When does Local Status Matter? – The Relationship between Reviewer Location and Helpfulness of Online Reviews[1]

Completed Research

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Abstract

Faced with an abundance of information on online review platforms, users must find helpful reviews written by reliable reviewers. Consumers reviewing local businesses (e.g., restaurants) can be categorized as either locals or travelers. For example, identifying as a local or a traveler signals different kinds of knowledge and perspective. Yet, it remains unclear how helpful such categories are to platform users. This study investigates the relationship between identification as a local reviewer and the helpfulness of one's online reviews. Using data from Yelp.com, we empirically test hypotheses derived from attribution theory. Our results suggest that neutral and positive reviews by locals tend to be perceived as more helpful than traveler reviews. Conducting an additional online experiment, we find that causal attribution mediates the impact of a reviewer's local status on helpfulness. Our findings carry valuable practical implications for both online review platforms and local offline businesses.

Keywords

Online Reviews, Helpfulness, Geographic Location, Causal Attribution.

Introduction

Whether on retailer websites like Amazon or online review platforms like Yelp or TripAdvisor consumers freely exchange marketplace information to help others find the optimal product or service. The value of such review platforms relies, however, on information being generated that users actually find helpful. The vast amount of information created online, in turn, can pose an information overload problem for customers looking for helpful information in reviews. Hence, finding online reviews with helpful information has become increasingly challenging because more and more reviews are written all the time. Although online review systems aim to reduce the information asymmetry between consumers and businesses, as well as search costs, providing consumers with vast information may in fact increase search costs and potentially be overwhelming. To mitigate this issue, online review systems employ a voting mechanism to let readers articulate whether they find a review helpful. These votes are associated with more sales (Forman et al. 2008). However, only a few reviews actually receive votes. Consequently, both academia and online review platforms strive to identify the determinants of helpfulness.

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For platforms that provide reviews of local offline businesses like restaurants, information on a reviewer's location gains additional meaning and creates a natural segmentation of reviewer groups. Depending on the location of the business under review, a reviewer emerges either as a traveler or a local. On platforms such as Yelp, the reviewer's location is prominently placed next to the review text. Thus, sharing the same location with the business makes a reviewer a local. Yelp, in particular, has been relentless in emphasizing that locals share their valuable information with the community. The company recently began providing statistics on reviews by locals and travelers[3]. Intuitively, locals should be able to access and present more informed local knowledge, which should positively influence the helpfulness of their reviews. Regardless of whether locals present information that is helpful in review texts, readers perceive locals as more trustworthy and thus perceive their reviews as more helpful (López and Farzan 2015). With this study we aim to further understand the relationship between a reviewer's geographic location and the helpfulness of their review by incorporating the valence of reviews and consumers' causal attributions. Therefore, we aim to answer the following research question:

How does the local status of reviewers affect the helpfulness of their online reviews?

Using two different quantitative methods, we employ attribution theory to examine the relationship between the local status and helpfulness. We argue that localness helps to convey that the reviewer is more knowledgeable about the area and thus more credible than a traveler would be. To empirically investigate our research question, we analyze observational data from Yelp.com. In keeping with prior literature (Chen and Lurie 2013), we categorize online reviews into positive, negative, and neutral reviews and we classify reviewers as either locals or travelers. Our results indicate that neutral and positive reviews by locals are perceived as more helpful, whereas negative ones are not. After analyzing the observational data, we analyze results from an online experiment suggesting that readers of online reviews indeed attribute negativity in reviews by locals rather to the reviewer's personal reasons. Conducting a moderated mediation analysis, we show that the influence of the local status on the helpfulness of a review is mediated by causal attribution. With this multi-method approach, our work contributes to the literature by examining the role of geographic location in determining the helpfulness of online reviews. We present empirical evidence for the previously unknown relationship between review valence (a review's rating), geographical location, and helpfulness. We contribute to the literature stream of attribution theory by providing experimental evidence suggesting that a reviewer's local status may change causal attribution. Finally, our results have practical implications for consumers and online review platforms. Consumers can specifically look for positive and neutral reviews by locals to find information they deem helpful. Online review platforms can help users with their search by facilitating the identification of positive and neutral reviews by locals (for example, by highlighting such reviews or improving recommendations).

