The Traveling Reviewer Problem – Exploring the Relationship between Offline Locations and Online Rating Behavior[1]

Jürgen Neumann
Paderborn University
juergen.neumann@uni-paderborn.de

Dominik Gutt
Paderborn University
dominik.gutt@uni-paderborn.de

Dennis Kundisch
Paderborn University
dennis.kundisch@uni-paderborn.de

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Abstract

Amongst the growing body of literature on the drivers of online ratings, the influence of customers' local offline environment on their ratings has largely been neglected. This study examines the relationship between ratings made outside of a customer's home area, i.e., when traveling, and the magnitude of online ratings. In line with our theory, we find that customers who rate while traveling give, on average, higher ratings than locals. This relationship is moderated by the posting time of a review relative to consumption, as travelers also post more positive ratings during or shortly after consumption compared to locals. Our identification strategy leverages panel data to control for unobservable reviewer heterogeneity and a clustering approach to mitigate reviewer-restaurant selection biases. We also investigate several additional factors such as travel distance, identification strategy of a reviewer's home city, and the size of the home city relative to the size of the travel destination. Our results come with substantial implications for a business' average rating and for customer decision making.

Keywords: Online Ratings, Online Offline Interplay, Econometrics, Affective (Mis-)Forecasting
JEL Classification: M15, M31, O32, D12

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1 Introduction

"Pleasure is found first in anticipation, later in memory."

- Gustave Flaubert

Online rating systems have become a key factor for the success of businesses trading both online and offline. By reducing the information asymmetry between sellers and their potential consumers, online ratings help the latter decide whether to purchase a good or a service, and thus facilitate purchase decisions both online (Chevalier and Mayzlin 2006) and offline (Luca 2016). Unsurprisingly, then, a growing body of literature has emerged, and with it, a substantial amount of empirical evidence collated from across different industries, attesting to the positive effect of online ratings. These include the effect of average ratings (Luca 2016), and of the number of ratings (Duan et al. 2008); on the online and offline sales of, for instance, movies (Chintagunta et al. 2010), books (Chevalier and Mayzlin 2006), and restaurants (Luca 2016). Studies find that, for example, a one-star increase in a restaurant's ratings on Yelp leads to an increase in that restaurant's revenue by between 5-9% (Luca 2016). A half-star increase in Yelp ratings allows a restaurant to achieve full bookings 19% more frequently (Anderson and Magruder 2012).

Due to the positive association of online ratings with firm performance, follow-up research has investigated a range of factors that drive and influence online rating behavior. For instance, there is empirical evidence that average online ratings of a hotel have increased by 12% when management responded to online reviews (Proserpio and Zervas 2016). Moreover, pre-announced rebates by sellers can positively affect the average rating as well as the number of ratings when the discount is made conditional on subsequent ratings being posted by the purchaser (Cabral and Li 2015). Irrespective of online ratings, one recently emerging stream of IS literature investigates the interplay between online behavior and the (local) offline world. This stream investigates the extent to which local offline conditions affect people's online behavior, and vice versa (e.g., Brynjolfsson et al. 2009, Greenwood and Agarwal 2016).

One missing piece between these two streams of research is to find out whether a customer's offline location has a systematic bearing on her online rating behavior. For example, do customers adopt different rating behaviors for businesses located in their local home area as opposed to when they post ratings on businesses located away from home e.g., when they are traveling? If there was such a systematic relationship between geographic location and the magnitude of online ratings, it would require businesses, customers, and online rating platforms to take this relationship into account when interpreting online ratings. If, for example, travelers were to give better ratings than locals, future potential customers should be aware of the number of online ratings made by travelers, as opposed to locals, when comparing businesses. Additionally, for most people going to restaurants arguably forms a large part of their vacation, and businesses are already trying to attract travelers by displaying Yelp or TripAdvisor badges in their windows. Thus, it is plausible that a sizeable number of online restaurant ratings are made away from home, which underscores the need to examine the connection between traveling and the magnitude of online ratings.

Our study, therefore, aims to enhance the understanding of the relationship between posting a rating while traveling and the corresponding magnitude of online ratings. More specifically, we delineate empirically testable hypotheses from affective forecasting (Patrick et al. 2007) and 'rosy view' theory (Mitchell et al.1997) which we test on our comprehensive online rating data set from Yelp.com. Thus, we try to answer the following research question:

Do people give systematically different online ratings to businesses patronized while traveling compared to businesses patronized in their home area?

Our empirical identification strategy hinges on geospatial variation of online ratings for businesses posted by Yelp users. Our results indicate that, when traveling, Yelp users give ratings that are approximately 0.1038 stars (Table 3) to 0.2704 (Table 4) stars higher in magnitude than the ratings of locals. This magnitude is quite substantial compared to effect sizes found in other literature on drivers of online rating magnitudes (e.g., Proserpio and Zervas 2016). Based on our theoretical background we argue that a major reason for this is because travelers make higher forecasts and have stronger memories of their affective state with respect to the trip – compared to locals – which positively influences the rating magnitude. We find that this relationship is moderated by the posting time of a review relative to consumption. While the overall relationship between posting a rating in temporal contiguity to consumption and the rating magnitude is strongly negative, travelers give more positive ratings than locals when rating in temporal contiguity to consumption. In sum, the positive relationship of rating while traveling overcompensates the negative association of posting a rating soon after consumption.

Therefore, our work makes a substantial contribution to the literature. We contribute to the growing stream of literature on drivers of online ratings as well as on the literature on the interplay between the online and the offline world. These results entail several substantial and straightforward implications. First, because travelers rate a particular business systematically differently from locals, as suggested by our results, attracting more online ratings from travelers who rate in temporal distance to consumption can help a business improve its average rating. Second, reviewers would be wise to account for potential differences in rating behaviors between locals and travelers in order to make an unbiased decision of which business to frequent, when comparing two businesses, for instance. Third, rating platforms should take measures in the design of online rating systems to help businesses and/or customers distinguish between ratings from travelers and locals.

