and restaurant type in the above relationships. Our results highlight the roles of competitors in restaurants' strategies to solicit fake reviews. Findings provide valuable managerial implications for online WOM platforms regarding online reputation management.

2. Literature review and hypothesis development

2.1. Literature review

Several studies have highlighted economic motivations, such as online reputation and profit, as clear drivers behind soliciting positive fake reviews (Luca and Zervas, 2016; Mayzlin et al., 2014). Based on semi-structured interviews, Gössling et al. (2019) revealed that managers confessed to adopting legally or ethically suspect strategies to solicit fake reviews. Saraiva (2020) noted that sellers with a very good or bad history of reviews display less incentives to fabricate fake reviews praising their products. Moreover, to maximize the impact of each fake review, sellers tended to concentrate on review manipulation at the initial stages following their entrance into the market (Saraiva, 2020). Hlee et al. (2021) also confirmed the above conclusion by finding that newly opened restaurants had more extreme positive reviews than long-running restaurants. Restaurants were more likely to receive unfavorable fake reviews when facing increased competition (Luca and Zervas, 2016). However, previous works focused on firms' own attributes and lacked the exploration of the critical role of competitors in motivating fake reviews.

On the other hand, more prior studies focused on the consequences of fake reviews compared with the antecedents of fake reviews. Some studies noticed the impact of fake reviews on firms' performance. Lappas et al. (2016) thought that even limited instances of fake reviews could significantly affect online visibility, and He et al. (2022) further demonstrated that fake reviews had a significant but short-term increase in average rating and review numbers. Once firms stop buying fake reviews, the average rating fall and the share of negative reviews increases significantly. As for the impact of fake reviews on consumers' perceptions and decisions, Shih et al. (2022) believed that fake reviews strongly shaped consumers' incorrect beliefs and attitudes in the early and mainstream phases. Consumers tended to assess reviews as real rather than fake and viewed negative reviews as more authentic than positive ones (Azimi et al., 2022). Consumer suspicion of an ulterior motive had a direct and mediation effect regarding brand trust and purchase intentions (Petrescu et al., 2022).

There are also some studies concentrated on the linguistic features of fake reviews. Li et al. (2020) found that fake reviews were more related to affective and social cues but less to perceptual cues. Wang and Kuan (2022) further compared fake reviews and deceptive writing. They found that fake reviews aligned more with deceptive writing in terms of the message-level variables such as length and psychological (affective, cognitive, social, and perceptual) cues, but aligned less with deceptive writing in terms of the formulation-level variables such as readability, pronouns, and part-of-speech tags. Banerjee and Chua (2017) found the comprehensibility, specificity, exaggeration, and negligence between authentic and fictitious reviews were largely inconsistent across three hotel categories (luxury, budget and mid-range). Banerjee and Chua (2021) noted that perceived exaggeration of reviews was negatively associated with perceived review authenticity. After that, Banerjee (2022) further confirmed the extent to which perceived exaggeration could explain perceived review authenticity depending on the category of hotels and reviews' polarity. Shan et al. (2021) demonstrated that review rating-sentiment inconsistency, content inconsistency, and language inconsistency were more salient in fake reviews than in authentic ones.

Table 1 presents a summary of relevant literature on fake reviews, organized by the antecedents and consequences associated with such reviews, and linguistic features of fake reviews. The extant literature has attributed fake reviews to firms' reputation, type, operating stage, and the existence of neighbors. Studies on the consequences of fake reviews have concerned firms' performance, and consumers' perceptions and decisions. Overall, there is a considerable amount of research into the consequences of fake reviews, while there is still limited research focusing on the antecedents of fake reviews. Most previous work exploring the antecedents of fake reviews has considered the impacts of firms' own attributes; comparatively, little research has regarded the effects of competitors. The present study fills this knowledge gap and enriches the literature on online reviews by simultaneously considering the effects of competitors' review manipulation and restaurants' market advantage over competitors on restaurants' fake review strategies.

2.2. Theoretical foundation: social comparison theory

Social comparison theory asserts that people generally evaluate their perceptions, behavior, and abilities in comparison with others to enhance personal characteristics. Comparison referents are usually similar others or someone with whom a person can somehow identify (Gentina et al., 2018). Two main effects govern this comparison: the assimilation effect and the contrast effect (Brewer and Weber, 1994; Morse and Gergen, 1970). Assimilation occurs when individuals conduct assimilative comparisons with superior referents, leading to self-enhancement (Buunk and Dijkstra, 2011; Taylor and Brown, 1988). The contrast effect manifests when people participate in downward contrastive comparisons with inferior referents to maintain and protect their self-esteem (Wills, 1981).

Social comparison theory has long been used to predict firms' strategies and growth (Greve, 2008). Researchers have since extended social comparison theory to online review competition between restaurants (Kilduff et al., 2010). Amid increasingly fierce market competition, restaurants tend to compare themselves to competitors – especially restaurants serving similar types of food – and adjust their business strategies (including soliciting fake reviews) accordingly (Lappas et al., 2016). When restaurants compare themselves with superior competitors, the assimilation effect follows. Restaurants then experience pressure to keep pace with competitors. Comparing themselves to inferior competitors engenders the contrast effect, causing restaurants to feel more confident and perform less online review manipulation.

The above two effects can also be influenced prospectively (i.e., by amplifying comparison concerns and competitiveness). For example, the online attention restaurants receive from customers can make restaurants more likely to perform better, whereas less attention can compromise firm performance (Garcia et al., 2013; Taylor and Lobel, 1989). As individual differences affect this comparison process, competing restaurants' attributes can further influence assimilation and contrast effects (Kilduff et al., 2010). Social comparison theory provides a basic explanation for why restaurants compare themselves with

Table 1
Summary of previous literature on fake reviews.