Related Literature

The helpfulness of online reviews has been the subject of previous literature from two perspectives: review characteristics and reviewer characteristics.[4] (See Hong et al. 2017 for an extensive literature review.) *Review* characteristics that can influence the helpfulness comprise the review's text and its associated rating, such as the length of a review or its deviation from the average rating (Mudambi and Schuff 2010). *Reviewer* characteristics include, amongst others, the reviewers' information disclosure (Forman et al. 2008) and expertise measured in number of reviews ever written or expert labels (Kuan et al. 2015). Reviewer characteristics such as badges and personal information are directly observable by the reader and can enhance or weaken the reviewer's credibility. If reviewers disclose personal information, such as real name, hobbies or location (Forman et al. 2008), their credibility increases, as does the review's helpfulness. In this work, we focus on local status as a reviewer characteristic.[5] In one experiment, it was found that

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[3] e.g., https://www.yelpblog.com/2017/09/locals-restaurants-san-francisco-san-diego.

[4] In keeping with earlier literature (e.g., Mudambi and Schuff 2010, Forman et al 2008), we stick to the term helpfulness. Yet, we acknowledge that the corresponding concent on Yelp.com is coined "usefulness".

[5] "Local status" could also be described as a construct that encompasses a geographical reference point that determines the distance to a restaurant. Theories that deal with such constructs, like the construal level theory also acknowlege several other "distances", such as temporal distance, that have been investigated in previous work (Huang et al. 2016). Yet, we restrict the scope of this study to the geographical aspect.

when a reviewer and a reader shared the same geographical location, the common ground created also increased helpfulness (Racherla and Friske 2012). Moreover, a survey study has investigated the relationship between review content characteristics, review valence, claims of expertise, and review helpfulness as the dependent variable (Willemsen et al. 2011). Yet, these studies has neglected the local status of a reviewer.

Our study is related to literature on the helpfulness of online reviews that employ attribution theory as a theoretical background. These studies usually investigate how certain circumstances change readers' perceptions of attribution. If readers attribute the review's content to the reviewer instead of to the product or service quality, helpfulness decreases (Chen and Lurie 2013). Sen and Lerman (2007) find for utilitarian goods that readers attribute negativity in reviews to product quality. This negativity bias is influenced by other factors. For instance, review texts that contain cues that indicate a short time between consumption of the service or product and publication of the review (temporal contiguity) lead to a higher helpfulness for positive reviews and to a lower helpfulness for negative reviews due to a change in causal attributions (Chen and Lurie 2013).

Finally, our study is closely related to those of López and Farzan (2014, 2015). Using a large data set from Yelp, they have found that reviewers' local expertise, measured by the number of reviews given in a neighbourhood, is positively correlated with the helpfulness of their reviews (López and Farzan 2014). Their follow-up study reveals based on manual annotations and interviews that readers are able to identify locals from reading the review text and that the positive correlation with helpfulness is not driven by local knowledge in the review text but rather by an increased trustworthiness due to the local status (López and Farzan 2015). Therefore, we aim to extend their findings on the influence of local status by using observable home locations in a large-scale empirical study. In addition, we contribute to the literature on negativity bias by connecting the influence of home locations to reviews' ratings (rating valence) and causal attributions. To the best of our knowledge, this study is the first to explore the relationship between the helpfulness of a review, the local status of a reviewer, and the review's valence. In contrast to the related previous research, we find that the trustworthiness of the local status substantially depends on the associated review's valence. Furthermore, we advance the literature by providing experimental evidence that this is driven by a change in causal attributions that readers make.