2 Related Literature

Two streams of research are relevant to our study. The first deals with the literature on online ratings and the second with the interplay between the online and offline world in general.

Previous studies have found that the average score of online ratings (usually on a scale from 1 to 5, for example) has a positive effect on revenues and sales (Luca 2016, Chevalier and Mayzlin 2006). Additionally, some studies suggest that the volume of textual online ratings (Archak et al. 2011) and the sheer number of ratings (Duan et al. 2008) also have a positive influence on sales. The positive relationship of online ratings and sales has been found for online (e.g. Chevalier and Mayzlin 2006, Cabral and Hortascu 2010) as well as for offline businesses (e.g., Anderson and Magruder 2012, Luca 2016). Consequently, as online ratings are widely believed to substantially influence sales and revenues, different drivers of online ratings have previously been investigated. First, the timing of a product review relative to its sales release (Li and Hitt 2008) can influence a product's online rating. Li and Hitt (2008) find that products exhibit higher ratings directly after their release which decrease later on, because people with a high preference for a product tend to post their ratings early. Second, another factor affecting online reviews can be social influence through past ratings (Muchnik et al. 2013). In a randomized experiment, the authors investigate how past ratings affect future ratings. They find that negative social influence through past ratings inspires others to correct manipulated ratings, while positive social influence is associated with a 25% increase in final ratings. Finally, Dellarocas and Narayan (2006) investigate factors that influence the propensity to post an online rating for a recently watched movie. They find that marketing expenditure and disagreement among critics positively affect this propensity and that consumers are more likely to post ratings, for both, very good and very bad movies

The second relevant stream of literature considers systematic connections between local offline conditions of people and their online behavior. The phenomena already studied by researchers include how online information retrieval affects consumers' offline shopping (Kuruzovich et al. 2008); how offline marketing communications (e.g. via TV) affect online searches (Joo et al. 2014); how the number of brick and mortar stores in a local market significantly affects customers' online purchases (Brynjolfsson et al. 2009); and how casual dating arranged via online services influence the local spread of sexually transmitted diseases (Chan and Ghose 2014, Greenwood and Agarwal 2016).

There are very few studies at the intersection between online ratings and online-offline interplay in general. However, Huang et al. (2016) represents one noteworthy exception. In this study, the authors investigate the correlation of psychological distances (spatial and temporal) with the magnitude of online ratings. They test two hypotheses delineated from construal-level theory using data from TripAdvisor. Their results indicate that the rating magnitude is positively correlated with spatial and temporal distance. Our study differs substantially from this work in scale and scope. First, we use the platform Yelp as a data source, which is frequently used by both locals and travelers whereas Huang et al. (2016) rely on data from TripAdvisor[2] which is primarily used by travelers. In particular, Huang et al. (2016) analyze distance in miles and thus focus on comparing short- with long-distance travelers. Second, our dataset contains more than twice as many observations. Third, we test a completely different theory as we investigate emotions expressed by consumers in review texts. Finally, our work

[2] Huang et al. (2016) operationalize spatial distance as the log-distance in miles between the indicated home location and the location of the reviewed business. To put it differently, all the reviewers in their study are arguably travelers, only to a different extent. In contrast to this, we identify reviews of people as locals and as travelers.

primarily investigates spatial distance instead of analyzing multiple distances and therefore we conduct relatively more empirical extensions on the role of spatial distance in comparison with Huang et al. (2016).

We contribute to the above streams of literature in that we try to shed light on the question of how the local real-world environment of reviewers systematically relates to the magnitude of the online ratings they provide.

3 Theoretical Background

To gain a better understanding of the theoretical mechanism underlying the focal relationship of this study we build on two closely-related theoretical concepts, namely: affective (mis-)forecasting and the "rosy view" theory.

Affective (Mis-)Forecasting

"Affective forecasting" is defined as the prediction of one's own future feelings (MacInnis et al. 2006) and refers to experiences such as generalized emotional states, bodily feelings, or preferences and tastes (Loewenstein and Adler 1995). For example, people might anticipate feeling good when they get a long-awaited job offer. Studies have highlighted the relevance of predicted feelings on a series of behavioral outcomes such as decision-making (e.g., Bell 1982, Zeelenberg et al. 1996). Due to the relevance of affective forecasting for behavioral outcomes, one would assume that the ability to induce affective forecasting could be highly valuable to marketers. Vivid images of a pleasant trip to Hawaii, for instance, could lead someone to predict very positive feelings for a holiday there which, in turn, might result in booking a trip to that destination. More generally, almost all decisions do to some extent predict future feelings (March 1978).

However, people often perform badly at predicting their future affective states (e.g., Loewenstein and Schkade 1999), which causes the experienced affect to deviate from the forecasted affect. This gap is defined as "affective misforecasting" (Patrick et al. 2007). Affective misforecasting can occur along three dimensions: people can misforecast the direction (by anticipating happiness instead of sadness), the duration, or the magnitude of the affect (by anticipating ecstatic joy instead of mild contentment). Research provides strong evidence that when the experienced affect is lower in magnitude than the anticipated affect, affective misforecasting has a negative effect on product and service evaluations (Patrick et al. 2007). People for instance evaluate a movie much lower when the forecasted affect was higher than the experienced affect, even after controlling for expectation disconfirmation and the level of experienced affect (Patrick et al. 2007).[3]

The "Rosy View"

In the evaluation of personal events, a special type of affective misforecasting can occur, which is referred to as the "rosy view" (Mitchell et al. 1997). Personal events such as vacations or trips are usually positively anticipated. The basic tenet of the rosy view is that the affective forecast of an event experience is usually higher in magnitude than the actual event experience, and that the recollection of the event is also more positive than the actual event experience (Mitchell et al. 1997). One study on trips to Disneyland argues that the positive anticipation and the recollection of affect are both higher in magnitude than during the actual experience (Sutton 1992). Moreover, Mitchell et al. (1997) provide exhaustive empirical evidence in support of the rosy view from three field experiments on events (vacation in Europe, a 3-week bicycle trip, and a Thanksgiving vacation).

