The Effects of Online Review Ratings: A Case Study of the Hotel Industry

Zhu Zhu

A dissertation

submitted to the Faculty of

the department of Economics

in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Boston College

Morrissey College of Arts and Sciences

Graduate School

March 2023

The Effects of Online Review Ratings:

A Case Study of the Hotel Industry

Zhu Zhu

Advisor: Michael Grubb, Ph.D.

Abstract

Online reviews have gained importance for consumers when shopping for experience goods. This dissertation documents the impact of Tripadvisor.com reviews on the hotel industry. In the first chapter, I investigate the causal impact of Tripadvisor review ratings on hotel performance via a regression discontinuity design. The results indicate that a 1-point increase in review rating leads to a 1.6% increase in revenue, a 1% increase in bookings, and a 0.4% to 0.6% increase in prices. Furthermore, the impact on bookings has increased over time. In the second chapter, I evaluate the welfare impact of Tripadvisor review ratings in providing information about quality. I develop a structural model of hotel demand and supply that takes price endogeneity and capacity constraints into consideration. Counterfactual experiments reveal that the removal of Tripadvisor from the status quo results in per-capita consumer surplus loss ranging from $0 to $5.8, with a more significant decrease in consumer surplus when prior knowledge about quality is less accurate. Hotels with higher quality than expected absent reviews benefit from review ratings, while the opposite is true for others. In the third chapter, I analyze the relative influence of Tripadvisor ratings on chain-affiliated and independent hotels and evaluate the value of Tripadvisor ratings compared to chain brands using the methodology developed in previous chapters. I find there is no significant difference in the effect of rating rounding on occupancy rates for chain-affiliated

hotels versus independent hotels. Counterfactual experiment results suggest that despite chain brands providing value to consumers, Tripadvisor ratings provide additional value of about \$0 to \$4 per capita. In scenarios where Tripadvisor was not present, Chain-affiliated hotels benefit from brand affiliation while independent hotels are harmed.

To mom and grandfather.

Thanks for your constant love and support.

Special thanks to M, whose push for tenacity rings in my ears.

Thank you for always being there for me.

Acknowledgments

I am grateful to all of those with whom I have had the pleasure to work during this project. I thank my Dissertation Committee–Michael Grubb, Richard Sweeney, and Charles Murry–for their valuable guidance and feedback. Especially, I am deeply grateful to my advisor Michael, who has provided me with extensive personal and professional guidance and taught me a great deal about both scientific research and life in general.

I thank Duane Vinson for making the STR data acquisition process smooth. I am grateful for the helpful discussions in the dissertation workshop and with Julie Mortimer, Michael Luca, Greg Lewis, and Brett Hollenbeck.

Contents

List of Tables

Chapter 1

The Causal Impact of Online Review Ratings On Hotel Performance: Evidence from Tripadvisor

1.1 Introduction

For many people, reading reviews online is an essential part of navigating the modern marketplace. In a 2020 survey by Statista, 40% of respondents in the United States reported reading product reviews online "always" or "frequently" before making a purchase. Online platforms, such as Yelp.com and Tripadvisor.com, allow consumers to share their experiences and provide information about the quality of various products or services. Existing studies have found these consumer reviews to have a notable impact on sales in various industries and attract more customers for firms with positive reviews (Chevalier and Mayzlin, 2006; Zhu and Zhang, 2010; Luca, 2011; Vermeulen and Seegers, 2009).

In this chapter, I focus on investigating the causal impact of online consumer reviews on hotel performance. By analyzing panel data that includes monthly financial performance and Tripadvisor rating history, I aim to address the following research questions: (1) Does

Tripadvisor rating has a causal impact on hotel performance, as measured by different performance indicators? (2) How the effects on these performance measures have changed over time?

Online customer reviews are crucial in the hospitality industry because hotel rooms are often considered "experience goods" in the sense that hotel services are intangible in nature. Evaluating service quality before consumption can be challenging for consumers, leading to significant uncertainty and requiring substantial information to reduce perceived risks and make informed decisions. This unique characteristic of hotel services implies the need for accessible and comprehensive information sources. As per Dickstein (2011) research, online reviews posted by other travelers are often considered more up-to-date, informative, enjoyable, and reliable compared to information from travel service providers. Hence, understanding the influence of online consumer reviews as a type of "informational intermediation" in mitigating the information asymmetry in the hotel booking process is crucial not just for hoteliers and marketers but also has significant implications for market efficiency and consumer welfare.

Although numerous academic studies have investigated the relationship between online consumer reviews and hotel performance (Schuckert, Liu, and Law (2015)), the current research on the sensitivity of hotel performance to changes in online review ratings is largely inconclusive. While some studies suggest a positive correlation between online review ratings and hotel performance (e.g., Ye, Law, and Gu (2009); Sayfuddin and Chen (2021)), others indicate that the impact is moderated by other factors, such as hotel star ratings (Lu, Ye, and Law (2014)), or even negligible (Pokryshevskaya and Antipov (2020)). In a meta-analysis of 25 research articles on the effect of electronic word of mouth (eWOM) on hotel performance, Yang, Park, and Hu (2018) suggest that the generalizability of previous research findings depends on factors such as the research setting, data structure, variable measurement, and model specification.

Furthermore, the majority of previous research has primarily demonstrated the correlation between review ratings and hotel performance, while facing the challenge that consumer ratings are inevitably associated with unobserved hotel quality and traditional word-of-mouth sentiments, which can cause omitted variable bias. For instance, a hotel that receives more positive reviews might be perceived as higher quality, but it could also be possible that the hotel is better located or has other features that influence guest satisfaction. Additionally, hotels can leverage other channels such as star ratings, brand affiliation, or advertisements to signal their quality and build their reputation, which might be confounded with their online reputation. Therefore, most of the existing estimates of the impact of changes in consumer ratings on hotel performance cannot be conclusively deemed as causal effects of ratings. This is evident in Yang et al. (2018), where the link between online consumer reviews and hotel performance was notably weaker in panel data studies that controlled for the time-invariant unobserved heterogeneity of hotels.