Authors	Research context	Methodology	Findings
Antecedents			
Cao (2020)	An analytical model	Mathematical Modeling	If firms are free to choose whether to manipulate online reviews, both firms will always choose to manipulate online reviews.
Saraiva (2020)	Reviews on Amazon.com	Econometric model: logistic model	Sellers with a very good or bad history of reviews display less incentive to fabricate reviews praising their products. Sellers tend to concentrate on review manipulation at the initial stages following their entrance into the market to maximize the impact from each fake review.
Hlee et al. (2021)	Yelp restaurant reviews	Econometric model: two-way analysis of variance	Newly opened restaurants have more extreme positive reviews than long-running restaurants. The proportion of reviews with extreme ratings of newly opened restaurants is highest in the restaurants' initial stage and subsequently decreased monotonically.
Siering and Janze (2019)	Yelp restaurant reviews	Econometric model: logistic model; machine learning approach	After critical health inspections, restaurants' health scores improve; however, the number of fake reviews increases for poorly-graded restaurants.
Wang et al. (2018)	Reviews on clothing products	Laboratory experimental design	Returning cash coupons if a consumer gives a five-star rating leads to a higher rate of positive fake reviews than when returning cash coupons directly without other requirements.
Luca and Zervas (2016)	Yelp restaurant reviews	Mathematical modeling	A restaurant is more likely to commit review fraud when its reputation is weak. Chain restaurants are less likely to publish fake reviews than independent restaurants. Restaurants are more likely to receive unfavorable fake reviews when facing increased competition.
Mayzlin et al. (2014)	Hotel reviews from TripAdvisor and Expedia	Econometric model: difference-in-differences approach	Hotels with neighbors are more likely to receive negative fake reviews than more isolated hotels. Independent hotels are more likely to engage in review manipulation. Small owners are more likely to engage in review manipulation than hotels owned by companies that own many hotel units. Hotels with a small management company are more likely to engage in review manipulation than hotels that use a large management company.
Anderson and Magruder (2012)	Yelp restaurant reviews and reservation availability data from a large online restaurant reservation website	Econometric model: regression discontinuity design	An extra half-star rating on Yelp causes restaurants to sell out 19% points more frequently, which suggests that restaurants have strong incentives to leave fake reviews.
Consequences			
Zhuang et al. (2018)	Hotel reviews from Expedia and TripAdvisor	Econometric model: difference-in-differences approach	Both the effects of adding positive reviews and deleting negative reviews on sales exhibit an inverted U-shaped curve.
Lappas et al. (2016)	Hotel reviews on TripAdvisor.com	Mathematical modeling	Even limited instances of fake reviews can significantly affect online visibility. The strategies of self-publishing positive reviews and posting negative reviews for competitors can be as much as 40% more effective than the other across different settings. A mixed strategy of self-publishing positive fake reviews and posting negative fake reviews about competitors is the most effective way for attackers to overtake their competitors in visibility.
He et al. (2022)	Fake reviews on Amazon.com	Mathematical Modeling	Fake reviews have a significant but short-term increase in average rating and review numbers. However, the average ratings fall and the share of one-star reviews increases after firms stop buying fake reviews.
Shih et al. (2022)	Reviews from a software program	Experimental Design	Deceptive online reviews strongly shape consumers' incorrect beliefs and attitudes in the early and mainstream phases. Once consumers have used a new product, they may change their evaluations. However, those deceptive online reviews still weaken the adjusting effect of real reviews and deviate consumers' beliefs and attitudes away from the actual adoption experience.
Azimi et al. (2022)	An online survey	Experimental Design	People tend to assess reviews as real rather than fake and view negative reviews as more authentic than positive ones. There are significant differences between the accuracy in identifying fake negative reviews (30% accuracy) and fake positive reviews (70% accuracy).
Petrescu et al. (2022)	An online survey	Experimental Design	Consumer suspicion of an ulterior motive has a direct and mediation effect regarding brand trust and purchase intentions.
Dellarocas (2006)	Internet opinion forums	Mathematical modeling	When a firm's manipulation strategy is a monotonically increasing/decreasing function of that firm's true quality, strategic manipulation of online forums increases/decreases the information value of a forum to consumers. When the accumulative precision of honest ratings is sufficiently high, the cost of manipulation to firms always outweighs the benefits.
Linguistic features			
Li et al. (2020)	Yelp restaurant reviews	Econometric model: logistic model	Affective and social cues are positively related to fake reviews, but perceptual cues are negatively related to fake reviews.
Wang and Kuan (2022)	Reviews on Yelp.com	Econometric model: logistic model	Fake reviews align more with deceptive writing in terms of the message-level variables such as length and psychological (affective, cognitive, social, and perceptual) cues. Fake reviews align less with deceptive writing in terms of the formulation-level variables such as readability, pronouns, and part-of-speech tags.
Banerjee and Chua (2017)	Authentic reviews from Agoda.com, Expedia.com and Hotels.com, and fake reviews from participants	Econometric model: logistic model	The comprehensibility, specificity, exaggeration, and negligence between authentic and fictitious reviews are largely inconsistent across three hotel categories (luxury, budget and mid-range).
Banerjee and Chua (2021)	An online survey	Experimental Design	Perceived specificity is positively related to perceived review authenticity, whereas perceived exaggeration shows a negative association. Epistemic

(*continued on next page*)

Table 1 (*continued*)

Authors	Research context	Methodology	Findings
			belief with respect to perceived justification for knowing significantly moderates both the relationship.
Banerjee (2022)	Authentic reviews from Agoda.com, Expedia.com and Hotels.com, and fake reviews from participants	Experimental Design	Fake reviews do not always emerge as being more exaggerated than authentic ones. The extent to which perceived exaggeration could explain the perceived authenticity of reviews depends on the hotel category (budget/luxury) and the polarity of reviews (positive/negative) at stake.
Shan et al. (2021)	Reviews on Yelp.com	lexicon-based sentiment extraction	This study confirms that three types of review inconsistency exist in online reviews: rating-sentiment, content, and language inconsistency. All of the above review inconsistency features are more salient in fake reviews than in authentic reviews.

competitors. This theory also provides a theoretical foundation for this study in terms of exploring why restaurants decide to solicit fake reviews.

2.3. Hypothesis development

Research has shown that 50 fake reviews are sufficient for a firm to surpass its competitors in terms of recommended rank on TripAdvisor (Lappas et al., 2016). Faced with a flood of fake reviews and an increasingly aggressive market, companies now seem to be in a "rat race" where they are forced to allocate resources to counteract fake reviews lest consumers' perceptions be biased against them (Dellarocas, 2006).

Social comparison occurs when competitors possess similar attributes; individuals then find themselves within a social context in which "doing better" translates to "doing better than others" (Festinger, 1954). With respect to market competition, a restaurant's key concern is to outshine its competitors and capture more market share. Competitors' manipulation of fake reviews thus influences restaurants' strategies – particularly for establishments offering the same food type within a competitive geographical distance. When a restaurant's competitors solicit more positive fake reviews, perceived strong competitiveness will activate the assimilation effect. This dynamic drives the restaurant to solicit more positive fake reviews to chase its competitors and ignites further competition around soliciting such reviews. As such, we hypothesize the following:

Hypothesis 1. *(H1): A growing number of positive fake reviews for a restaurant's competitors can more strongly motivate the restaurant to solicit positive fake reviews.*

Review valence is a core aspect of online reputation that can shape potential customers' purchase decisions. Mounting evidence suggests that higher review valence can promote customers' purchase intentions and choices (Chevalier and Mayzlin, 2006; Tsao et al., 2015; Vermeulen and Seegers, 2009). In light of the importance of review valence, many firms solicit positive fake reviews to boost their online reputation (Luca and Zervas, 2016; Mayzlin et al., 2014).

Under the effect of social comparison, outperforming one's competitors will make a restaurant more confident (Garcia et al., 2020). A restaurant may therefore be satisfied with its profitable market status and be averse to reputational loss (i.e., reputational damage when the restaurant is found to have solicited fake reviews). One of the most robust human biases in decision making is loss aversion: a tendency to prefer acquiring gains over equivalent losses. In this scenario, the anticipated value of a loss exceeds the anticipated value of an objectively equivalent gain (Inesi, 2010). People who are loss-averse often unconsciously evaluate outcomes relative to a reference point and are more sensitive to negative departures (losses) than to positive ones (gains) (Andersson et al., 2016). When a restaurant holds an advantageous market position, in order to preserve gains and avoid losses, the establishment is more likely to be conservative regarding risk and will thus devote less effort to soliciting fake reviews. By contrast, when a restaurant's review valence is lower than its competitors', the restaurant occupies an inferior position in the market; it may wish to turn the tide by soliciting more fake reviews in this case, the risks of reputational damage notwithstanding. We hence hypothesize the following:

Hypothesis 2. *(H2): A restaurant's review valence advantage over its competitors can reduce the restaurant's motivation to solicit positive fake reviews.*

Review volume is a key indicator of the popularity of restaurants among customers (Xie and So, 2018). Shifting trends in review volume reflect recent variation in restaurants' popularity in addition to implying restaurants' prospective popularity. Increasing prospective popularity suggests that a restaurant is receiving more customer attention; potential restaurant customers are akin to the "audience" in social comparison theory.