But how come that the forecasted affect is usually higher than the experienced affect? First, self-determined trips or leisure activities in general are associated with positive feelings because their purpose is, in fact, to satisfy emotional needs (Mitchell et al. 1997). Additionally, positive visions about the future are mostly pervasive, desirable, but also inaccurate (Taylor and Brown 1988). Also, anticipations of future feelings generally consider the event as a whole. Second, when experiencing an event, people are often distracted with details, complexity, and peripheral cues that have not been part of the anticipated affect. These may distract from the experience of the event, e.g., overcrowded and complicated public transport on the way to an evening out. Although reducing the enjoyment in that particular moment, distractions are nevertheless fleeting and not as important as the trip as a whole.

[3] Note that even though affective misforecasting and expectation disconfirmation theory (e.g., Cardozo 1965, Oliver 1980, Anderson 1973) are similar at first glance, because they rely on comparing something like an "ex ante" and "ex post" status, both are distinct from each other. While affective misforecasting is an affective emotional concept, expectation disconfirmation is a cognitive concept (Patrick et al. 2007). In the domain of product evaluation, expectation disconfirmation is much more concerned with predictions and actual product *performance* (such as the functionality of a kitchen tool), whereas affective misforecasting is based on the anticipated and experienced feelings evoked by the product (such as the affective experience evoked by a hedonic product or service, like a theatre or restaurant visit).

Finally, in retrospect, the memory of the event is more positive than the evaluation of the actual experience (“rosy retrospective”). This is because people tend to exhibit a selective memory of the good aspects of an event (Greenwald 1980) to enhance self-esteem (Loftus 1980), and because they strive to align pre-event forecasts with post-event memories to achieve a consistency of memories (Ross and Conway 1986).

3.1 Research Environment

Online ratings as digitized customer experiences are a major feature of the current digital era. Consequently, in the past years, online rating websites experienced tremendous growth. Yelp is perhaps the most widely-recognized platform recording online ratings for a huge variety of services (including restaurants, sightseeing spots, health care, amongst others). Yelp was founded in 2004, and up until the middle of 2018, more than 163 million customer reviews have been published (Yelp 2018). The number of average unique visitors per month was 104 million (Yelp App: 32 million; Website: 72 million) in the second quarter of 2018 (Yelp 2018). On the Yelp website, people can review experiences of businesses, for example, on a scale from 1-5, in addition to adding a textual review. Moreover, Yelp allows its users to interact with each other by setting up friend lists, uploading photos, providing private information, and giving tips to other users. Users can, in turn, rate reviews of other users as “helpful”, “funny”, or “cool”. With a current market capitalization of approximately $4.01 billion (Yahoo Finance 2018), Yelp represents a global cornerstone in the aggregation of digitized customer experiences. Unsurprisingly, practitioners and academics alike are keen to understand the factors that influence these ratings and a significant body of literature has emerged on the different facets of online rating systems (e.g., Dellarocas 2003, Chevalier and Mayzlin 2006). To maintain the quality of its online reviews, Yelp has installed a review filter to detect fraudulent reviews and a study argues that this filter works quite effectively (Luca and Zervas 2016). This underlines our choice of Yelp as the ideal data source in our empirical study, and of event experiences in particular (such as restaurant visits), as this is Yelp’s hallmark.

3.2 Hypotheses Development

In our research environment, users post the feelings they experienced in relation to an event, such as a restaurant visit, in the form of online ratings on Yelp. Prior literature has established that the expression of feelings such as anger or excitement (Sundaram et al. 1998), especially when extremely negative and positive (Hu et al. 2017), is a major driver for providing online ratings. Expressing positive emotions or "venting negative feelings" have thus been found to play a key role in the motivation of users to digitize their event experience (Hennig-Thurau 2004). Thus, it seems natural that, to a large extent, online ratings of hedonic events reflect someone's affective response to an event, as opposed to online ratings of products such as kitchen tools, which might rather reflect the functional properties of a product.

The 'rosy view' implies that when going on a trip, the forecasted affect of people taking a trip (travelers) is generally higher than the actual experienced affect, as depicted in Figure 1 on the left side of the V-shaped curves. Additionally, according to the rosy view, the affective state after the event will converge with the affective state before the event, due to e.g., selective memory or upholding a positive self-image (Mitchell et al. 1997).