These challenges associated with measuring the effect of online consumer reviews, including the endogeneity of online reviews, have been discussed in an earlier work by Bar-Isaac, Tadelis, and Zettelmeyer (2008). They propose using natural experiments, such as changes in online reputation systems, to identify the causal impact of reputation on consumer behavior, as well as using instrumental variables and other econometric techniques to address endogeneity. Since their study, a handful of studies have utilized quasi-experimental techniques to uncover the distorting effects of systems that report rounded ratings, which are typically represented using stars, bubbles, or other graphical images (Anderson and Magruder, 2012; Luca, 2011; Wang, Li, and Yi, 2019). However, literature that employs such techniques and focuses specifically on the hotel industry is scarce. Sayfuddin and Chen (2021) and Pokryshevskaya and Antipov (2020) are the rare examples but their results differ significantly.

Pokryshevskaya and Antipov (2020) studies the hotels in Rome, Italy. Due to the limited availability of demand data, they examine the causal effect of Tripadvisor's bubble rating on hotel popularity, measured by the number of people viewing the hotel's page. Using a regression discontinuity design, they find that the bubble presentation of ratings does not create any significant jumps of views at cutoffs, suggesting that the TripAdvisor bubble rating system does not introduce any bias in the quality signals for the hotels in their sample. Acknowledging their findings differ from those of similar studies, the authors offer several potential explanations. For instance, simply viewing a hotel's page does not necessarily translate to a booking, as noted by Koulayev (2014). The authors acknowledge that bubble ratings may still affect the likelihood of actual bookings. Additionally, the majority (74%) of hotels in their sample had a rating of four bubbles or higher, which may limit the generalizability of the results to lower-rated hotels where ratings may carry greater weight.

Sayfuddin and Chen (2021) examines the impact of Tripadvisor review ratings and revenues for hotels in Texas using monthly data from January 2014 to December 2017. They employ a regression discontinuity design that leverages TripAdvisor's rating rounding system and report a 2.2-3.0% increase in monthly hotel revenues from an exogenous one-point increase in ratings.

My contribution to this study expands upon previous research in several ways. Rather than focusing solely on one popular travel destination or geographic area, I conduct my analysis on nine distinct geographic locations across the United States. These areas include both tourist hotspots such as Miami Beach, as well as areas primarily for business travel, such as Chicago and Dallas. By controlling for various geographic market conditions, the findings of this study are more robust and informative. Moreover, while most existing literature focuses solely on revenue as a measure of hotel performance, this study takes a more comprehensive approach by examining the causal effects of online reviews on both demand (measured by occupancy rate) and price (measured by average daily rate). This broadens the scope of analysis and allows for a more nuanced understanding of how online reviews impact hotel performance. Finally, this study extends the work of Sayfuddin and Chen (2021) by exploring the heterogeneity in the effect of online review ratings over time. Using data from the beginning of Tripadvisor in 2000 to December 2019 when online reviews gained significant popularity, this study provides insights into how the effect of online reviews has evolved over time.

There are two main findings in this chapter. First, Tripadvisor review ratings have a significant causal impact on hotel performance. The effect on revenue is greater than on booking and room rates, with a 1-point increase in review rating resulting in a 1.6% increase in revenue per available room (RevPAR), a 1% increase in occupancy rate, and a 0.4% to 0.6% increase in average daily rate (ADR). These effects are statistically significant for all three performance measures. Second, the impact has grown from 2000 to 2019. The increasing trend is more pronounced in occupancy rate and RevPAR than in ADR.

The structure of this chapter is as follows. In Section 1.2, the relevant literature is reviewed. Section 1.3 outlines the data used in this study. Section 1.4 establishes a positive correlation between changes in a hotel's rating and its performance through fixed-effect regressions. Section 1.5 introduces the regression discontinuity framework, which exploits Tripadvisor's rating rounding system to identify the exogenous variations in a hotel's rating with respect to unobserved factors that affect its performance. Section 1.6 addresses concerns about the potential for rating manipulation and provides evidence validating the results of the regression discontinuity design.

1.2 Literature Review

This study draws upon several branches of literature. Firstly, it builds on existing research that has documented the impact of online reviews on sales and revenue performance. Previous findings have examined various aspects of online reviews, such as ratings and volume, and have varied across different industries. For example, Chevalier and Mayzlin (2006) investigated the effect of consumer reviews on book sales at Amazon.com and Barnesandnoble.com. Their findings indicated that an improvement in a book's reviews led to an increase in relative sales at that particular site. Similarly, Hu, Liu, and Zhang (2008) studied a panel of books, DVDs, and videos from Amazon.com's Web Service and found that consumers not only valued favorable reviews but also paid attention to other contextual information such as the reviewer's reputation and exposure. Zhu and Zhang (2010) discovered that online reviews had an impact on the sales of video games, with a heightened influence observed for less popular games and games with a more seasoned player base. Duan, Gu, and Whinston (2008) examined the effect of online reviews on movies' daily box office performance and showed that the rating of online user reviews had no significant impact on movies' box office revenues after accounting for the endogeneity between review ratings and sales. Cui, Lui, and Guo (2012) analyzed a panel of new products from Amazon.com and found that the average rating had a stronger effect on search products, while the volume of reviews was more important for experience products. The volume of reviews was also found to have a significant effect on new product sales in the early period, with the effect decreasing over time. Despite the mixed results found in these studies regarding the impact of review ratings, they all emphasize the effect of online reviews on consumers' purchase decisions.

In contrast to other experience goods such as books, movies, or video games, the hospitality industry - including hotels and restaurants - has unique characteristics that could affect the effect of online reviews. Firstly, hotels and restaurants provide tangible products that involve physical experiences, which can create more uncertainty for consumers prior to making a purchase decision. Secondly, the perishable nature of the services offered in the hospitality industry means that hotels and restaurants have limited capacity, and their inventory cannot be stored for future use. In contrast, books, movies, and video games have no expiration date and can be consumed almost anytime, which implies more risk in selecting the right hotel or restaurant at a specific point in time. Thirdly, hotels and restaurants are service-intensive products that require high levels of interaction between the customer and the service provider. On the other hand, books and movies require little to no interaction between the customer and the service provider. Therefore, the quality of the service provided in the hospitality industry can have a significant impact on the customer's overall experience, making online reviews a more critical source of information. Lastly, hotels and restaurants are high-involvement purchases, meaning that customers invest significant time and money in their decision-making process. As a result, customers are more likely to rely on the experiences of others as a source of information when making such purchases.