The audience can amplify comparison concerns and competitive behavior (Garcia et al., 2013). The more prospective popularity a restaurant receives, the better it wants to perform to customers. In terms of online review competition, prospective popularity can affect restaurants' strategies when soliciting subsequent fake reviews. Restaurants whose prospective popularity is growing are generally more motivated to compete with competitors on soliciting positive fake reviews (Banerjee et al., 2020). At the same time, given that restaurants with increasing prospective popularity are likely to exhibit competitive behavior, they may feel more optimistic about reputational losses if fake reviews are detected (Ariely et al., 2005). Therefore, restaurants with higher prospective popularity should display more competitive behavior in soliciting positive fake reviews as postulated below:

Hypothesis 3a. *(H3a): A restaurant's prospective popularity can amplify the positive impact of competitors' number of positive fake reviews on the restaurant's motivation to solicit positive fake reviews.*

Hypothesis 3b. *(H3b): A restaurant's prospective popularity can alleviate the negative impact of a review valence advantage over its competitors on the restaurant's motivation to solicit positive fake reviews.*

With respect to online review competition, restaurant type (e.g., chain or independent) easily distinguishes competitors. Chain brands evoke specific brand associations in consumers' minds (Erdem and Swait, 1998); by contrast, independent restaurants only represent themselves. The latter establishments rely heavily on their online reputation to attract customers. They are also more concerned about online reviews than chain restaurants and are thus more likely to compare their online reputation with their competitors'. Social comparison theory posits that individual differences can influence the comparison process (Garcia et al., 2020; Kilduff et al., 2010). People with a stronger social comparison orientation (i.e., with a pronounced interest in comparing others' attributes to those of oneself) are especially likely to demonstrate competitive behavior (Gibbons and Buunk, 1999). Independent restaurants possess stronger competitiveness and are more motivated than chains to engage in review manipulation.

Moreover, chain restaurants' revenue does not just rely on online reputation thanks to the chain's established brand reputation; therefore, chain restaurants have less to gain from online review manipulation (Luca and Zervas, 2016). Chain restaurants may also incur higher costs than independent restaurants because once solicited fake reviews are detected, the entire brand's reputation will suffer. Chain restaurants hence have less motivation than independent restaurants to commit review fraud. Thus, chain restaurants may be less involved in competing with their competitors by soliciting positive fake reviews given the brand's overall reputation. We hypothesize the following as a result:

Hypothesis 4a. *(H4a): The positive impact of competitors' number of positive fake reviews on a restaurant's motivation to post positive fake reviews is weaker for chain restaurants than for independent restaurants.*

Hypothesis 4b. *(H4b): The negative impact of a review valence advantage over competitors on a restaurant's motivation to post positive fake reviews is stronger for chain restaurants than for independent restaurants.*

Based on the preceding discussion and hypotheses, we developed the research framework displayed in Fig. 1.

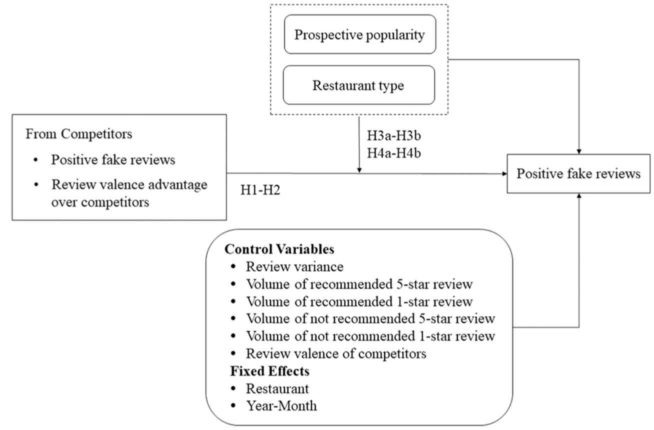

Fig. 1. Research framework.

3. Methodology

3.1. Data collection

The process of soliciting fake reviews is a "black box": the invisible nature of fake reviews presents an obstacle for researchers aiming to explore firms' motivations to solicit these reviews. Scholars are still seeking to measure fake reviews and reveal the mechanism behind solicitation. Luca and Zervas (2016) applied Yelp's review detection algorithm to discern filtered fake reviews. In this study, we also referred to Yelp reviews to unveil restaurants' motivations to solicit fake reviews.

We collected restaurants' review data from Yelp.com. As the leading local business review site in the United States with more than 200 million reviews and hundreds of millions of photos (Yelp, 2021), Yelp has been a pioneer in using recommendation software since the site launched in 2004. Yelp's recommendation algorithm can automatically predict whether a review is genuine; suspected fake reviews are placed at the bottom of the restaurant's Yelp homepage and tagged as "not currently recommended" (all reviews, regardless of whether they are recommended, are accessible; see Fig. 2). On this basis, a restaurant's manager can pinpoint fake reviews from competitors. Yelp thus provides abundant data including recommended reviews, reviews that are not recommended, and restaurants' general information. Although Yelp's exact recommendation algorithm has not been publicly disclosed, the algorithm's results are readily available. This unique platform design enabled us to explore the generation mechanism behind fake reviews more directly. Similar to Luca and Zervas's (2016) study, we used the results of Yelp's review detection algorithm as a proxy for fake reviews.

The Yelp data of our study was obtained from a metropolitan city in the U.S., which is the home to a vast number of restaurants and customer reviews. The Yelp data were processed using several steps. First, we obtained recommended reviews and not-recommended reviews for nearly all restaurants in this City on Yelp from November 2004 to November 2018. Review valence was scored on a scale of 1–5 (1 = poor, 5 = excellent). For each restaurant, we identified its type based on whether the restaurant had other branches in the city: if so, then the restaurant was deemed a chain; if not, the restaurant was labeled independent. Second, we processed recommended reviews and not-recommended reviews for each restaurant and extracted the monthly review variance and review volume. Next, similar to Luca and Zervas (2016), we identified two restaurants as competitors when they had at least one identical Yelp food label and were within a 0.5-mile radius of each other (calculated by longitude and latitude on a map). Third, we combined recommended reviews and not-recommended reviews for each restaurant and its competitors. The above data were then merged into an unbalanced panel dataset based on competitive relationships at the "Restaurant × Month" level. Our final dataset contained 78,131 observations from 972 unique restaurants.

3.2. Variable measurement

3.2.1. Dependent variable

$LnNotReS5_{it}$ refers to the logarithm of the number of not-recommended 5-star reviews for restaurant i in month t; this variable has been used to measure positive fake reviews in prior research (Luca and Zervas, 2016).

3.2.2. Independent variables

$LnCompeNotReS5_{i,t\text{-}1}$ is measured by the logarithm of the average not-recommended 5-star review volume of competitors offering the same food type within 0.5 miles for restaurant i in month t-1.

$RatingAdv_{i,t\text{-}1}$ refers to the advantage of restaurant i over its competitors based on review valence in month t-1, measured by taking the average review valence of restaurant i minus the average review valence of its competitors offering the same type of food within 0.5 miles in month t-1.