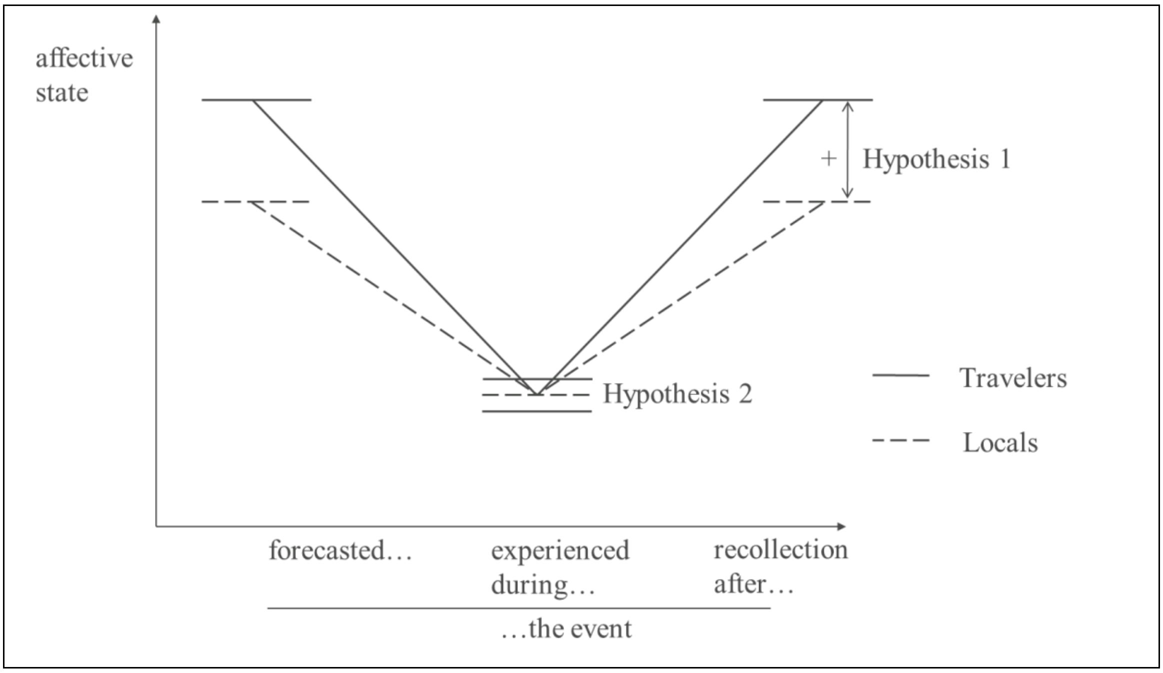


Figure 1. The Rosy View

Similarly to travelers going on a trip, people who experience hedonic events in their local areas (locals) also form predictions of their affective states during the event. As prior research has shown, locals are also prone to affective misforecasting (Patrick et al. 2007). In contrast to travelers, it is plausible that the prediction of affective states of locals involves less uncertainty and events are less scarce and less dearly awaited than a vacation trip that is usually planned in advance. Thus, the forecasted affect of locals is, on average, lower than the forecasted affect of travelers. After the event, as demonstrated in prior studies (Mitchell et al. 1997, Sutton 1992), the recollection of the affect should converge to the level of the forecasted affect, i.e., to a higher level for travelers than for locals.

As a result, we expect to find a positive relationship between the magnitude of online ratings and posting a rating as a traveler. This is because the posting of ratings usually happens a while after consumption when the affective state converges back to the forecasted state. This allows us to formulate our first hypothesis:

Hypothesis H1: Travelers post ratings higher in magnitude compared to locals.

However, prior research has shown that the affective states during hedonic events are substantially lower compared to the affective state forecasted and remembered. This is because during the event, people are distracted by unpleasant details and easily become disappointed because their forecasted affective state was too high. As shown in prior research, this can lead to lower evaluations of the event (Mitchell et al. 1997, Patrick et al. 2007). Therefore, when posting a rating in close temporal proximity to consumption, the ratings should be lower in magnitude compared to ratings posted a while after consumption. Thus, we formulate our second hypothesis:

Hypothesis H2: The positive relationship between traveling and the magnitude of online ratings is moderated by the posting time of a rating relative to consumption.

4 Research Setup

Based on our theoretical background, we hypothesized that there is a positive relationship between going on a trip and the magnitude of online ratings which is moderated by the time span between the actual experience and the posting of a rating. In this section, we empirically test these hypotheses using online rating data from Yelp.

4.1 Data

We obtained the data directly from Yelp – to ensure excellent data quality –in the course of the ninth round of their dataset challenge. Table 1 reports the summary statistics of our dataset. Our set includes a total of 388,559 individual reviews from 35,265 different reviewers who rated a total of 15,538 different businesses in 60 different cities between 2011 and 2016. In particular, we obtained the magnitude of a rating ($RATING$) and the complete rating history of all the users in our sample. Based on this, we computed a reviewer's average rating ($REVIEWER\_AVG\_RATING$) and a reviewer's review count ($REVIEWER\_NUM\_REV$) at the time a reviewer posted a review. On a business level, we compute the average rating of a business ($BUSINESS\_AVG\_RATING$) and the number of reviews a business has ($BUSINESS\_NUM\_REV$) at the time a business received a review. Using a customized web crawler we obtained population data from city-data.com in December 2016, which provided us with, for example, the number of inhabitants according to the 2012 Census (POP). We also used our web crawler to collect the reviewers' home locations as indicated in their Yelp profile.

Table 1: Summary Statistics

	N	Mean	Std. Dev.	Min	Max
$RATING$	388,559	3.72	1.16	1	5
$TRAVEL$	388,559	0.58	0.49	0	1
$TEMP\_CONTIGUITY$	388,559	0.04	0.19	0	1
$BUSINESS\_NUM\_REV$	388,559	261.3	531.99	0	6412
$BUSINESS\_AVG\_RATING$	388,559	3.69	0.72	0	5
$REVIEWER\_NUM\_REV$	388,559	57.71	120.75	0	2000
$REVIEWER\_AVG\_RATING$	388,559	3.53	1.02	0	5
POP (in thousand inhabitants)	60	104.24	230.52	0.011	1,537,058

4.2 Main Variables

Finally, we computed our main variables of interest. First, to capture whether a rating has been given while the user was on a trip, we computed a dummy variable ($TRAVEL$), which equals 1 when a user has posted a review while traveling and 0 if she has posted a review in her home area. Home areas and travel areas are defined at the metropolitan area level. All 60 cities in our sample stem from the five different metropolitan areas of Las Vegas, NV, Madison, WI, Phoenix, AZ, Pittsburgh, PA, and Urbana-Champaign, IL. We revisit the computation of this variable in further analyses and robustness checks.