There has been a plethora of literature showing the significant impact of online reviews on firms' performance in the hospitality industry. Anderson (2012) analyzed the correlation between hotel performance and online reputation score (measured by ReviewPRO's Global Review IndexTM) and found that a 1% increase in a hotel's online reputation score led up to a 0.89% increase in price as measured by the hotel's average daily rate (ADR), a 0.54% increase in occupancy rate, and a 1.42% increase in revenue per available room (RevPAR). However, the effect found cannot be interpreted as causal. Luca (2011) used a regression discontinuity design to investigate the marginal impact of Yelp.com star ratings on restaurants. The study found the average star rating has a significantly positive effect on the revenue of restaurants. Blal and Sturman (2014) used data from STR and Tripadvisor and find a differential relationship between online reviews and RevPAR by chain scale segments for hotels in the London metropolitan market. Using the hierarchical linear modeling method their result indicated review rating has a greater effect on RevPAR for luxury hotels, while the volume of reviews has a greater effect on RevPAR for lower-tier hotels. Lewis and Zervas (2016) used a large dataset of hotel reviews and pricing information and found that an increase in review ratings has a positive effect on hotel occupancy rates and is positively correlated with prices. Sayfuddin and Chen (2021) studied the impact of Tripadvisor reviews on the revenue of hotels in Texas via regression discontinuity design. They found a 1-star increase in rating leads to an increase of 2.2%-3% in hotel monthly revenue.

Secondly, my methodology relates to research using regression discontinuity design (RDD) in estimating the impact of online reviews. Except for the aforementioned Luca (2011), Sayfuddin and Chen (2021), and Pokryshevskaya and Antipov (2020), Hollenbeck, Moorthy, and Proserpio (2019) use RDD and find online ratings have a causal effect on hotels' advertise spending from the demand side, with high-rated hotels spending less on advertising than low-rating hotels. Anderson and Magruder (2012) employ RDD to estimate the effect of average Yelp.com ratings on restaurant reservations in San Francisco, finding that a half-star increase in rating results in a 19 percentage points increase in the probability of selling out during prime dining times, with the effect being larger for restaurants that have external accreditation. On the other hand, Wang et al. (2019) uses RDD to examine the effect of consumer reviews on a Chinese shopping website. They find the star presentation can create negative, rather than positive, jumps at cutoffs. The authors provide the following reasoning. Consumers restrict their attention to a star category resulting in the "best" sellers in a lower star category being better off than the "worst" sellers in a higher star category, leading to decreased incentives for review manipulation and fostering trust and confidence in the review system and sellers. For those sellers that are just below the cutoffs, simply crossing over the cutoffs would not lead to higher sales, unless they substantially improve their service quality to attract consumers.

1.3 Background and Data

The data comes from two sources. The first is Smith Travel Research (STR), which provides a property-year-month level panel of hotel financial performance data. The second is TripAdvisor.com, where I collected the entire historical records of online reviews for hotels in the STR data set. My sample does not include motels, B&Bs, hostels, vacation rentals, Airbnb, etc. Although I have data available until December 2022, I dropped the data from 2020 onwards because of the pandemic, considering the travel restrictions and hotel close down during the period. The entire dataset covers a total number of 1188 hotels. The time span is from January 2000 to December 2019.

1.3.1 Data from STR

STR (Smith Travel Research) is a widely used data provider for the hotel industry, and many studies have utilized their data to examine various aspects of hotel performance (Mayzlin, Dover, and Chevalier, 2014; Farronato and Fradkin, 2022; Gibbs, Guttentag, Gretzel, Yao, and Morton, 2018). I acquire data from STR for 1,848 hotel properties in 9 major US cities or municipal areas, including Nashville, Miami Beach, Houston, New York City, Washington DC, Atlanta, Phoenix, Chicago, and Dallas. Each location is referred to as a "Market" in the data. The data cover 70% of the market.

For each hotel property, I observe its operating market as well as the following monthly metrics which are the standard metrics to measure financial performance in the hospitality industry: (1) occupancy rate, which refers to the percentage of hotel rooms that are occupied during the day; (2) average daily room rate (ADR), which measures the average revenue generated per *occupied* room in a hotel on a given day; and (3) average revenue per available room (RevPAR), which is calculated as occupancy rate times ADR. It is used to measure the revenue generated from rooms, per *available room*, in a given time period.

In my data, hotel identities are masked with generically generated code by STR. After dropping hotels with missing data in particular months, I have 1416 hotel properties included in my STR sample.

1.3.2 Data from TripAdvisor.com

Founded in 2000, Tripadvisor was an early adopter of user-generated reviews. It is widely considered to be one of the largest online platforms for hotel reviews because it has a large user base that generates a huge volume of reviews. A study by comScore found that in 2012, 50% of all travelers worldwide used TripAdvisor in their travel planning process[1]. Tripadvisor has been frequently cited and utilized by numerous academic papers as a source for analyzing the impact of online reviews (Anderson, 2012; Hollenbeck et al., 2019; Lewis and Zervas, 2016; Sayfuddin and Chen, 2021).

Tripadvisor reviews come from registered users on the platform. Every user can write a review. Every reviewer must also post an overall rating about a hotel. TripAdvisor review ratings are in bubbles. Users can leave one to five bubbles for a given hotel property. Moreover, Tripadvisor provides an overall rating for each hotel property. The overall rating reflects the average of all the reviews submitted by users for a particular hotel property. It is important to point out that the overall rating is on a 1-5 scale with an increment of 0.5 bubbles. The bubble ratings are displayed alongside each hotel's listings. The displayed bubble ratings summarize the experiences of travelers and serve as a quick reference for others considering a trip to the same location.[2] Figure 1.4 and 1.5 show examples of how bubble ratings are displayed on Tripadvisor.

To match with the STR data, I collected all the reviews for hotels in the STR data-covered locations on Tripadvisor.com. For each review, I record the integer rating given by the reviewer. I then aggregated ratings to the hotel-year-month level by computing the cumulative and monthly average ratings and counts of reviews. My data does not contain the review text to maintain hotel anonymity.

While I didn't have access to snapshots of the displayed bubbles, I had the ratings for each individual review. To determine each hotel's previous history of displayed bubbles, I calculated the average rating available for each date, rounded to the nearest 0.5 bubbles. For example, a property with an average 2.74-bubble rating will be rounded down to 2.5 bubbles, while a property with an average 2.75-bubble rating will be rounded up to 3 bubbles. While TripAdvisor uses a proprietary algorithm to generate the display of ratings, it is generally

[1] https://www.comscore.com/Clients/Understanding-and-Impacting-the-Consumer-Journey-with-TripAdvisor

[2] TripAdvisor's explanation on their bubble rating system: https://www.tripadvisor.com/TripAdvisorInsights/w810

deemed as the rounded average rating of all the reviews received by a hotel. There are a number of existing research use the rounding of average ratings as displayed bubbles as previously cited in Section 1.1.