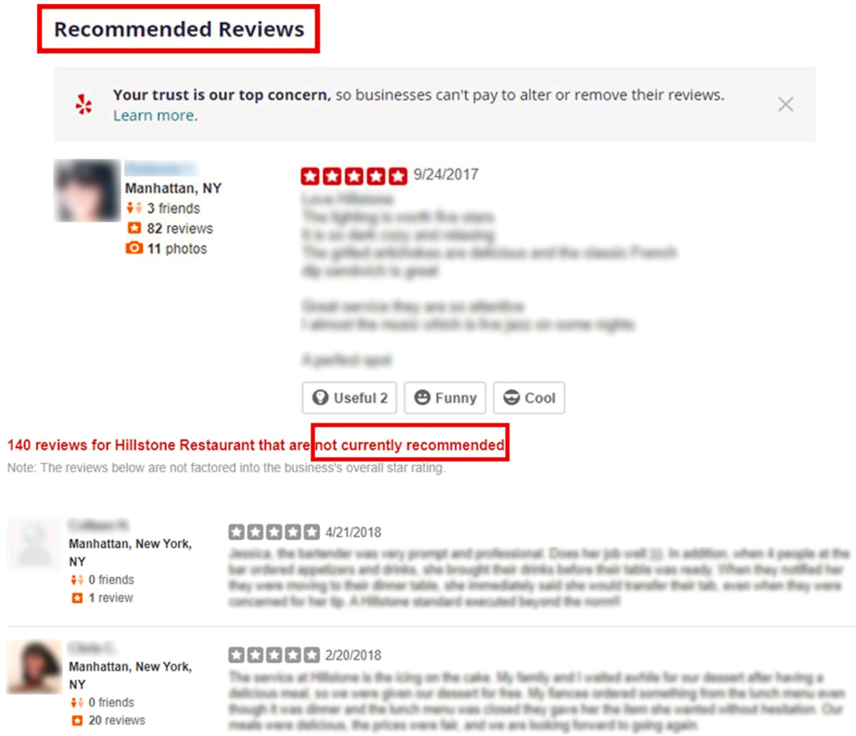

Fig. 2. Screenshot of recommended reviews and not-recommended reviews on Yelp.

3.2.3. Moderating variables

$ProsPop_{i,t\text{-}1}$ refers to the popularity trend of restaurant i in month t-1, evaluated based on the difference in recommended review volume for restaurant i from month t-2 to month t-1. $ProsPop_{i,t\text{-}1}$ is calculated by taking the recommended review volume of restaurant i in month t-1 minus the recommended review volume of restaurant i in month t-2.

Table 2
Variable descriptions.

Variable	Description
Dependent Variable	
$LnNotReS5_{it}$	Logarithm of not-recommended 5-star review volume for restaurant i in month t
Independent Variables	
$LnCompeNotReS5_{i,t\text{-}1}$	Logarithm of average not-recommended 5-star review volume of competitors offering the same type of food within 0.5 miles for restaurant i in month t-1
$RatingAdv_{i,t\text{-}1}$	Difference value in average review valence between competitors and restaurant i offering the same type of food within 0.5 miles in month t-1
Moderating Variables	
$ProsPop_{i,t\text{-}1}$	Difference value in recommended review volume for restaurant i from month t-2 to t-1
$Chain_i$	Restaurant i type: 1 = chain restaurant, 0 = independent restaurant
Control Variables	
$VarRating_{i,t\text{-}1}$	Review variance of recommended reviews for restaurant i in month t-1
$LnReS5_{i,t\text{-}1}$	Logarithm of recommended 5-star review volume for restaurant i in month t-1
$LnReS1_{i,t\text{-}1}$	Logarithm of recommended 1-star review volume for restaurant i in month t-1
$LnNotReS5_{i,t\text{-}1}$	Logarithm of not-recommended 5-star review volume for restaurant i in month t-1
$LnNotReS1_{i,t\text{-}1}$	Logarithm of not-recommended 1-star review volume for restaurant i in month t-1
$CompeAvgRating_{i,t\text{-}1}$	Average review valence of competitors offering the same type of food within 0.5 miles for restaurant i in month t-1

$Chain_i$ refers to the type of restaurant i, coded as 1 if the restaurant is a chain and 0 otherwise. We defined a restaurant with more than one other branch in the City as a chain; otherwise, the restaurant was deemed independent.

3.2.4. Control variables

To examine the impact of market competition on positive fake reviews, we controlled for several factors on three levels: the recommended review level, the not-recommended review level, and the competitor level. First, we controlled variables at the recommended review level. Review variance is a main factor in firms' online reputation and can influence customers' purchase decisions. Studies have shown that consumers generally prefer relatively consistent reviews rather than extreme disagreement; higher review variance is accompanied by uncertainty and risk (Meyer, 1981; Wang et al., 2015). Thus, review variance needs to be considered when manipulating online reviews. We controlled the review variance and used $VarRating_{i,t\text{-}1}$ to represent the review variance of recommended reviews for restaurant i in month t-1. According to prior work, a poor or excellent review volume can heavily influence fake reviews (Luca and Zervas, 2016). Thus, we used $LnReS5_{i,t\text{-}1}$ to represent the logarithm of the recommended 5-star review volume for restaurant i in month t-1 and used $LnReS1_{i,t\text{-}1}$ to represent the logarithm of the recommended 1-star review volume for restaurant i in month t-1.

Second, given the proliferation of fake reviews in the market, prior positive fake reviews may improve a firm's reputation whereas negative fake reviews may reduce it. These factors are essential to consider when restaurants are pondering whether to engage in review manipulation. Thus, we controlled the effects of both positive and negative fake reviews at the not-recommended review level. Positive fake reviews, $LnNotReS5_{i,t\text{-}1}$, were measured by the logarithm of the not-recommended 5-star review volume for restaurant i in month t-1. Negative fake reviews, $LnNotReS1_{i,t\text{-}1}$, were measured by the logarithm of the not-recommended 1-star review volume for restaurant i in month t-1.

Third, at the competitor level, earlier work has reported that the presence of competitors significantly affects firms' review manipulation

Table 3
Descriptive statistics of variables.

Variable	Obs	Mean	Std. Dev	Min	Max	VIF
$LnNotReS5_{it}$	85,279	0.300	0.488	0	4.762	–
$LnCompeNotReS5_{i,t-1}$	84,457	0.451	0.224	0	2.918	1.13
$RatingAdv_{i,t-1}$	83,925	-4.90e-05	0.531	-3.324	2	2.73
$ProsPop_{i,t-1}$	82,855	0.041	5.539	-74	136	1.07
$Chain_{i}$	85,425	0.146	0.353	0	1	1.01
$VarRating_{i,t-1}$	79,091	1.091	0.870	0	8	2.02
$LnReS5_{i,t-1}$	84,053	1.401	0.791	0	4.812	2.25
$LnReS1_{i,t-1}$	84,053	0.287	0.461	0	2.944	2.24
$LnNotReS5_{i,t-1}$	84,457	0.302	0.489	0	4.762	1.25
$LnNotReS1_{i,t-1}$	84,457	0.055	0.203	0	3.850	1.06
$CompeAvgRating_{i,t-1}$	84,341	4.036	0.136	2	5	1.13

(e.g., Mayzlin et al., 2014). We thus used $CompeAvgRating_{i,t-1}$ to represent the average review valence of competitors offering the same type of food within 0.5 miles of restaurant i in month t-1.

Moreover, log transformations were used for several variables to address the normality problem. Table 2 lists the descriptions of variables in this study, and Table 3 displays descriptive statistics for all variables and their variance inflation factors (VIFs). All VIF values were less than 10, indicating that multicollinearity was not a problem in our dataset. The Pearson's correlation matrix appears in Table 4; as shown, the correlations among independent variables and the control variable were weak in our model estimation.