Second, we compute the variable $TEMP\_CONTIGUITY$ which captures the point in time a user has posted a review relative to the time of consumption of the respective service of a business. We let this variable be a dummy variable that equals 1 if a review has been posted during, or shortly after, consumption and 0 otherwise. We identify the point in time of the post relative to consumption based on contiguity cues and temporal distance cues (Table 2). These cues are contained in the review texts that come with each rating. The identification strategy based on this set of contiguity cues has been applied and validated for Yelp reviews by Chen and Lurie (2013).

Table 2: Temporal Contiguity and Distance Cues

Temporal Contiguity Cues	today, this morning, just got back, and tonight
Temporal Distance Cues	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday, yesterday, last night, last week, weekend, weekday, last month, and last year

Note: In line with Chen and Lurie (2013), if a review contains words from both categories, we assume close temporal proximity.

4.3 Empirical Model

To investigate the relationship between rating while traveling and the temporal contiguity on the magnitude of a user's online rating, we can estimate the following model:

$$\begin{aligned} Y_{ijt} = \beta_0 + \beta_1 TRAVEL_{ijt} + \beta_2 TEMP\_CONTIGUITY_{ijt} + \beta_3 TRAVEL_{ijt} \\ * TEMP\_CONTIGUITY_{ijt} + \zeta X_{it} + \xi Z_{ijt} + \delta_i + \varphi_j + \theta_t + \epsilon_{ijt} \end{aligned} \tag{1}$$

where Y_{ijt} represents the rating magnitude $RATING$ of reviewer i's rating for business j in month t. The key variables of interest in equation (1) are the dummy variables $TRAVEL$ and $TEMP\_CONTIGUITY$ and the interaction of both variables. $TRAVEL$ indicates whether a rating has been posted while a reviewer was traveling and $TEMP\_CONTIGUITY$ identifies whether a review has been posted in close temporal proximity to consumption of the service or not. X_{it} and Z_{ijt} are vectors of reviewer-level and business-level control variables, respectively. δ_i, φ_j, θ_t represents reviewer-, business-, and month-level fixed effects. ϵ_{ijt} represents the random error term.

4.3 Identification

There may be reasons to believe that there are various obstacles that obstruct the identification of the relationship between traveling and the magnitude of online ratings. First, we need to rule out that time-invariant unobserved heterogeneity between the populations of travelers and locals bias our results. To do that, we introduce reviewer-level fixed effects and leverage within-reviewer differences in their local and travel ratings. Moreover, we can control for time-varying reviewer characteristics by including $REVIEWER\_AVG\_RATING$ and $REVIEWER\_NUM\_REV$. Second, to rule out that our results are biased by time-invariant unobserved heterogeneity between restaurants – because there may be low quality restaurants especially aiming for one-shot interactions with tourists – we also introduce restaurant level fixed effects. Additionally, we can control for the number of reviews a business has ($BUSINESS\_NUM\_REV$) and the average rating of a business ($BUSINESS\_AVG\_RATING$). After presenting our empirical baseline results, we investigate further selection-related endogeneity concerns in more detail.

4.4 Empirical Results

First, the results of column (1) of Table 3 show that the coefficient for $TRAVEL$ is positive and highly significant. The magnitude and the sign of the coefficient (β_1: 0.1038) suggests that travelers post ratings significantly higher in magnitude than locals, irrespective of the time of posting relative to consumption.

Table 3: Baseline Results

Variable	*RATING*
$TRAVEL$	**0.1038***** (0.0114)
$TRAVEL * TEMP\_CONTIGUITY$	0.0359*** (0.0203)
$TEMP\_CONTIGUITY$	—0.0993*** (0.0129)
Control Variables	✓
Reviewer-level Fixed Effects	✓
Business-level Fixed Effects	✓
Month-level Fixed Effects	✓
Obersvations	388,559
Adj. R²	0.2652

Note: Robust standard errors are in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Therefore, we find support for our Hypothesis H1. Second, while the overall relationship between posting a rating in temporal contiguity to consumption and the rating magnitude is strongly negative (β_2: —0.0993), travelers give more positive ratings than locals when rating in temporal contiguity to consumption (β_3: 0.0359). Therefore, we also find support for Hypothesis H2. In sum, the positive relationship of rating while traveling ($\beta_1 + \beta_3$) overcompensates the negative association of posting a rating soon after consumption (β_2).

4.5 Further Analyses

We would like to get further insights into the mechanism that drives the relationship between traveling and the magnitude of online ratings. In particular, we would like to investigate two potential selection effects that might bias our baseline results. First, travelers might go to systematically different restaurants when traveling as opposed to those they are patronizing at home. If reviewers systematically go to better restaurants when traveling, our baseline estimates might be upward biased. To rule out this concern, ideally, we would have to run an experiment assigning reviewers to comparable restaurants at home and while traveling. Naturally, this is not possible. To mimic this experiment, however, we conduct k-means Jaccard clustering to identify clusters of very similar restaurants. After applying standard scree plots to determine the optimal number of restaurant cluster, we end up with eight clusters. We run our baseline model specifications separately for the eight restaurant clusters.[4] Table 4 displays the results of these analyses and the coefficients for $TRAVEL$ remain qualitatively unchanged from our baseline results. In fact, the coefficients for $TRAVEL$ in the cluster analysis are on average larger the coefficient in the baseline model. These results provide support for the claim that our results are not driven by reviewers patronizing systematically different restaurants while traveling compared to the restaurants they visit at home.