1.3.3 Data Merge

STR requires the researcher to merge data and send the merged data back to STR. They will generate a generic code for each hotel property and send it back with an id for each hotel and identity information removed such as names, addresses, brand affiliation, phone numbers, etc. Following this protocol, I merged STR data and the aggregated monthly Tripadvisor review rating data by comparing the hotel name, addresses, postal codes, and phone numbers. In practice, merging two datasets on this information is challenging. For instance, many hotels have different formats of addresses in the datasets. Also, some hotels have the same addresses or names. To ensure that the two datasets were merged correctly, I use the Python package FuzzyWuzzy to match hotels on their names, addresses, phone numbers, and zip codes. The fussy match algorithm produces a score of 0–100 to measure the extent to which two strings match with each other[3]. A score of 100 suggests a perfect match while a score of 0 suggests that hotel names do not match at all.

I keep a subsample of hotels with a score above 85, and manually checked matches with score below 100 by checking the actual Tripadvisor listings. For the incorrectly matched hotels, I manually search if the hotel in the STR data has a listing on Tripadvisor.

After merging, I identified 1,188 hotel properties in the STR data with their corresponding listings on Tripadvisor. Among these properties, 849 properties have at least one review by the end of 2019. There are a total of 2,420,504 reviews. In the remaining sections, the term "hotels" will be used to refer to hotel properties.

Table 1.1 reports the summary statistics. Figure 1.1 shows the number of Tripadvisor reviews

[3] I compare strings from both a single variable such as hotel name and a combination of variables such as hotel name and address to use the information to the best extent for matching hotels in two datasets.

for hotels in my sample has grown over time. The growth was taken off in 2009 and declined after 2016. Figure 1.2 shows the average monthly Tripadvisor ratings in my sample. The plot on the left-hand side shows the cumulative average of review ratings for each year based on an average hotel-year-month observation. The plot on the right-hand side shows the average review ratings for an average hotel-year-month observation for each year. Over time, the overall average rating has risen from 3.6 in 2007 to 4 in 2016 and has remained stable since. Additionally, the average monthly review rating has increased from 2.2 in 2007 to 3.7 in 2016 and has declined to 3.4 in 2019.

Table 1.1: Summary Statistics

	N	Mean	Std	Min	25th pct.	50th pct.	75th pct.	Max
Occupancy rate (%)	173,686	71.2	16.6	0.4	60.7	73.4	84.1	100.0
ADR (average daily rate) ($)	173,686	126.1	90.7	12.9	70.9	105.7	152.0	2552.6
RevPAR (revenue per available room) ($)	173,686	93.7	76.6	0.3	43.7	73.4	116.2	1711.0
Average review rating	115,111	3.9	1.0	1.0	3.5	4.0	4.5	5.0
Average review count	115,111	28.2	81.6	2.0	2.0	8.0	24.0	2226.0

a. The sample size N for occupancy rate, ADR, and RevPAR include all 1,188 hotels in my sample.
b. The sample size N for Review rating, and Review count include all 849 hotels that have at least one review on Tripadvisor by the end of 2019.
c. Each observation is a hotel-month.

1.4 Fixed-effect Regressions

1.4.1 Model Specification

To establish the positive relationship between hotel performance and review ratings, I adopt fixed-effect regression models. Specifically, I regress the monthly performance outcomes on the average review rating of the month while controlling for hotel fixed effects and market-

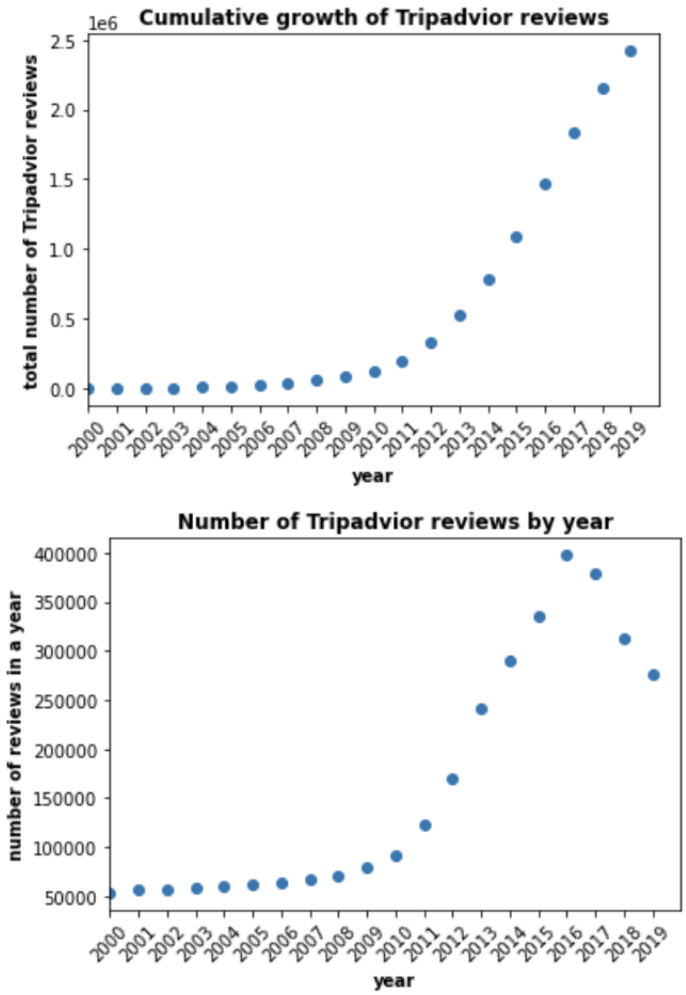

Figure 1.1: Number of Tripadvisor reviews in my data over time

year-month fixed effects. The empirical specification of the regression model is as

$$y_{j,t} = \beta_{1,t} Rating_{j,t} + \beta_2 \mathbf{1}\{IsReviewed\}_{j,t} + h_j + \tau_t \times m_j + \epsilon_{j,t} \tag{1.1}$$

where t denotes a certain year-month time period; $y_{j,t}$ is the natural logarithm of each of the performance measures, namely monthly average occupancy rate, ADR, and RevPAR. $Rating_{j,t}$ is the cumulative average review rating for the hotel up to the time period t; h_j is the hotel fixed effect; $\tau_t \times m_j$ is the market-year-month fixed effect; $\epsilon_{j,t}$ is an error term. Because there are some hotels that have performance data but have not yet been reviewed by time period t, I include a dummy variable $\mathbf{1}\{IsReviewed\}_{j,t}$ to control for the effects of