Theoretical Background and Hypotheses

When readers evaluate a review for helpfulness, they make inferences about the reviewer and the subject being reviewed. To describe this inference process, consumer research often draws on attribution theory (Weiner 1972). In a nutshell, this theory explains how individuals' attitudes towards a certain outcome change based on the cause they believe to be responsible for this result. For instance, teachers think different of students depending on whether they believe (i.e., attribute) that their bad performances come from a lack of effort or a lack of ability. Building on this theory, Kelley (1973) explains how consumers develop causal attributions, that is, which factor a consumer *attributes* as the reason for an actor's behavior. Studies provide evidence that causal attributions drive consumer behavior and attitudes (Folkes 1988), also regarding the evaluation of online reviews (e.g., Chen and Lurie 2013). If readers are able to observe a reviewer's location, they gain additional insights about the information source. We argue that the reviewer's localness can alter readers' beliefs, even in the absence of evidence of helpful local knowledge in the review text. Therefore, we employ attribution theory to explain how readers incorporate such information into their decision-making process. In general, attribution theory analyzes how people derive causal relationships from information (Kelley 1973). It studies how people use their understandings of the world to answer questions such as this one: if people do something nice for you, are they nice in general, or do they expect something in return? One can apply this theory to online reviews as well: is the high food quality as described in a review truly caused by the high quality of the restaurant, or does the reviewer have other reasons for writing a positive review? Indeed, readers attribute negativity in product and service ratings to low product and service quality, whereas they attribute positivity to the reviewer's personal reasons (Mizerski 1982). Although many studies have investigated this relationship and termed it the negativity bias (Chen and Lurie 2013; Sen and Lerman 2007), there exists evidence that this relationship is driven by a confirmation bias. Readers consider reviews as less helpful if their initial beliefs are not confirmed (Yin et al. 2016). If a review does deviate too much from the average rating (a consumer's initial belief), it is perceived as less helpful. The discounting principle of attribution theory explains the development of causal inferences in more detail. Consumers discount the impact of the cause if they recognize other valid external causes (Kelley 1973). For instance, consumers might consider a positive review as less helpful after finding out that the reviewer received a payment for writing it. In this case, readers discount their assessment of helpfulness when an external reason (for example, writing a positive review for payment) is present. The relationship between the valence of a message and causal attributions is central to attribution theory, the discounting principle, and related literature on the helpfulness of online reviews (Chen and Lurie 2013; Mizerski 1982). For instance, a reader might attribute a positive review to the reviewer not wanting to be associated with negative emotions or damage to the restaurant's reputation. Thus, the reader believes that there is an external cause for the positivity of the review and discounts the corresponding assessment of helpfulness. Similarly, a reader might attribute a negative review to someone who complains a lot in general and discount the assessment accordingly.

Because the valence of reviews is a main factor for causal attribution, we consider the local status of a reviewer for neutral, positive, and negative reviews in the development of our hypotheses. First, we consider the local status of a reviewer regardless of the review's valence. We argue that local consumers are more likely to become knowledgeable about their specific local area. They face lower costs in accumulating local knowledge and need to invest less time and money to reach the market compared to travelers; therefore, they are able to experience multiple businesses in the market at a lower cost and build broader local knowledge. Also, they are more likely to share close connections with other locals and be able to exchange market information with them. Supporting this argument, studies show that (even online) geographical proximity of consumers creates more social ties between them (Takhteyev et al. 2012). Due to these aspects, readers of reviews believe that locals are more credible which is associated with increased helpfulness (López and Farzan 2015). Thus, consumers should be more likely to attribute the information in the review text rather to the service:

Hypothesis 1: Online reviews given by locals are perceived as more helpful than those given by travelers.

Second, we incorporate the review's valence and focus on negative reviews by locals. When evaluating the helpfulness of an online review, readers compare the valence of the review to their initial beliefs about the product or service under review and the reviewer (Yin et al. 2016). If those beliefs are disconfirmed, readers assess the review to be less helpful. Naturally, consumers also have beliefs about the expertise of locals (López and Farzan 2015). Intuitively, a consumer would ask a local about good places to eat when visiting a new city, because, as presented above, locals have an easier access to valuable market information. However, this also entails that locals should be more skilled in finding restaurants that match their taste. Consequently, a negative review by a local also reveals that the local made a bad decision by going to the restaurant. Thus, a negative review is more likely to signal low market expertise than a positive review because consumers believe that negativity in reviews signals poor decision-making (Angelis et al. 2012). A lower market expertise is an external cause for the negativity of the review; readers will thus attribute the negativity rather to the reviewer than to the service and discount their assessment of perceived helpfulness accordingly. Hence, we formulate our second hypothesis:

Hypothesis 2: The positive relationship between the reviewer's localness and the perceived helpfulness of that review is moderated by the negativity of the review, such that negative reviews by locals are perceived as less helpful than positive reviews by locals.