3.3. Estimation models

We adopted a two-way fixed-effects panel data model to examine restaurants' motivations to solicit fake reviews. Different from a normal fixed-effects panel data model, the two-way model enabled us to control both the heterogeneity of individual restaurants and the effects of different time periods. Additionally, because changes in monthly review valence trends appear on restaurants' homepages on Yelp.com, restaurants are more likely to be concerned with their dynamic online reputation and devise fake review strategies to improve their reputation amid market competition. Thus, as in prior studies on fake reviews (Luca and Zervas, 2016), we empirically investigated restaurants' motivations to solicit positive fake reviews on a monthly basis. The specific estimation model is presented in Eq. (1):

$$\begin{aligned} LnNotReS5_{it} = {} & \beta_0 + \beta_1 LnCompeNotReS5_{i,t-1} + \beta_2 RatingAdv_{i,t-1} + \beta_3 ProsPop_{i,t-1} \\ & + \beta_4 Chain_i + \beta_5 VarRating_{i,t-1} + \beta_6 LnReS5_{i,t-1} + \beta_7 LnReS1_{i,t-1} \\ & + \beta_8 LnNotReS5_{i,t-1} + \beta_9 LnNotReS1_{i,t-1} + \beta_{10} CompeAvgRating_{i,t-1} \\ & + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where i denotes the restaurant ($i = 1, \ldots, I$); t denotes the month ($t = 1, \ldots, T$); δ_i denotes restaurant fixed effects; γ_t denotes time fixed effects; and ε_{it} denotes the usual disturbance terms. The coefficients β_1 and β_2 were of primary interest in this study: a significantly positive estimate of β_1 would provide support to H1, whereas a significantly negative estimate of β_2 would lend support to H2.

We also assessed the moderating effects of prospective popularity and restaurant type on competitors' positive fake review strategies and review valence advantage, respectively. The equation with interaction terms can be written as follows:

$$\begin{aligned} LnNotReS5_{it} = {} & \beta_0 + \beta_1 LnCompeNotReS5_{i,t-1} + \beta_2 RatingAdv_{i,t-1} + \beta_3 ProsPop_{i,t-1} \\ & + \beta_4 Chain_i + \beta_5 VarRating_{i,t-1} + \beta_6 LnReS5_{i,t-1} + \beta_7 LnReS1_{i,t-1} \\ & + \beta_8 LnNotReS5_{i,t-1} + \beta_9 LnNotReS1_{i,t-1} + \beta_{10} CompeAvgRating_{i,t-1} \\ & + \beta_{11} LnCompeNotReS5_{i,t-1} * ProsPop_{i,t-1} + \beta_{12} RatingAdv_{i,t-1} * ProsPop_{i,t-1} \\ & + \beta_{13} LnCompeNotReS5_{i,t-1} * Chain_i + \beta_{14} RatingAdv_{i,t-1} * Chain_i \\ & + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Significantly positive estimates of β_{11} and β_{12} would provide support to H3a and H3b, and significantly negative estimates of β_{13} and β_{14} would lend support to H4a and H4b. Finally, we combined the four interaction terms to estimate all effects.

4. Data analysis and results

4.1. Main results

We initially performed a Hausman test to determine whether to use a fixed-effects or random-effects panel model and found that the test rejected the original hypothesis (Hausman, 1978); therefore, the fixed-effects specification appeared more suitable for our model. Furthermore, to control the effects of different time periods, we referred to time and restaurant fixed-effects panel data models.

Our main estimation results are reported in Table 5. As the baseline model, Model 1.1 included the sample of 78,131 observations with an R^2 value of 0.2296 and an adjusted R^2 value of 0.2279. Model 1.1 consisted of the two main variables of interest as noted in Eq. (1). The coefficient of $LnCompeNotReS5_{i,t-1}$ was estimated to be positive and significant (coeff. = 0.1094, $p < 0.01$); that is, a restaurant would solicit more positive fake reviews as its competitors solicited more fake reviews. Meanwhile, the coefficient of $RatingAdv_{i,t-1}$ was estimated to be negative and significant (coeff. = −0.1175, $p < 0.01$), suggesting that a restaurant would solicit fewer positive fake reviews when holding a review valence advantage over its competitors. Based on these findings for Model 1.1, H1 and H2 were empirically supported.

We also evaluated the moderating effects of prospective popularity and restaurant type using Eq. (2); results are shown in Models 1.2 and 1.3. Model 1.2 revealed that the moderating effects of $ProsPop_{i,t-1}$ with $LnCompeNotReS5_{i,t-1}$ (coeff. = 0.0046, $p < 0.01$) and $RatingAdv_{i,t-1}$ (coeff. = 0.0021, $p < 0.01$) were significantly positive. The effect of the

Table 4
Correlation matrix of variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1. *LnCompeNotReS5*	1									
2. *RatingAdv*	0.0017	1								
3. *ProsPop*	0.0021	0.0055	1							
4. *Chain*	-0.0018	-0.0091*	-0.0001	1						
5. *VarRating*	0.0870*	-0.5988*	-0.0127*	-0.0083*	1					
6. *LnReS5*	0.2954*	0.3664*	0.2105*	0.0740*	-0.0090*	1				
7. *LnReS1*	0.1469*	-0.4811*	0.1116*	0.0239*	0.6129*	0.2501*	1			
8. *LnNotReS5*	0.2429*	0.0544*	0.0272*	0.0207*	0.0045	0.3942*	0.1741*	1		
9. *LnNotReS1*	0.0538*	-0.0948*	0.0141*	0.0038	0.0759*	0.1208*	0.1989*	0.1348*	1	
10. *CompeAvgRating*	0.1942*	-0.0121*	0.0005	0.0532*	-0.0465*	0.1399*	-0.0564*	0.0426*	-0.0234*	1

* $p < 0.05$.

Table 5
Main results.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4
LnCompeNotReS5	0.1094 ***	0.1095 ***	0.1109 ***	0.1110 ***
	(0.0099)	(0.0099)	(0.0102)	(0.0102)
RatingAdv	-0.1175 ***	-0.1159 ***	-0.1190 ***	-0.1175 ***
	(0.0051)	(0.0052)	(0.0052)	(0.0053)
ProsPop	-0.0057 ***	-0.0081 ***	-0.0057 ***	-0.0081 ***
	(0.0003)	(0.0007)	(0.0003)	(0.0007)
Chain	-0.0134 ***	-0.0134 ***	-0.0071	-0.0072
	(0.0043)	(0.0043)	(0.0110)	(0.0110)
VarRating	-0.0550 ***	-0.0555 ***	-0.0550 ***	-0.0556 ***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
LnReS5	0.2068 ***	0.2063 ***	0.2067 ***	0.2062 ***
	(0.0031)	(0.0031)	(0.0031)	(0.0031)
LnReS1	0.0461 ***	0.0482 ***	0.0463 ***	0.0485 ***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
LnNotReS5	0.2861 ***	0.2855 ***	0.2860 ***	0.2855 ***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
LnNotReS1	0.0773 ***	0.0776 ***	0.0772 ***	0.0776 ***
	(0.0076)	(0.0076)	(0.0076)	(0.0076)
CompeAvgRating	-0.0530 ***	-0.0518 ***	-0.0526 ***	-0.0513 ***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)
*LnCompeNotReS5 * ProsPop*		0.0046 ***		0.0046 ***
		(0.0012)		(0.0012)
*RatingAdv * ProsPop*		0.0021 ***		0.0021 ***
		(0.0006)		(0.0006)
*LnCompeNotReS5 * Chain*			-0.0130	-0.0128
			(0.0218)	(0.0218)
*RatingAdv * Chain*			0.0127	0.0131
			(0.0092)	(0.0092)
Constant	0.1238 **	0.1197 **	0.1216 **	0.1174 **
	(0.0539)	(0.0539)	(0.0539)	(0.0539)
Year Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	78,131	78,131	78,131	78,131
R-squared	0.2296	0.2299	0.2296	0.2299
Adjusted R-squared	0.2279	0.2282	0.2279	0.2282

Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

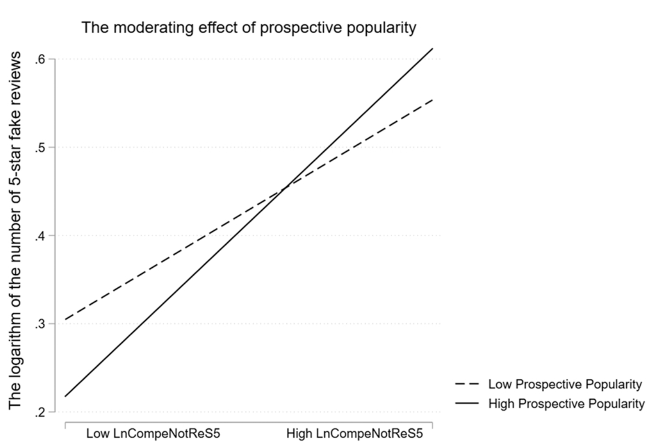

Fig. 3. Interactive effect of prospective popularity of a restaurant and its competitors' fake positive reviews on the restaurant's motivation to solicit fake positive reviews.

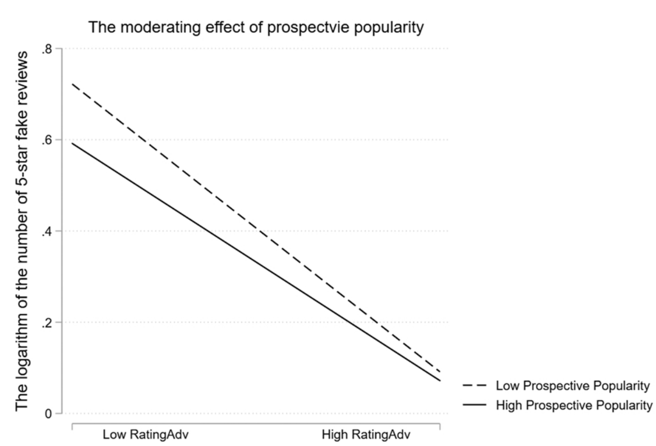

Fig. 4. Interactive effect of prospective popularity of a restaurant and review valence advantage over its competitors on the restaurant's motivation to solicit fake positive reviews.

increased number of competitors' positive fake reviews was stronger, and the effect of a review valence advantage was weaker, when a restaurant enjoyed greater prospective popularity. Thus, H3a and H3b could not be rejected. Moreover, Fig. 3 illustrates how a restaurant's prospective popularity moderated the effect of competitors' fake positive reviews on the restaurant's motivation to solicit fake reviews. The restaurants with high prospective popularity show a steeper slope than those with low prospective popularity. Fig. 4 further depicts how a restaurant's prospective popularity moderated the effect of this restaurant's review valence advantage over its competitors on the restaurant's motivation to solicit fake reviews. The restaurants with low prospective popularity show a steeper slope than those with high prospective popularity.

In addition, the direct effect of $Chain_i$ was negative and significant (coeff. $= -0.0134$, $p < 0.01$), which coincided with Luca and Zervas's (2016) study on Yelp indicating that chain restaurants were less likely to

Table 6
Robustness check 1: Results for competitors within 0.3 miles.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4
LnCompeNotReS5	0.1019 ***	0.1022 ***	0.1040 ***	0.1043 ***
	(0.0105)	(0.0105)	(0.0108)	(0.0108)
RatingAdv	-0.1219 ***	-0.1204 ***	-0.1235 ***	-0.1221 ***
	(0.0056)	(0.0057)	(0.0058)	(0.0058)
ProsPop	-0.0057 ***	-0.0083 ***	-0.0057 ***	-0.0083 ***
	(0.0003)	(0.0007)	(0.0003)	(0.0007)
Chain	-0.0138 ***	-0.0138 ***	-0.0042	-0.0042
	(0.0047)	(0.0047)	(0.0119)	(0.0119)
VarRating	-0.0585 ***	-0.0590 ***	-0.0586 ***	-0.0591 ***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
LnReS5	0.2116 ***	0.2112 ***	0.2115 ***	0.2111 ***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)
LnReS1	0.0501 ***	0.0521 ***	0.0503 ***	0.0524 ***
	(0.0054)	(0.0054)	(0.0054)	(0.0054)
LnNotReS5	0.2696 ***	0.2689 ***	0.2695 ***	0.2689 ***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
LnNotReS1	0.0744 ***	0.0748 ***	0.0743 ***	0.0747 ***
	(0.0083)	(0.0083)	(0.0083)	(0.0083)
CompeAvgRating	-0.0887 ***	-0.0880 ***	-0.0884 ***	-0.0876 ***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)
*LnCompeNotReS5 * ProsPop*		0.0050 ***		0.0050 ***
		(0.0012)		(0.0012)
*RatingAdv * ProsPop*		0.0020 ***		0.0020 * **
		(0.0007)		(0.0007)
*LnCompeNotReS5 * Chain*			-0.0195	-0.0196
			(0.0230)	(0.0230)
*RatingAdv * Chain*			0.0130	0.0133
			(0.0101)	(0.0101)
Constant	0.2730 ***	0.2708 ***	0.2709 ***	0.2687 ***
	(0.0617)	(0.0617)	(0.0617)	(0.0617)
Year Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	66,521	66,521	66,521	66,521
R-squared	0.2220	0.2223	0.2220	0.2223
Adjusted R-squared	0.2200	0.2203	0.2200	0.2203

Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

solicit positive fake reviews than independent establishments. However, in Model 1.3, the moderating effects of $Chain_i$ on $LnCompeNotReS5_{i,t\text{-}1}$ and $RatingAdv_{i,t\text{-}1}$ were each insignificant. H4a and H4b were hence not supported. In other words, chain and independent restaurants exhibited no significant difference in fake review solicitation upon encountering competition. The difference between chain and independent restaurants on social comparison orientation was not sufficient to distinguish their review manipulation strategies. We estimated the above effects collectively, and Model 1.4 implied similar results.

4.2. Robustness check

To examine the robustness of our conclusions, we adopted two approaches to re-examine our findings. Results were similar across supplementary materials. First, the main empirical results presented above were based on restaurants' competitors offering the same type of food within a 0.5-mile radius. To further explore this competitive effect, we considered a 0.3-mile and 0.7-mile radius to verify the robustness of our findings. We re-estimated empirical models with re-aggregated data. Findings for competitors within 0.3 miles appear in Table 6 and were consistent with our earlier results. Table 7 shows findings within 0.7 miles. The main effects of competitors' positive fake reviews and a restaurant's review valence advantage on soliciting positive fake reviews maintained explanatory power. The moderating effect of a restaurant's prospective popularity on its review valence advantage within 0.7 miles was insignificant but still positive. As the radius widened, the competitive relationship between a restaurant and its competitors diminished, potentially diminishing the restaurant's motivation to pursue greater popularity amid market competition. Thus, the effect of prospective popularity appeared to decline in magnitude based on competitors offering the same type of food within 0.3 miles, 0.5 miles, and 0.7 miles. Accordingly, the moderating effect of a restaurant's prospective popularity on its review valence advantage diminished in kind. Overall, our results remained stable under different geographical distances.