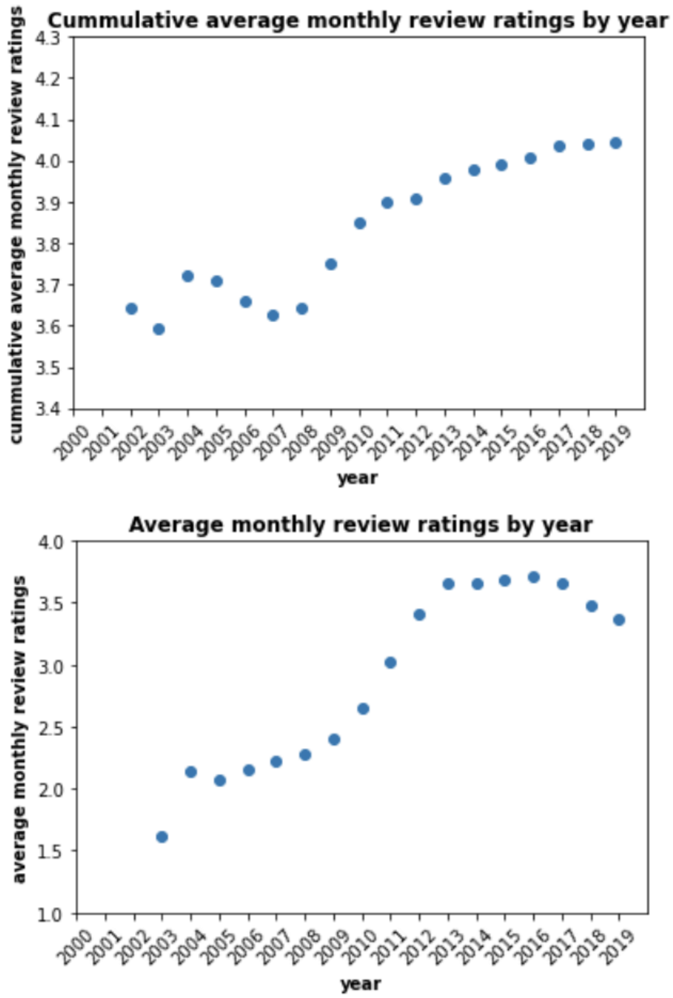

Figure 1.2: Tripadvisor review ratings in my data over time

having at least one Tripadvisor review by time period t.

The coefficient of interest is $\beta_{1,t}$. A statistically significant and positive β_1 shows evidence that Tripadvisor ratings are positively correlated with hotel performance. In a separate specification, I examine the effect of ratings over time by interacting ratings with the dummies indicating a specific 5-year period. These time dummy variables indicate whether t is during the 2000-2004 or 2005-2009 or 2010-2014 or 2015-2019 years.

1.4.2 Results

Table 1.2: Result - Fixed-effect regressions with all hotels

	(1) ln_Occ_jt (I)	(2) ln_Occ_jt (II)	(3) ln_ADR_jt (I)	(4) ln_ADR_jt (II)	(5) ln_RevPAR_jt (I)	(6) ln_RevPAR_jt (II)
Rating	0.028***		0.030***		0.058***	
	(0.007)		(0.005)		(0.008)	
2000-2004 period×*Rating*		0.017**		0.029***		0.046***
		(0.007)		(0.005)		(0.008)
2005-2009 period×*Rating*		0.024***		0.030***		0.054***
		(0.007)		(0.005)		(0.008)
2010-2014 period×*Rating*		0.024***		0.036***		0.060***
		(0.007)		(0.005)		(0.008)
2015-2019 period×*Rating*		0.033***		0.026***		0.058***
		(0.007)		(0.005)		(0.008)
IsReviewed	-0.055**	-0.048*	-0.096***	-0.100***	-0.151***	-0.147***
	(0.027)	(0.027)	(0.018)	(0.018)	(0.032)	(0.032)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
N	173686	173686	173686	173686	173686	173686
Adjusted R-squared	0.58	0.58	0.97	0.97	0.92	0.92

a. Columns indicate the dependent variables in fixed-effect regressions equation(1.1), namely the log of occupancy rate, ADR, and RevPAR.
b. N is the sample size. Each observation is a hotel-year-month.
c. Standard errors are double clustered at market-year-month level and hotel level.
d. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

The estimates of the primary fixed-effect specification in equation (1.1) are presented in Table 1.2. The results reveal a significant positive correlation between all three performance measures and the overall average ratings. However, the occupancy rates demonstrate the smallest correlation, with its regressions displaying a lower adjusted R-squared, suggesting that other factors beyond review ratings (and controls) may influence occupancy rates.

As shown in columns 2, 4, and 6, the coefficients of the 5-year period and rating interactions indicate that there is a significant correlation between hotel performance and ratings and that this correlation has become stronger over time, particularly in the period from 2010-2019. Especially for occupancy rate, the correlation with ratings has been increasingly stronger over the 5-year periods.

Nonetheless, the estimates of the fixed-effect regressions cannot be interpreted as causal because it is possible that review ratings are correlated with other unobservables that are associated with hotel performance but are not captured by the fixed-effect specifications, for example, the unobserved changes in hotel service quality or changes in a hotel's world-of-mouth reputation. Omitting such factors leads to biased estimates of the effects of review ratings.

1.5 Regression Discontinuity Design

1.5.1 Model Specification

To identify the causal impact of review ratings on hotel performance, I adopt a regression discontinuity framework, which utilizes TripAdvisor's rounding system as described in 1.3.2. For example, consider two hotels A and B, with average ratings of 3.24 and 3.25, respectively. TripAdvisor rounds A's rating down to 3 bubbles, while B's is rounded up to 3.5 bubbles. As a result, although A and B have similar underlying ratings, the rounding system increases B's displayed rating by 0.25 and decreases A's displayed rating by 0.24. Because such changes in displayed ratings due to rounding are exogenous and are independent of the underlying perceived quality of the hotel since the average rating of A and B are almost the same. Hence, if there is a difference in the performance of the two hotels, it can be attributed to the 0.5-bubble difference in their Tripadvisor ratings, which is independent of their inherent quality, other things being equal.