Note that we do not argue that negative reviews by locals are not perceived as less helpful than any other review. Our second hypothesis suggests that the signal of expertise that stems from being a local is weaker for negative reviews when compared to positive ones. It is developed based on the notion that review valence and local status change causal attributions. We argue that giving a negative review as a local disconfirms beliefs of market expertise which in turn implies that readers attribute negativity by the local rather to the reviewer than to the service. This should not be the case for negative reviews by travelers. For instance, if a traveler publishes a negative review on a restaurant because they did not like the atmosphere, readers should be less likely to assume that this opinion is driven by the reviewer. In contrast, if this review was written by a local, consumers could believe that a local should be able to assess the atmosphere beforehand, for example by asking friends. In this case, readers would believe that the negativity of the review is to some extent driven by the reviewer and causal attributions change accordingly. Thus, we formulate a third hypothesis to test whether such changes in attributions are indeed tied to the underlying theoretical mechanism that occurs when consumers read reviews by locals and travelers:

Hypothesis 3: Readers attribute negative reviews by locals rather to the reviewer than to the product when compared with negative reviews by travelers.

Analysis of Field Data

Figure 1 depicts our research framework in a stylized way and provides an overview of our 2 studies. To empirically test our hypotheses H1 and H2, we began by analyzing field data and estimating an econometric model. We will test H3 in the subsequent experimental analysis.

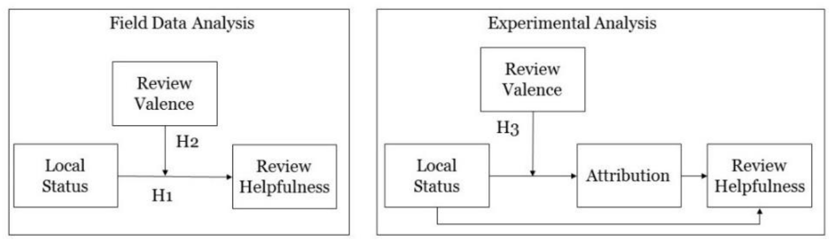

Figure 1. Research Framework

Data

In line with prior research (Liu et al. 2018), we used data published by Yelp during the ninth round of the Yelp Dataset Challenge due to its richness and high granularity. From this data, we composed a sample containing the complete review histories up to the beginning of 2017 for four U.S. cities: Champaign (IL), Madison (WI), Phoenix (AZ), and Pittsburgh (PA). In line with existing literature (Chen and Lurie, 2013), we restricted our sample to each city's top 20 restaurants in terms of total review count to ensure high levels of reader and reviewer involvement. The data also contains various user- and review-related variables along with the review's text. Because the dataset provided no information on reviewers' locations, we collected the current location for each reviewer manually in July 2017 to create a unique dataset. In this manual process, we searched the top 20 restaurants for the reviews in our dataset to fill this gap in the data. Table 1 presents descriptive statistics on a review and a reviewer level. Our sample consists of 47,390 reviews from 32,016 users for 80 restaurants. To empirically validate our hypotheses, we generated variables regarding location and review valence as well as various control variables. For each review, we compared the business's location with the reviewer's location on a city level to identify whether the review was written by a local or a traveler. Thus, the dummy variable *LOCAL* took on the value of 1 if the review was written by a reviewer whose geographic location coincided with the business's. *HELPFUL* represents the number of other users (readers) who voted this review to be helpful. *REVIEW_STARS* captures the review's rating on a scale from 1 to 5. In line with previous studies, we generated several review characteristics from the review's rating and text. A review with a rating of 4 or 5 is *POSITIVE*, and a review with a rating of 1 or 2 is *NEGATIVE* (Chen and Lurie 2013). We measured the length of a review by counting the words and adding a squared term because both too few and too many words might be seen as less helpful (*WORDS* and *WORDS*^{2}) (Kuan et al. 2015). For each review, we calculated the average rating and the review count of a business before the review's publication (*PRE_BUSINESS_REV_AVG* and *PRE_BUSINESS_REV_COUNT*). The review extremity (*EXTREMITY*) describes the absolute difference of the review's rating from the average rating of a business (Kuan et al. 2015). *TEMP_CONTIGUITY* is a dummy variable that indicates whether the review text contains cues that demonstrate a short period of time between consumption of the service and publication of the review (Chen and Lurie 2013). We also observed how many users voted the review to be "cool" or "funny" (*COOL, FUNNY*). On a reviewer level, next to information on the average rating (*USER_AVG_STARS*) and the number (*USER_REVIEW_COUNT*) of all reviews a reviewer has ever written, we observed other reviewer characteristics that Yelp supports with its design. We examined the number of votes (cool, funny, useful) a reviewer had sent (*NUM_SENT*). On Yelp, users are able to compliment other users (for example, on photos provided). *NUM_COMPLIMENTS* captures the number of compliments a reviewer has received. *NUM_FRIENDS* shows how many friends a user has registered, and *NUM_FANS* shows how many other users are following the reviewer. Reviewers can also hold an Elite Yelper badge. Such a badge is given only to reputable and active reviewers who write helpful reviews. *NUM_YEARS_ELITE* presents the total number of years a reviewer has been recognized as an Elite Yelper.