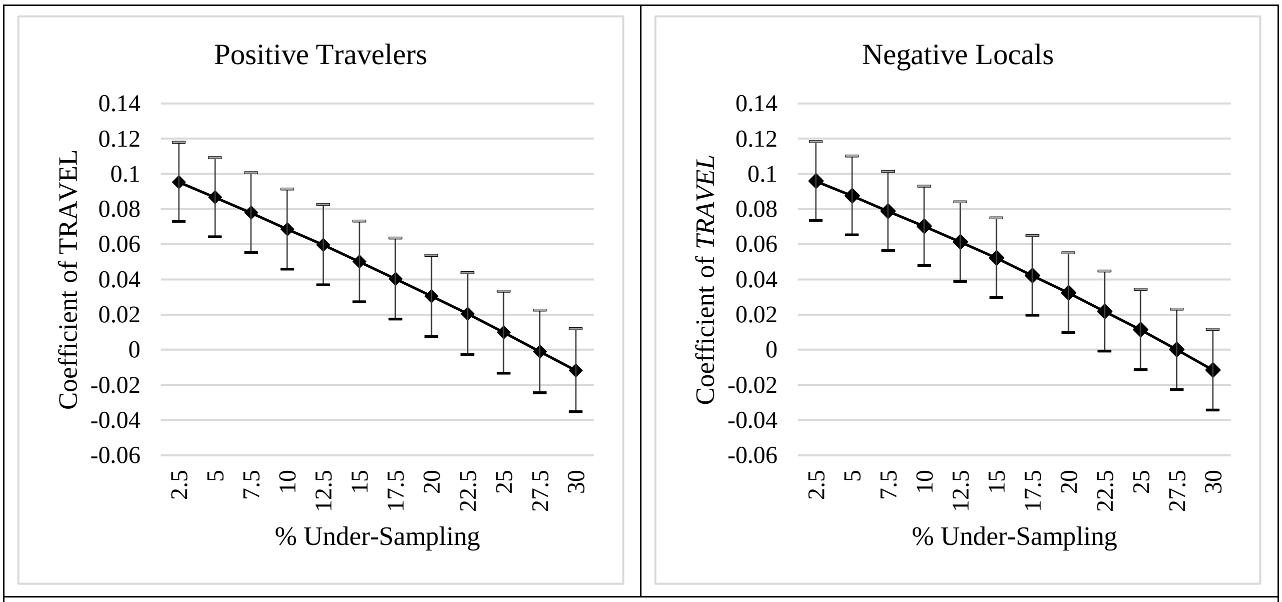
Table 4: Clustering Results

Cluster #	1	2	3	4	5
Variable	*RATING*	*RATING*	*RATING*	*RATING*	*RATING*
$TRAVEL$	**0.0471**	**0.2704*****	**0.151*****	**0.0746****	**0.0602**
	(0.0529)	(0.0709)	(0.0233)	(0.0275)	(0.0506)
$TRAVEL$	0.0465	-0.5581	-0.2767*	-0.1642	-0.0043
$* TEMP\_CONTIGUITY$	(0.2634)	(0.3878)	(0.1335)	(0.1409)	(0.2395)
$TEMP\_CONTIGUITY$	-0.1241	0.0290	-0.0355	-0.0598	-0.0075
	(0.1184)	(0.0965)	(0.0311)	(0.0276)	(0.0633)
Control Variables	✓	✓	✓	✓	✓
Business-level FE	✓	✓	✓	✓	✓
Individual-level FE	✓	✓	✓	✓	✓
Month-level FE	✓	✓	✓	✓	✓
N	4,814	2,290	32,627	26,939	8,192
Adj. R2	0.2025	0.3108	0.2619	0.2515	0.2657

Note: Robust standard errors are in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

[4] We can only run regressions for 5 of the 8 clusters because we do not observe any within-reviewer variation for 3 of the 8 clusters.

Second, there might be an endogeneity concern if there is a systematic difference in the propensity to post a review between the population of traveling reviewers and home reviewers. Reviewers might be more inclined to post a review when traveling than while at home, or vice versa. Two adverse scenarios that might bias our results are when travelers have a higher propensity to post positive ratings – which we call positive travelers – and when locals have a higher propensity to post negative ratings – which we call negative locals. Even though we cannot directly control for this because the individual propensity to post a review is unobservable, we can estimate the potential strength of the bias that is required to invalidate our results. We can identify ratings by positive travelers by conducting a median split and taking the 50% positive ratings. By conducting a median split of ratings by locals and taking the 50% negative ratings we identify negative locals. Next, we can re-estimate our baseline model and randomly under-sample the populations of ratings by positive travelers and negative locals at increasing rates to check when our baseline results become insignificant. We under-sample both populations by rates of 2.5%, then by 5%, then 7.5% and so on. Figure 2 displays plots of coefficients for β_1 ($TRAVEL$) at the different under-sampling rates. Our analysis shows that our results turn insignificant at under-sampling rates of 22.5%. Thus, if our results were driven by mere differences in the propensity to post a review, positive locals or negative travelers must have a 22.5% higher propensity to post a review relative to the rest of the reviewers.



Note: Diamond symbols indicate the magnitude of the coefficient of *TRAVEL* at the respective under-sampling rates. Vertical lines indicate 95% confidence intervals.

Figure 2. Coefficients of *TRAVEL* for Different Under-Sampling Rates

Moreover, we would like to investigate whether the difference in rating magnitude between travelers and locals is driven by the city size of the destination of travel. For example, travelers from a relatively small city coming to a bigger city might rate differently compared to travelers from a big city coming to a relatively small city. We split our variable $TRAVEL$ into two new variables: $BIGGER\_TO\_SMALLER$ and $SMALLER\_TO\_BIGGER$. The former is 1 if a reviewer posts a review while traveling and the metropolitan area of her travel destination has more inhabitants than his home area. The variable is 0 otherwise. The latter variable is 1 if a reviewer's metropolitan home area has fewer inhabitants than her travel destination. We run our baseline regression replacing $TRAVEL$ with $BIGGER\_TO\_SMALLER$ and $SMALLER\_TO\_BIGGER$ and the results in Table 5 show that the coefficients of the new variables are statistically significant, positive, and very similar in magnitude, suggesting that there are no substantial differences in ratings between the two groups of travelers.