The implementation of the regression discontinuity analysis is as the following. First, I restrict the sample to all hotel-year-month observations with a rating less than a bandwidth of 0.10 from the rounding thresholds. I compare the treatment groups (hotel-year-month observations whose rating is rounded up) to the control groups (hotel-year-month observations whose rating is rounded down). Specifically, a binary treatment variable T is defined as

$$T = \begin{cases} 0, \text{if } Rating \text{ is rounded down } (Rating \text{ falls below a rounding threshold}) \\ 1, \text{if } Rating \text{ is rounded up } (Rating \text{ falls above a rounding threshold}) \end{cases}$$

For example, when a hotel-year-month has an average rating of 3.24, then the rating is displayed as 3 bubbles on Tripadvisor such that $T = 0$; Similarly, when a hotel-year-month has an average rating of 3.25, then the rating is displayed as 3.5 bubbles on Tripadvisor such that $T = 1$.

I estimate the average effect of an exogenous 0.5 increase in Tripadvisor ratings on hotel performance while controlling for hotel fixed effect and market-year-month fixed effect. The regression is as the following:

$$y_{jt} = \alpha_t T_{j,t} + \phi_t Rating_{j,t} + h_j + \tau_t \times m_j + \varepsilon_{jt} \tag{1.2}$$

where $y_{j,t}$ is the outcome variable, which is the natural logarithm of each hotel performance measure; $Rating_{j,t}$ is the underlying un-rounded rating for hotel j in year-month t, which is computed as the cumulative average rating; h_j is the hotel fixed effect; $\tau_t \times m_j$ is the market-year-month fixed effect; $\varepsilon_{j,t}$ is an error term.

The coefficient of interest is α_t which indicates the average effect of a 0.5-bubble increase in Tripadvisor displayed rating on performance that is not contributed to the underlying perceived quality of the hotel. The coefficient of the underlying rating ϕ indicates the effect of the average rating that depends on consumers' perceived underlying quality of the hotel. Again, I allow the effect of ratings to change over the years by interacting $T_{j,t}$ and $Rating_{j,t}$ with the 5-year period dummies as a separate specification. I also allow for potential non-linear reactions to rating to control for non-linear reactions to gradual changes in rating.

In my main specification, the sample of hotel-year-month observations is restricted to those that are within 0.1, in terms of the average rating, of a rounding threshold. As robustness checks, I consider alternative bandwidths of 0.12 and 0.15. I demonstrate that the results are not influenced by the choice of bandwidth as shown in the appendix.

1.5.2 Results

Table 1.3 shows the main results of the regression discontinuity design based on a sample of hotel-year-month observations within a 0.1-point radius of a discontinuity. The result shows that Tripadvisor reviews have a causal impact on hotel performance and the impact is larger on revenue. An exogenous 1-point lift in Tripadvisor rating leads to a 1% increase in occupancy rate and 0.4% to 0.6% increase in ADR, and a 1.6% increase in RevPAR, with the effects being more significant for occupancy rate and RevPAR than ADR. The coefficients indicate the effects of a 0.5-point increase in Tripadvisor rating. I scaled them up to the effects of a 1-point increase in Tripadvisor rating for standardization.

The RevPAR effect size found in my study is consistent with the results of prior research on the impact of online reviews on hotels. For instance, Sayfuddin and Chen (2021) investigates the influence of Tripadvisor ratings on revenue for Texas hotels from January 2014 to December 2017 using a regression discontinuity design. They find that a 1-point increase in rating results in a 2.2% rise in monthly revenue with the same bandwidth choice of 0.1 points to rounding thresholds. However, in comparison to similar studies in the restaurant industry (Anderson and Magruder, 2012; Luca, 2011), the effect of Tripadvisor ratings on hotel performance in my data set is weaker. This is not surprising since hotels typically have an alternative official rating of quality, such as "five-star hotels" or "four-star hotels", which categorizes them based on their perceived quality and characteristics. As a result, if two hotels have a similar perceived quality and the same official rating of quality, an exogenous increase in consumer ratings of 0.5-bubble should not significantly improve the performance of one hotel compared to the other. Another explanation for the small effect size observed in my data is that it only captures the effect of consumer ratings on Tripadvisor. It is possible that consumers consult multiple review platforms when selecting hotels. If consumers have already obtained information about a hotel from other online sources before visiting Tripadvisor, the impact of changes in Tripadvisor ratings on their purchasing decisions may be less significant.

Table 1.4 presents the impacts of Tripadvisor ratings by the 5-year periods. The results indicate that the effect of rounding up the rating has grown in significance and magnitude, especially after 2015. During the time between 2015 to 2019, the effect of a 1-point increase in Tripadvisor rating has led to a 2% to 2.2% increase in occupancy rate, an 8%-10% increase in ADR, and a 3% increase in RevPAR.

Figure 2.3 visualizes the effect of rounding up the ratings on occupancy rate and the number of reviews posted on Tripadvisor for the hotels in my sample during each 5-year period. The box plot is based on the estimates of the treatment effects in Table 1.4 column 2. The line plot is the number of reviews posted on Tripadvisor during each 5-year period in my sample. As the volume of reviews increases over time, we can observe a corresponding growth in the impact of rounding up the ratings on the occupancy rate.

Table 1.3: Result - Regression discontinuity average effect (Bandwidth = 0.1)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
T(Round up)	0.005***	0.005***	0.003**	0.002*	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Rating	0.024***	0.071***	0.034***	-0.066***	0.058***	0.005
	(0.004)	(0.023)	(0.002)	(0.014)	(0.004)	(0.026)
$Rating^2$		-0.007**		0.014***		0.008**
		(0.003)		(0.002)		(0.004)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effets	yes	yes	yes	yes	yes	yes
N	30705	30705	30705	30705	30705	30705
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Table uses the sample with ratings within 0.1 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