		N	Mean	Std. Dev.	Min	Max
Review Level	*HELPFUL*	47390	0.975	2.786	0	247
	POSITIVE	47390	0.768	0.422	0	1
	NEGATIVE	47390	0.106	0.308	0	1
	LOCAL	47390	0.346	0.476	0	1
	REVIEW_STARS	47390	4.068	1.093	1	5
	EXTREMITY	47390	0.818	0.696	0	5
	WORDS	47390	118.720	110.854	1	981
	WORDS²	47390	26382.687	62089.615	1	962361
	FUNNY	47390	0.421	2.028	0	166
	COOL	47390	0.599	2.484	0	234
	TEMP_CONTIGUITY	47390	0.031	0.174	0	1
	PRE_BUSINESS_REV_COUNT	47390	442.365	363.866	0	1734
	PRE_BUSINESS_REV_AVG	47390	4.073	0.345	0	5
Reviewer Level	*USER_AVG_STARS*	32016	3.825	0.662	1	5
	USER_REVIEW_COUNT	32016	72.228	171.621	1	5596
	NUM_YEARS_ELITE	32016	0.645	1.675	0	13
	NUM_FANS	32016	5.286	31.143	0	1734
	NUM_FRIENDS	32016	61.779	248.552	0	7847
	NUM_SENT	32016	279.575	4455.603	0	529730
	NUM_COMPLIMENTS	32016	88.473	1404.943	0	163353

Table 1. Descriptive Statistics

Empirical Model and Results

We dealt with count data because our dependent variable of interest was the number of helpful votes a review had received. Furthermore, our dependent variable was a count variable that exhibited overdispersion. Therefore, we used negative binomial regression in our empirical analysis (estimating a zero-inflated binomial regression would yield similar results).

$$USEFUL_{ij} = \exp\big[\beta_0 + \beta_1 NEGATIVE_{ij} + \beta_2 POSITIVE_{ij} + \beta_3 LOCAL_i + \beta_4\big(LOCAL_i * NEGATIVE_{ij}\big) + \beta_5\big(LOCAL_i * POSITIVE_{ij}\big) + \gamma X_{ij} + \zeta Y_i + \delta_j + \epsilon_{ij}\big] \quad (1)$$