Table 5: Big versus Small Cities

Variable	*RATING*
$BIGGER\_TO\_SMALLER$	**0.1007***** (0.0158)
$SMALLER\_TO\_BIGGER$	**0.1128***** (0.0229)
$TEMP\_CONTIGUITY$	—0.00854*** (0.0099)
Control Variables	✓
Reviewer-level Fixed Effects	✓
Business-level Fixed Effects	✓
Month-level Fixed Effects	✓
Obersvations	388,559
Adj. R^2	0.2652

Note: Robust standard errors are in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

In our baseline specification, the variable $TRAVEL$ is 1 if a reviewer from Pheonix, AZ is posting a review in Pittsburgh, PA, for example. In other words, we only leverage traveling activities between metropolitan areas. Yet, we would also like to investigate short-distance traveling activities within metropolitan areas, for example, when someone from Scottsdale, AZ posts a rating in Glendale, AZ – both located in the area of Phoenix, AZ.

Table 6: Within-Area Variation

Variable	*RATING*
$TRAVEL$	**0.0239***** (0.0035)
$TRAVEL$ $*\,TEMP\_CONTIGUITY$	0.0705*** (0.0122)
$TEMP\_CONTIGUITY$	—0.2132*** (0.0088)
Control Variables	✓
Reviewer-level Fixed Effects	✓
Business-level Fixed Effects	✓
Month-level Fixed Effects	✓
Obersvations	936,007
Adj. R²	0.2880

Note: Robust standard errors are in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

For this, we recoded the variable $TRAVEL$ on the basis of each of our 60 different cities so that the variable is 1 if someone from Scottsdale, AZ posts a review for a business in Glendale, AZ. Reassuringly, our results depicted in Table 6 remain qualitatively unchanged but, as expected, decrease in magnitude, because affective forecasting should be higher for longer trips than for shorter trips within metropolitan areas.

Finally, we would like to investigate the theoretical mechanism we suggest to be responsible for the difference in ratings by travelers and locals, namely, their affective states. In a nutshell, we hypothesized that that ratings by travelers will be higher due to higher affective states prior and after the consumption experience (see Figure 1). To strengthen the applicability of this theory in our context, we identify emotions in review texts. As previous studies (e.g., Sridhar and Srinivasan 2012, Yin et al. 2014, Yin et al. 2016), we use the Language Inquiry Word Count package (LIWC) to psychologically analyze the reviews' texts (see Pennebaker et al. 2015). LIWC provides variables, which assess the general emotional tone in the analyzed text. The emotional tone is a summary statistic that ranges from 0 to 100 and indicates whether a text conveys mainly positive (>50 indicates a positive, joyous and upbeat tone (Pennebaker et al. 2015)) or negative (<50 indicates emotions such as sadness, anxiety, or hostility (Pennebaker et al. 2015)) emotions. We re-estimate our empirical model with emotional tone as dependent variable and our results (displayed in Table 7) suggest that traveling is in fact related to a more positive tone in review texts, i.e., to higher affective states.

Table 7: Emotional Tone

Variable	*EMO_TONE*
$TRAVEL$	**0.5807*** (0.2556)
$TRAVEL$ $* \, TEMP\_CONTIGUITY$	0.4557 (0.4542)
$TEMP\_CONTIGUITY$	—4.2113*** (0.2873)
Control Variables	✓
Reviewer-level Fixed Effects	✓
Business-level Fixed Effects	✓
Month-level Fixed Effects	✓
Obersvations	383,401
Adj. R^2	0.1524

Note: Robust standard errors are in parentheses. $^{*}p < 0.05$; $^{**}\, p < 0.01$; $^{***}\, p < 0.001$.

4.6 Robustness Checks

Even though we incorporate various control variables and fixed effects, we would like rule out a number of additional concerns to verify the robustness of our results. Most importantly, we would like to investigate our assumption that reviewers truthfully report their home areas on their Yelp profiles. While reviewers have the option to indicate their location on their Yelp profile, this category is ambiguous. To some reviewers it could mean “hometown”, to some it could mean “current residency”, and to some it could mean “place where I spend most of my time”. Thus, we followed a different, more data-driven strategy and define a user’s home area along the following three criteria: (1) A user has posted at least 50% of her total review count in this area; (2) The date difference between the first and the last review a user has posted is at least 360 days, to rule out that we specify a possible holiday destination where a user posted the majority of her ratings as her usual rating area; (3) The user has posted at least three reviews in this metropolitan area. We re-estimate our baseline model and our results remain qualitatively unchanged.

Additionally, we conducted the following robustness checks: We re-estimate our baseline model (1) controlling for how many ratings a user has already given in a certain area to rule out concerns of user experience in this area; (2) running an ordered logistic regression model with fixed effects to account for the truncation of our dependent variable RATING; (3) excluding all reviews without temporal contiguity and temporal distance cues; (4) restricting our sample only to the first review in each city while traveling to rule out a generally higher preference with the city; (5) restricting our sample only to recent reviews (less than two years old) as an additional way to account for potential changes in self-reported reviewer locations; (6) restricting our sample to restaurants with the same category assigned by Yelp (e.g., Traditional American Restaurants, Italian Restaurants, etc.) to increase the comparability of restaurants at home and while traveling; (7) restricting our sample to restaurants with the same price category assigned by Yelp – the website has 4 different price categories. Our results remain qualitatively unchanged in all of the above robustness checks.

5 Discussion of Theoretical Mechanism

There are numerous studies supporting the claim that emotions are a major driver of online ratings which supports our choice of affective (mis-)forecasting and the rosy view as our theoretical lens. Nevertheless, one might argue that there are alternative theoretical mechanisms which govern the relationship between a user's offline location and her online rating behavior.