Table 1.4: Result - Regression discontinuity effect by 5-year periods (Bandwidth = 0.1)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
2000-2004 period×T(Round up)	-0.029*	-0.028*	-0.008	-0.008	-0.037*	-0.036*
	(0.016)	(0.016)	(0.010)	(0.010)	(0.019)	(0.019)
2005-2009 period×T(Round up)	-0.004	-0.004	0.008***	0.008***	0.004	0.004
	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
2010-2014 period×T(Round up)	0.004	0.004	-0.003	-0.003	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
2015-2019 period×T(Round up)	0.010***	0.011***	0.005***	0.004**	0.015***	0.015***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
2000-2004 period ×*Rating*	0.023**	-0.085	0.028***	0.074*	0.051***	-0.011
	(0.011)	(0.070)	(0.007)	(0.044)	(0.012)	(0.081)
2005-2009 period ×*Rating*	0.013***	0.039	0.026***	0.027	0.039***	0.067*
	(0.005)	(0.030)	(0.003)	(0.019)	(0.005)	(0.034)
2010-2014 period ×*Rating*	0.028***	0.170***	0.052***	0.054**	0.079***	0.225***
	(0.005)	(0.042)	(0.003)	(0.027)	(0.006)	(0.048)
2015-2019 period ×*Rating*	0.048***	0.334***	0.034***	-0.373***	0.082***	-0.039
	(0.006)	(0.045)	(0.004)	(0.029)	(0.006)	(0.052)
2000-2004 period× $Rating^2$		0.016		-0.006		0.009
		(0.010)		(0.007)		(0.012)
2005-2009 period× $Rating^2$		-0.004		0.000		-0.004
		(0.004)		(0.003)		(0.005)
2010-2014 period× $Rating^2$		-0.020***		0.000		-0.020***
		(0.006)		(0.004)		(0.007)
2015-2019 period× $Rating^2$		-0.039***		0.056***		0.017**
		(0.006)		(0.004)		(0.007)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
N	30705	30705	30705	30705	30705	30705
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Table uses the sample with ratings within 0.1 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

1.6 Identification

The regression discontinuity methodology hinges on the random assignment of hotels to either side of rounding thresholds. The identification assumption is that as average ratings get closer to rounding thresholds, the predetermined characteristics of hotels that affect performance become more alike. By limiting the sample to hotels with comparable ratings, the performance of hotels that have average ratings rounded up can be compared to the performance of hotels that have average ratings rounded down.

Otherwise, if the entire sample was examined, I could face potential endogeneity problems.

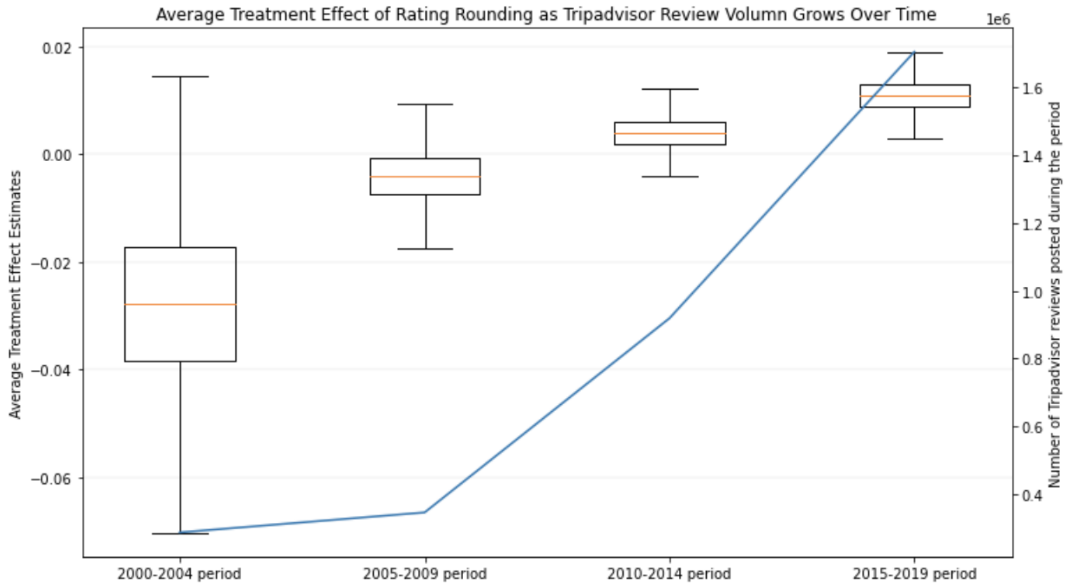

Figure 1.3: The effect of rounding up the ratings on occupancy rate as Tripadvisor review volume grows over time

a. The effect of rounding up is based on the result in Table 1.4 column 2.
b. The review count is based on the Tripadvisor reviews for the hotels in my sample.

For example, hotels with high and low review ratings may differ significantly, and changes in review ratings may be correlated with changes in factors unrelated to Tripadvisor. Hotel demand and revenue could also change due to the changes in other factors that are correlated with changes in review ratings. However, I expect these differences to diminish as the average ratings become increasingly similar.

Thus, in order to establish identification, it is crucial to verify the assumption that any variations not related to Tripadvisor are uncorrelated with the rounding of a hotel's average rating. One potential issue that may undermine this assumption is the manipulation of review ratings. If hotel managers know the rounding of the average rating has a significant impact on sales, they might resort to means to game the system. In fact, review manipulation has been detected on multiple platforms. When it gains prevalence, review manipulation could be detrimental to the credibility of the platform. One example is Mayzlin et al. (2014), where Tripadvisor is found to suffer more from promotional reviews than Expedia.com and independent hotels are more likely to post promotional reviews than branded-chain hotels. This type of behavior could bias the OLS estimates in my analyses if there is a correlation between a firm's performance and the decision to game the system. In the following of this section, I examine the potential sources of misleading outcomes and argue that review manipulation does not create a false correlation between ratings and performance within the regression discontinuity framework.

First, it could be the case that hotels with especially high (or alternatively with especially low) performance are more likely to game the system. However, for the regression discontinuity estimates to be biased, it would have to be the case that these hotels stop manipulating reviews once they get above a certain discontinuity. For example, a hotel would submit inflated reviews to go from a 3.2 rating and stop when it gets to a 3.25 rating. However, if this is the case, the hotel could still get reviews with lower ratings next, which could bring the average rating back down. Therefore, in order to undermine the validity of the regression discontinuity identification, there must be systematic manipulation of the system, not just isolated instances. In other words, hotels must exhibit a specific behavior of increasing their review ratings when the average rating dips below a rounding threshold, and they must cease this manipulation as soon as the threshold is exceeded.

Next, I provide a test from McCrary (2008). The idea is that If hotels were manipulating Tripadvisor ratings in a manner that would influence the regression discontinuity results, I would expect a significantly larger cluster of hotels just above the rounding thresholds in my data. I perform the test as the following. Because the potential review manipulation comes through posting individual reviews. To conduct the test, I begin with data on the hotel-review level, meaning that a hotel with two reviews would have two entries. I then monitor the cumulative average rating after each review. If any gaming had occurred, it would be indicated by a disproportionate number of reviews with cumulative average ratings that approach the rounding thresholds.