In this model, reviewer i received $USEFUL_{ij}$ votes for a review of business j. X, Y represents vectors of review- and reviewer-related control variables as introduced in Table 1, respectively. Vector δ captures time-invariant, restaurant-related heterogeneity in the form of fixed effects to alleviate concerns that our selection of top 20 restaurants bias our results, since they might receive more positive reviews in general. Neutral reviews (those with a 3-star rating) represented the base case in our model. Thus, every coefficient had to be interpreted relative to neutral reviews. A positive estimate for β_1, for instance, indicates that readers perceived negative reviews as more helpful than neutral ones. The estimate for β_3 shows the estimated change in helpfulness of a local reviewer who has written a neutral review. The sum of β_3 and β_4 then indicates the estimated change in helpfulness for local reviewers who wrote a negative review. Thus, if the estimate for β_3 is positive and for β_4 is negative, negativity moderates the positive relationship of being a local. Table 2 shows empirical results for our model. It presents estimated coefficients for Equation (1) Column (1). One can see that the coefficient for *LOCAL* is statistically significant and positive (0.105). Thus, we can conclude that readers perceive neutral reviews by locals as more helpful than neutral reviews by travelers. The interaction term *LOCAL*POSITIVE* is small and statistically insignificant. The sum of the coefficients for *LOCAL* and *LOCAL*POSITIVE* remains statistically significant and positive. Therefore, we can extend our results on the positive relationship between reviewer's localness and helpfulness to positive reviews by locals. In other words, readers perceived both neutral and positive reviews by locals as more helpful than similar reviews by travelers. Therefore, we accepted our first hypothesis.

	(1)
Variable	*HELPFUL*
NEGATIVE	0.463*** (0.0352)
POSITIVE	−0.138*** (0.0247)
LOCAL	0.105*** (0.0347)
*LOCAL*NEGATIVE*	−0.139*** (0.0478)
*LOCAL*POSITIVE*	0.00834 (0.0373)
Review- and User-level Controls	✓
Restaurant Fixed Effects	✓
Note: N=47,390. Robust standard errors in parentheses. *:p<0.10;**:p<0.05;***:p<0.01	

Table 2. Baseline Results

To validate our second hypothesis, we examined the coefficient for the interaction term LOCAL*NEGATIVE, which is, as our results suggest, statistically significant and negative. The difference between LOCAL and LOCAL*NEGATIVE (0.105 – 0.138= –0.033) is even slightly negative, so the positive relationship of being a local and the helpfulness of one's reviews does not hold for negative reviews by locals. Thus, we found support for our second hypothesis. Because we do not estimate a linear model, we cannot interpret the magnitude of these coefficients directly. To this end, we calculated the incidental rate ratio (IRR) for selected coefficients. For our first model, the IRR of LOCAL is 1.11. This result suggests that positive and neutral reviews by locals are associated with an 11% increase in the expected number of helpful votes.We conducted a series of robustness checks to ensure validity of our results. First, the emotional tone that reviewers conveyed through their reviews' texts may have affected helpfulness. One might argue that emotions associated with a restaurant visit differ for locals and travelers. Therefore, we used the text analysis tool Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al. 2015) to obtain a measure for the emotional tone in a review text. Our results remained qualitatively unchanged after this measure was added as a control variable. Second, our choice of top restaurants could have influenced our results. Therefore, we re-estimated our model for the top 10, 30, or 40 restaurants and got qualitatively unchanged results. Third, we validated our results by re-estimating our model for businesses of different categories such as "Nightlife" and "Bars," again with qualitatively unchanged results.

Analysis of an Online Experiment

Next, we present an online experiment that simultaneously investigates the impact of a reviewer's local status on attributions and helpfulness.

Procedure

To investigate this attribution effect, we conducted an experiment on a commercial online crowdworking platform. The design of our experimental task looked like this: first, each participant had to answer several demographical questions about gender, age, and so. Next, we introduced each participant to a scenario in which a small chain of 3–5 restaurants was investigating how people perceived online reviews on Yelp. Participants were asked to imagine that they were looking for a restaurant in Phoenix, Arizona, and that during their search, they found a review for the restaurant 'Joey' there. To investigate whether readers attribute negativity in reviews by locals less to the service and more to the reviewer, we used four different reviews (Figure 1) and randomly assigned each participant to one of these reviews. Similarly to Chen and