On the one hand, one might argue that locals can rely on local knowledge which is not available to buyers living outside of the local market (e.g., Feick and Price 1987, Ivkovic and Weisbenner 2005). Local knowledge could be acquired informally, for instance through non-digitized word-of-mouth, through personal experience with the business owner, or through knowledge about a business' neighborhood. If locals used local knowledge in addition or instead of online ratings, this might enable them to find businesses that better match their taste compared to travelers. Previous literature has established that if businesses match a buyer's specific taste well, this results in higher ratings (e.g. Sun 2012, Chen et al. 2017). Thus, we would expect higher ratings from locals compared to travelers. Based on the empirical evidence presented in our study, we argue that this mechanism is unlikely to be at play in our research environment.

On the other hand, it is also conceivable that online ratings are more leveraged by travelers which enables them to find businesses that better match their tastes compared to locals, who make less use of online ratings. Users can generally match businesses to their taste along two dimensions, the vertical dimension, which could be price for instance (e.g., Shaked and Sutton 1982), and the horizontal dimension, which could correspond to location or subjective taste (e.g., Hotelling 1929). If users could find businesses that better match their taste while traveling due to the use of online ratings, we would expect results to differ qualitatively from our baseline results, if we were to restrict the possibility of vertical and horizontal differentiation. For example, if our results were driven by a user's tendency to go to pricey top notch restaurants while traveling which, in turn, leads to higher ratings, we would expect to find insignificant results for our baseline model when restricting our sample to low- and medium-priced restaurants only. When we present results from subsamples that restrict the possibility of horizontal (by restricting our samples to restaurants from certain categories) or vertical differentiation (by restricting our model to restaurants with certain price categories), our results remain, by and large, qualitatively unchanged for these subsamples. Thus, as outlined in our section on robustness checks, we argue that our results are not driven by travelers that find a better taste match compared to locals.

One might also argue that there is a mismatch between the theoretical level of affective (mis-)forecasting / the rosy view (from which we delineate hypotheses on a trip level) and the empirical level (where we investigate single consumption instances). This would be a cause for concern if users had multiple consumption instances per trip. We would for instance underestimate the magnitude of the relationship, if affect has a decreasing marginal influence on the magnitude of online ratings. Even though this might by partially true, we argue that it is unlikely that our results are influenced by this because most travelers only have one consumption instance per trip for which they post an online rating. Also, the alternative theoretical angles discussed above (local knowledge and preference matching by travelers) arguably represent theory on the consumption level. However, the results of our empirical analyses support the claim that our results are unlikely to be explained by these theoretical mechanisms on the consumption level.

Third, there might be apprehensions against the application of our (emotion-based) theoretical lens by questioning the extent to which emotions are actually reflected in online ratings. To refute these doubts, we replace our dependent variable with a well-established measure of the emotional tone of a review obtained from the LIWC (Pennebaker et al. 2015). Reassuringly, our results as presented in Table 7 remain qualitatively unchanged compared to our baseline results, supporting the claim that online reviews by travelers are associated with a more positive tone and that this relationship is moderated by the posting time of a review. In summary, the empirical evidence presented in our study supports the claim that our results can be well explained by our theoretical lens and that other theoretical angles discussed here are unlikely to explain our results.

Finally, the observed relationship between the magnitude of online rating behavior and the posting time of an online rating might be partially driven by the theoretical mechanism of regulatory focus (Florack et al. 2013, Higgins 1998). Following this theory, negative experiences (e.g., food poisoning) might prompt more immediate online ratings whereas positive experiences (e.g., outstanding service by a waiter) might not prompt an immediate posting of online ratings. In this way, low online ratings posted in temporal contiguity to consumption might be posted due to a so-called "prevention focus", whereas higher ratings might be motivated by a "promotion focus". To rule out that TEMP_CONTIGUITY operates solely through a prevention focus of users, we re-estimated our baseline model adding EMO_TONE as a control variable to control for negative emotions. Even though the magnitude of TEMP_CONTIGUITY declines in this case, our results remain qualitatively unchanged, supporting the claim that the relationship between review posting time and the online rating magnitude is, if at all, only partially driven by a prevention focus.

6 Conclusion

This study tries to shed light on the interplay between offline locations and the online rating behavior of individuals by delineating hypotheses from affective forecasting and rosy view theory and testing these hypotheses on a rich data set from Yelp.com. First, we hypothesize that travelers should, on average, post higher online ratings compared to locals, because they form higher forecasts and memories of their affective state with regard to a particular event (e.g., a restaurant visit). Second, we hypothesize that this relationship is moderated by the time a rating is posted relative to the time of consumption, e.g., the time of eating at a restaurant. Empirically, we find support for both hypotheses controlling for a wide variety of observable and time-invariant unobservable factors. In our data set, travelers who rate a business give, on average, ratings that are between, approximately, 0.27 and 0.1

stars higher in magnitude than the ratings by locals. Giving a rating while traveling also overcompensates the overall negative impact of rating in close temporal proximity to consumption.

Our study comes with substantial implications for businesses, customers, and online rating platforms. First, businesses can aim to attract ratings of travelers who rate with temporal distance to consumption as one option to increase their average rating. Second, when potential customers are comparing the mean ratings of two businesses to make a decision, the geographical background of the raters and temporal cues in their reviews should be taken into consideration to make an educated decision. Third, rating platforms can, in the interest of their customers – the businesses and Yelp users – consider facilitating the identification of whether a review was made by a traveler or a local during or after consumption. Nevertheless, this research also comes with limitations. For example, this study does not aim to establish whether travelers are too positive or whether locals are too critical in their assessment of a restaurant. This limitations present promising avenues for future research.

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