Second, to avoid arbitrary time-unit selection, we checked the robustness of our results under different time units. Our main empirical results were based on monthly data; accordingly, we re-estimated all variables by quarter. We used the same methods and equations as in Models 1.1–1.4 to re-estimate empirical models with re-aggregated quarterly data. Findings are displayed in Table 8. We also used full-time Yelp data between 2004 and 2018 in our main empirical results. Given the ballooning effect of fake reviews on market competition in recent years, we estimated our results using Yelp data between 2015 and 2018. Results are shown in Table 9. In general, the findings in Tables 8 and 9 aligned with our main results.

5. Discussion and implications

5.1. Discussion

Given the proliferation of fake reviews on online WOM platforms amid intense market competition, firms' motivations to solicit fake reviews on these platforms have become a popular topic in academia and industry. In this paper, we presented a novel perspective on competition to explore restaurants' motivations to solicit positive fake reviews. We proposed a research framework illustrating the interaction between a restaurant and its competitors to engage in review manipulation. This

Table 7
Robustness check 1: Results for competitors within 0.7 miles.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4
LnCompeNotReS5	0.0325 ***	0.0323 ***	0.0303 ***	0.0300 ***
	(0.0074)	(0.0074)	(0.0079)	(0.0079)
RatingAdv	-0.0680 ***	-0.0678 ***	-0.0691 ***	-0.0689 ***
	(0.0034)	(0.0034)	(0.0035)	(0.0036)
ProsPop	-0.0053 ***	-0.0067 ***	-0.0053 ***	-0.0067 ***
	(0.0003)	(0.0007)	(0.0003)	(0.0007)
Chain	-0.0105 **	-0.0105 **	-0.0182 *	-0.0183 *
	(0.0044)	(0.0044)	(0.0109)	(0.0109)
VarRating	-0.0140 ***	-0.0139 ***	-0.0140 ***	-0.0139 ***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
LnReS5	0.1953 ***	0.1953 ***	0.1952 ***	0.1952 ***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
LnReS1	0.0315 ***	0.0315 ***	0.0316 ***	0.0316 ***
	(0.0045)	(0.0045)	(0.0045)	(0.0045)
LnNotReS5	0.2789 ***	0.2787 ***	0.2788 ***	0.2787 ***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
LnNotReS1	0.0493 ***	0.0494 ***	0.0493 ***	0.0494 ***
	(0.0077)	(0.0077)	(0.0077)	(0.0077)
CompeAvgRating	-0.0202	-0.0200	-0.0197	-0.0195
	(0.0133)	(0.0133)	(0.0133)	(0.0133)
*LnCompeNotReS5 * ProsPop*		0.0029 **		0.0029 **
		(0.0012)		(0.0012)
*RatingAdv * ProsPop*		0.0003		0.0003
		(0.0006)		(0.0006)
*LnCompeNotReS5 * Chain*			0.0172	0.0173
			(0.0215)	(0.0215)
*RatingAdv * Chain*			0.0087	0.0087
			(0.0089)	(0.0089)
Constant	0.0117	0.0111	0.0107	0.0100
	(0.0534)	(0.0534)	(0.0534)	(0.0534)
Year Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	77,300	77,300	77,300	77,300
R-squared	0.2091	0.2092	0.2091	0.2092
Adjusted R-squared	0.2073	0.2074	0.2073	0.2074

Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

study first focused on the direct effect of competitors' solicitation of fake reviews and a restaurant's market advantage over its competitors based on review data gathered from Yelp.com. The moderating effects of prospective popularity and restaurant type were also considered.

Our results show that competitors' aggressive solicitation of fake reviews can significantly enhance a restaurant's motivation to solicit more positive fake reviews, whereas a higher advantage on review valence can significantly reduce a restaurant's motivation to solicit such reviews. These findings highlight the role of restaurant–competitor interaction. Aggressive solicitation strategies can trigger a restaurant's motivation to surpass its competitors and become more engaged in competition by soliciting fake reviews, which could partially explain the seemingly countless fake reviews appearing on online WOM platforms. On the contrary, a restaurant's market advantage over its competitors with respect to review valence can lead the restaurant to be satisfied with its profits and reduce its motivation to solicit fake reviews.

Moreover, we found prospective popularity to positively moderate a restaurant's motivation to solicit positive fake reviews. This finding implies that high prospective popularity (as evidenced by strong customer attention) can compel restaurants to solicit more positive fake reviews. Greater customer interest increases restaurants' competitive motivations (Hoffman et al., 1954). They will therefore likely participate more actively in competition around fake reviews to maintain presumably positive customer concern. We also observed that chain restaurants were less likely than independent restaurants to solicit positive fake reviews, which accorded with Luca and Zervas's (2016) conclusions. However, chain and independent restaurants demonstrated no significant difference in soliciting positive fake reviews when considering their competitors. An alternative explanation is as follows: although chain restaurants gain less from review manipulation than do independent restaurants, massive peer pressure from competitors in soliciting positive fake reviews could lead to an insignificant difference between chain and independent restaurants' review manipulation (Lappas et al., 2016; Luca and Zervas, 2016). Another possible explanation is our restaurant-type classification. We categorized restaurants based on whether they had more than one branch in the City, which is a somewhat broad criterion. Restaurants with more than one branch could instead be divided into groups, such as independent and similarly sized (i.e., relatively small) restaurants versus chains and similarly sized (i.e., relatively large) restaurants. Our classification scheme represents a limitation of this study as we discuss later.

5.2. Theoretical implications

This research makes several contributions to the literature on fake reviews. First, our study is among the first to apply a novel perspective on competition to investigate the interaction between a restaurant and its competitors in soliciting positive fake reviews. This study

Table 8
Robustness check 2: Results by quarter.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4
LnCompeNotReS5	0.0280 ***	0.0275 ***	0.0286 ***	0.0281 ***
	(0.0086)	(0.0086)	(0.0088)	(0.0088)
RatingAdv	-0.0172 ***	-0.0172 ***	-0.0179 ***	-0.0179 ***
	(0.0045)	(0.0045)	(0.0046)	(0.0046)
ProsPop	0.0022 ***	-0.0006	0.0022 ***	-0.0006
	(0.0005)	(0.0013)	(0.0005)	(0.0013)
Chain	-0.0042	-0.0042	-0.0015	-0.0015
	(0.0031)	(0.0031)	(0.0082)	(0.0082)
VarRating	-0.0052 **	-0.0053 **	-0.0052 **	-0.0054 **
	(0.0023)	(0.0023)	(0.0023)	(0.0024)
LnReS5	0.0555 ***	0.0556 ***	0.0554 ***	0.0555 ***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
LnReS1	-0.0008	-0.0004	-0.0006	-0.0002
	(0.0053)	(0.0053)	(0.0053)	(0.0053)
LnNotReS5	0.8080 ***	0.8072 ***	0.8079 ***	0.8072 ***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
LnNotReS1	0.0518 ***	0.0522 ***	0.0517 ***	0.0521 ***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)
CompeAvgRating	-0.0030	-0.0027	-0.0027	-0.0023
	(0.0123)	(0.0123)	(0.0123)	(0.0123)
*LnCompeNotReS5 * ProsPop*		0.0051 **		0.0051 **
		(0.0021)		(0.0021)
*RatingAdv * ProsPop*		0.0022 *		0.0022 *
		(0.0012)		(0.0012)
*LnCompeNotReS5 * Chain*			-0.0058	-0.0057
			(0.0165)	(0.0165)
*RatingAdv * Chain*			0.0055	0.0057
			(0.0085)	(0.0085)
Constant	-0.0196	-0.0207	-0.0210	-0.0222
	(0.0491)	(0.0491)	(0.0491)	(0.0491)
Year Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	27,159	27,159	27,159	27,159
R-squared	0.7577	0.7577	0.7577	0.7577
Adjusted R-squared	0.7564	0.7565	0.7564	0.7565

Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

innovatively discovered that competition persists even in restaurants soliciting positive fake reviews. We grounded restaurants' motivations to solicit fake reviews in theory by building a conceptual framework through social comparison theory (Festinger, 1954); our work introduces this psychological theory into research in online review competition. Moreover, by exploring the effects of competitors' strategies to solicit fake reviews, we uncovered restaurants' motivations to chase competitors on positive fake reviews and highlighted one reason behind the unhealthy development of market competition. Our comparison of the market positions of restaurants and their competitors also revealed why restaurants tend to solicit fewer fake reviews when holding a market advantage.