Lurie (2013), we developed these four reviews by choosing a positive review of average length from the sample and rewrote positive aspects so that they would become negative. We collected random reviewer data (a picture, a name, values for review count, and so on) to create a fictional reviewer profile, Jonathan Z., who lives either in Phoenix, Arizona, or in Atlanta, Georgia. To ensure that participants noticed the reviewer location, we added specific cues to the review text. For the local reviewer, we added one of three phrases: "Trust me, I know what I am talking about, I am from Phoenix," "I will definitely come here again," or "Even though I live close by, I'll never come here again." Similarly, for the nonlocal reviewer, we added one of these phrases: "As far as I can tell, because I am not from Phoenix," "I would definitely come here the next time I am in Phoenix," or "I regret coming here on my trip, I should have tried another place instead." Participants had to read the review for at least one minute before being able to proceed with the task. Afterward, they had to answer questions regarding product and reviewer attributions. We did not allow them to look at the review again to ensure that the questions would not change their perceptions. Additionally, we excluded all contributors who assigned themselves several times to the task based on IP address and unique worker ID provided by the crowdworking platform. A total of 220 participants (117 females) took part in the experiment. Each participant earned a fixed fee of $0.15. Of the 108 participants who were assigned to the local condition, 59 saw the negative review and 49 the positive one. Among the 112 who saw a review by a traveler, 50 were shown a negative review and 62 a positive one.

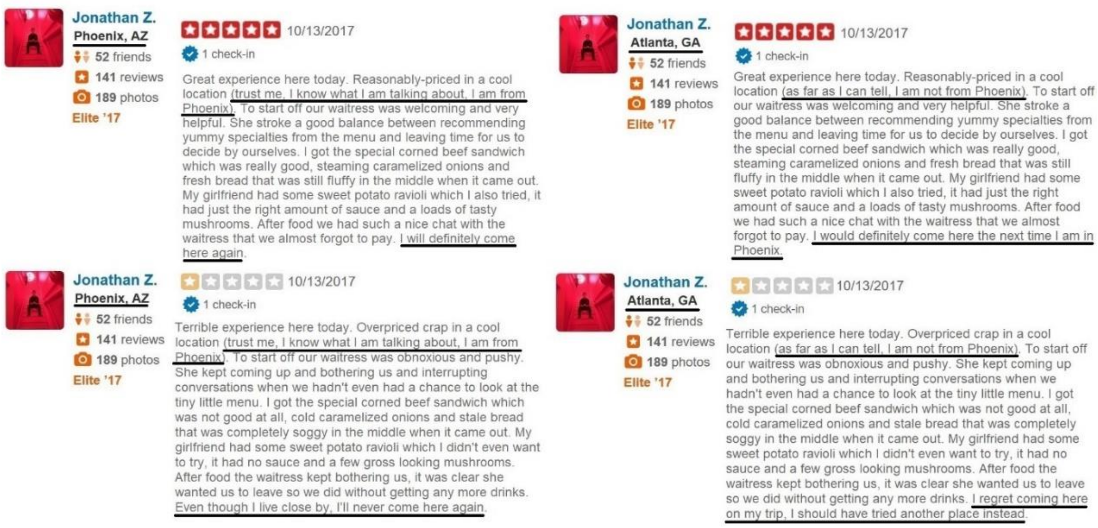

Figure 2. Reviews Used in the Experiment (Local Cues Are Underlined)

Measures

We asked the participants on a 9-point-scale from 1 = very unlikely to 9 = very likely whether they would consider this review in their decision-making process (Sen and Lerman 2007). Following previous studies (e.g., Chen and Lurie 2013)(Chen and Lurie 2013)(Chen and Lurie 2013)(Chen and Lurie 2013)(Chen and Lurie 2013), we measured reviewer attribution on a 9-point-scale, ranging from 1 = minimal role to 9 = maximal role, asking the question, "What do you think, how large a role personal factors (e.g., the character, personal style, attitudes, mood, location, popularity of the reviewer) played in the decision of the reviewer to write the review?" Similarly, to measure product attribution, we asked: "What do you think, how large a role the restaurant experience (e.g., food quality, service) played in the decision to write the review?" In addition, we asked the participants how hard they found it to answer these questions and how difficult it was to imagine that the reviewer was looking for a restaurant. Finally, we added a manipulation check for the valence of the review in which we asked if the participant believed that the reviewer was rather satisfied or rather not satisfied with the experience. To find out whether readers attributed the review's information more to the product than to the reviewer, we calculated causal attribution as the difference between product and reviewer attribution, so that higher values meant that readers attributed the information primarily to the product or service (Chen and Lurie 2013). Similarly, negative values indicated that readers attributed the information primarily to the reviewer. As causal attribution was measured as the difference between answers to two 9-point-scales, with values ranging from –8 to 8.

Results

We conducted t-tests to analyze our experimental data[6]. First, because we found significant differences in the answers to our manipulation check, we concluded that the manipulation of the review's valence was successful (mean for negative condition 1.92 vs. positive condition 7.52 with $p<0.001$). Second, we analyzed whether the participants would use the review in their decision-making process. On average (but not statistically significant), the positive review of the local was given a higher value (mean 7.41) than the positive review of the traveler (mean 7.05). For the negative review, however, the review by the traveler was rated higher than the one by the local. This is in line with our previous empirical results. More importantly, for differences in causal attribution, we found that there is a statistically significant difference between negative reviews of locals (mean 0.3559) and of travelers (mean 1.0200) with a p-value of 0.0896. Here, causal attribution is higher for travelers, which indicates that readers tend to attribute the negativity of locals to the reviewer, supporting our third hypothesis. For the positive case, attribution is higher for locals (mean 0.8980) than for travelers (mean 0.7903). However, this finding lacks statistical significance (p-value 0.3919). Moreover, the clearly different results between the positive and the negative reviews indicate that the somewhat boastful style of our phrases did not make the local reviewer less trustworthy in general. If boasting would have an impact, it should affect both conditions similarly. Finally, we conducted a moderated mediation analysis with the review valence as the moderator, the local status as the independent variable, the attribution as the mediator, and helpfulness as the dependent variable. As in previous studies (Chen and Lurie 2013), we computed a bias-corrected, bootstrapped confidence interval for the conditional indirect effects. For the positive review, we obtained a confidence interval of (–0.0692, 0.1761). For the negative review, the interval was (–0.4497, –0.0077). Because 0 is not inside the confidence interval for the negative review, we can conclude that mediation for the negative review was successful.

Conclusion and Discussion

In this study, we present the results of a field data and an experimental analysis. The aim of the field data analysis was to disentangle correlations between local status, review valence, and the helpfulness of a review, which are observed in the field. The aim of the experimental analysis was to delve deeper into the underlying mechanism, i.e., causal attribution, which cannot be observed in our field data set, hence we condcuted an experiement. Our results suggest that neutral and positive reviews by locals are perceived as more helpful. Yet, negative reviews by locals do not differ in helpfulness from those by travelers. To investigate whether readers develop different causal attributions for positive and negative reviews by locals and travelers as stated in our third hypothesis, we present a second study providing experimental evidence which indicates that readers of online reviews indeed attribute negativity of local reviewers more to personal reasons of the reviewer than to bad service quality. From the results of a moderated mediation analysis, we conclude that causal attribution mediates the effect of local status on helpfulness. Thus, we also contribute to the theory of causal attribution by analyzing how the location of an information provider influences causal attributions. Our study has practical implications for online review platforms and consumers. Platforms focusing on local offline businesses such as Yelp and TripAdvisor can facilitate consumers' search for helpful information by highlighting positive and neutral reviews by locals. Consumers can explicitly look for such reviews to reduce their search costs. Naturally, our work comes with limitations that open avenues for future research. We do not investigate whether our results hold for all restaurants. Future research could extend our study beyond the top 10 to 40 restaurants considered. Also, future studies could study the impact of the local status on different groups of readers (e.g., local versus foreign readers). Furthermore, the development of our hypotheses relies on initial beliefs readers have regarding local reviewers. To this end, we propose a qualitative study that examines what beliefs potential consumers hold when reading a review by a local.

[6] Nonparametric tests yield qualitatively unchanged results.

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