Second, we evaluated the impact of competitors' number of positive fake reviews on restaurants' motivations to solicit such reviews through a direct empirical approach, offering a theoretical complement to this research stream. Given the inherently unobservable nature of fake review solicitation, most earlier studies pertained to neighboring competitors; scant research has provided direct empirical evidence. Our work bridges this gap by leveraging filtered fake reviews from Yelp's review recommendation algorithm, which has been shown to be highly accurate (Luca and Zervas, 2016). Our effort thus offers more direct and concrete results regarding fake reviews than prior studies that compared reviews across different review systems (e.g., Mayzlin et al., 2014).

Third, we further explored the key role of restaurant type relative to fake reviews. We extended Luca and Zervas's (2016) work by estimating the degree to which chain restaurants assign importance to brand effects under fierce market competition. Our findings demonstrated that chains and independent restaurants adopt similar strategies to solicit positive fake reviews when facing competition. Therefore, differences in restaurant types cannot be regarded as influencing establishments' concerns about online reputation.

5.3. Practical implications

Customers tend to be unconsciously disturbed by online fake reviews because they cannot ascertain whether a review is genuine. Although some algorithms can pinpoint fake reviews, fraudulent fake reviews remain a noteworthy problem for consumers and online WOM platforms. Thus, our findings on restaurants' fake review strategies provide several practical implications.

First, we recognized that exposure to competitors' positive fake reviews can drive a restaurant to solicit positive fake reviews. Available fake review detection systems, such as Yelp's, filter fake reviews to the bottom of each restaurant's homepage. Restaurant managers can then easily identify fake reviews from competitors. Competitors may monitor reviews similarly on their own homepages. This system design provides

Table 9
Robustness check 2: Results from 2015 to 2018.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4
LnCompeNotReS5	0.1116 ***	0.1123 ***	0.1156 ***	0.1162 ***
	(0.0144)	(0.0144)	(0.0151)	(0.0151)
RatingAdv	-0.1003 ***	-0.0953 ***	-0.1018 ***	-0.0969 ***
	(0.0090)	(0.0091)	(0.0092)	(0.0092)
ProsPop	-0.0058 ***	-0.0077 ***	-0.0058 ***	-0.0077 ***
	(0.0004)	(0.0011)	(0.0004)	(0.0011)
Chain	-0.0262 ***	-0.0263 ***	-0.0065	-0.0071
	(0.0074)	(0.0074)	(0.0234)	(0.0233)
VarRating	-0.0445 ***	-0.0456 ***	-0.0445 ***	-0.0456 ***
	(0.0042)	(0.0042)	(0.0042)	(0.0042)
LnReS5	0.2077 ***	0.2062 ***	0.2076 ***	0.2061 ***
	(0.0052)	(0.0052)	(0.0052)	(0.0052)
LnReS1	0.0298 ***	0.0348 ***	0.0299 ***	0.0349 ***
	(0.0079)	(0.0080)	(0.0079)	(0.0080)
LnNotReS5	0.3473 ***	0.3463 ***	0.3472 ***	0.3462 ***
	(0.0054)	(0.0054)	(0.0054)	(0.0054)
LnNotReS1	0.0733 ***	0.0743 ***	0.0730 ***	0.0740 ***
	(0.0126)	(0.0126)	(0.0126)	(0.0126)
CompeAvgRating	-0.0534 **	-0.0493 *	-0.0520 **	-0.0477 *
	(0.0259)	(0.0259)	(0.0260)	(0.0260)
*LnCompeNotReS5 * ProsPop*		0.0032 *		0.0032 *
		(0.0017)		(0.0017)
*RatingAdv * ProsPop*		0.0039 ***		0.0039 ***
		(0.0010)		(0.0010)
*LnCompeNotReS5 * Chain*			-0.0360	-0.0349
			(0.0412)	(0.0412)
*RatingAdv * Chain*			0.0116	0.0131
			(0.0152)	(0.0152)
Constant	0.0636	0.0483	0.0557	0.0400
	(0.1044)	(0.1045)	(0.1046)	(0.1047)
Year Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	30,196	30,196	30,196	30,196
R-squared	0.2879	0.2883	0.2879	0.2884
Adjusted R-squared	0.2868	0.2872	0.2867	0.2872

Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

a reference for restaurants and promotes fierce competition related to fake reviews. Therefore, we recommend that online WOM platforms hide filtered fake reviews or improve their detection systems such that fake reviews are only visible to the focal restaurant itself. Not being able to determine the number of competitors' fake reviews can obscure restaurants' reference points, potentially reducing the volume of fake reviews and creating a healthier competitive environment.

Second, our findings revealed that a restaurant becomes more motivated to solicit fake reviews when it has a disadvantage on review valence relative to market competition. Therefore, we suggest that online WOM platforms seek to enhance their review recommendation algorithms. On one hand, these platforms should adopt stricter algorithms to filter reviews for restaurants with lower review valence than their competitors. On the other hand, these platforms should institute policies to penalize restaurants with more fake reviews than their competitors, such as by placing an "Uncredible" tag on their homepage to alert customers or lower these establishments' search rankings. In addition, to encourage review credibility and healthy competition, we suggest that online WOM platforms offer incentives to restaurants with fewer filtered reviews. For example, platforms can reward restaurants with fewer fake reviews with a higher search ranking or discounts on advertising. Platforms can also apply a "Premium quality" banner to further publicize these restaurants. These initiatives could more effectively filter fake reviews, help customers make better-informed decisions, and dissuade companies from soliciting fraudulent feedback.

5.4. Limitations and future directions

This study has several limitations that illuminate possible directions for future research. First, because of the unobservable nature of fake review solicitation, data from Yelp's review detection algorithm may not be fully accurate, which is an inherent issue in this research area. Second, our dataset was limited to a single City obtained from a review platform (Yelp); our findings may not be generalizable to other cities and countries. Therefore, data should be gathered from other regions to re-estimate our results and promote generalized conclusions. Third, we focused on the competitive mechanism of positive fake reviews. Although we controlled for negative fake reviews, the mechanism of negative fake reviews between companies still needs to be investigated. Fourth, our restaurant classification was rather broad. The only criterion – having more than one branch in the City – cannot fully differentiate restaurants. Restaurants could be segmented more rigorously in future work. Finally, due to social distancing and other contact restrictions, the COVID-19 outbreak has drastically changed the restaurant industry. Scholars should continue collecting data to more deeply explore restaurants' motivations to solicit fake reviews.

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