To be specific, I count the number of reviews in each 0.05 interval on the 1-to-5 rating scale and calculated the density of reviews within each interval. For instance, in the case of reviews with monitored cumulative average ratings that fall within the interval of [3.25, 3.3],

$$\text{Density of } [3.25, 3.3] = \frac{\text{Number of reviews with monitored cumulative average rating in } [3.25, 3.3]}{\text{Total number of reviews}}$$

Next, I construct a binary variable to indicate intervals that are just above rounding thresholds, for example [3.25, 3.3], [3.75, 3.8]. I run a regression with the density of the rating interval as the dependent variable, and the binary indicator of whether the interval is just above a rounding threshold as the independent variable. That is,

$$\text{Density of rating interval } i = \mathbf{1}\{i \text{ is just above rounding threshold}\} + \omega_i \tag{1.3}$$

where i is a 0.05 interval of ratings, (for example [1, 1.05], [1.05, 1.1]...).

The result of this test is in Table 1.9 in the appendix. The test result indicates that there is no clustering of hotels near the discontinuity, suggesting that the regression discontinuity design is not affected by gaming. Figure 1.6 shows there is no jump in the density of the reviews near the rounding thresholds.

1.6.1 Conclusion

In conclusion, I find Tripadvisor review ratings have a significant positive impact on hotel performance. A 1-point increase in Tripadvisor rating leads to a 0.6% increase in occupancy rate and a 1.6% increase in revenue per available room (RevPAR). The effect has increased over time. The increasing trend is more pronounced in occupancy rate and RevPAR than in ADR.

The regression discontinuity estimates not only help determine the causal impact of Tripadvisor but also shed light on how consumers utilize the platform. First, it highlights that Tripadvisor reviews are becoming a crucial factor in driving hotel demand as consumers are increasingly relying on online reviews for making decisions. It would be interesting to see how hotel managers are responding, for example, whether they react by improving quality or through review manipulation. Furthermore, to which extent their responses depend on the penetration of online reviews.

Second, the average rating on Tripadvisor plays a significant role in consumer behavior, with consumers showing a significant response to changes in the average rating. This indicates that consumers use the rounded rating as a quick and easy reference instead of scrutinizing all the available information. It also suggests that searching for information online is costly for consumers. They may be constrained in terms of attention and therefore opt for the less time-consuming although less detailed rounded rating. It would be interesting to see more empirical evidence on how consumers search and aggregate information on platforms like Tripadvisor and the extent to which their behaviors are affected by the design of the platform.

1.7 Appendices

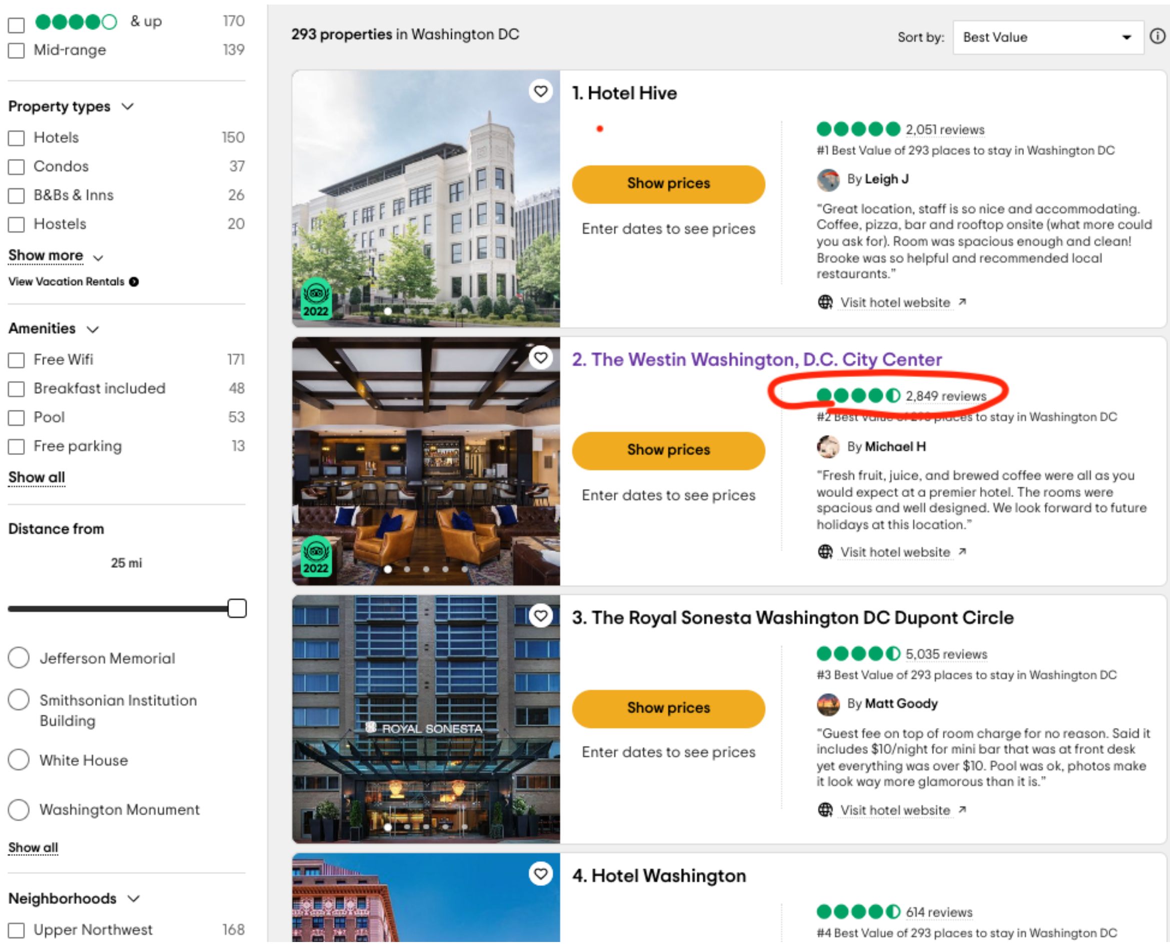

Figure 1.4: Hotel Listings on Tripadvisor

- This picture is shown to users when they search for hotels in a specific destination on Tripadvisor.com.
- The picture is taken in March 2023.

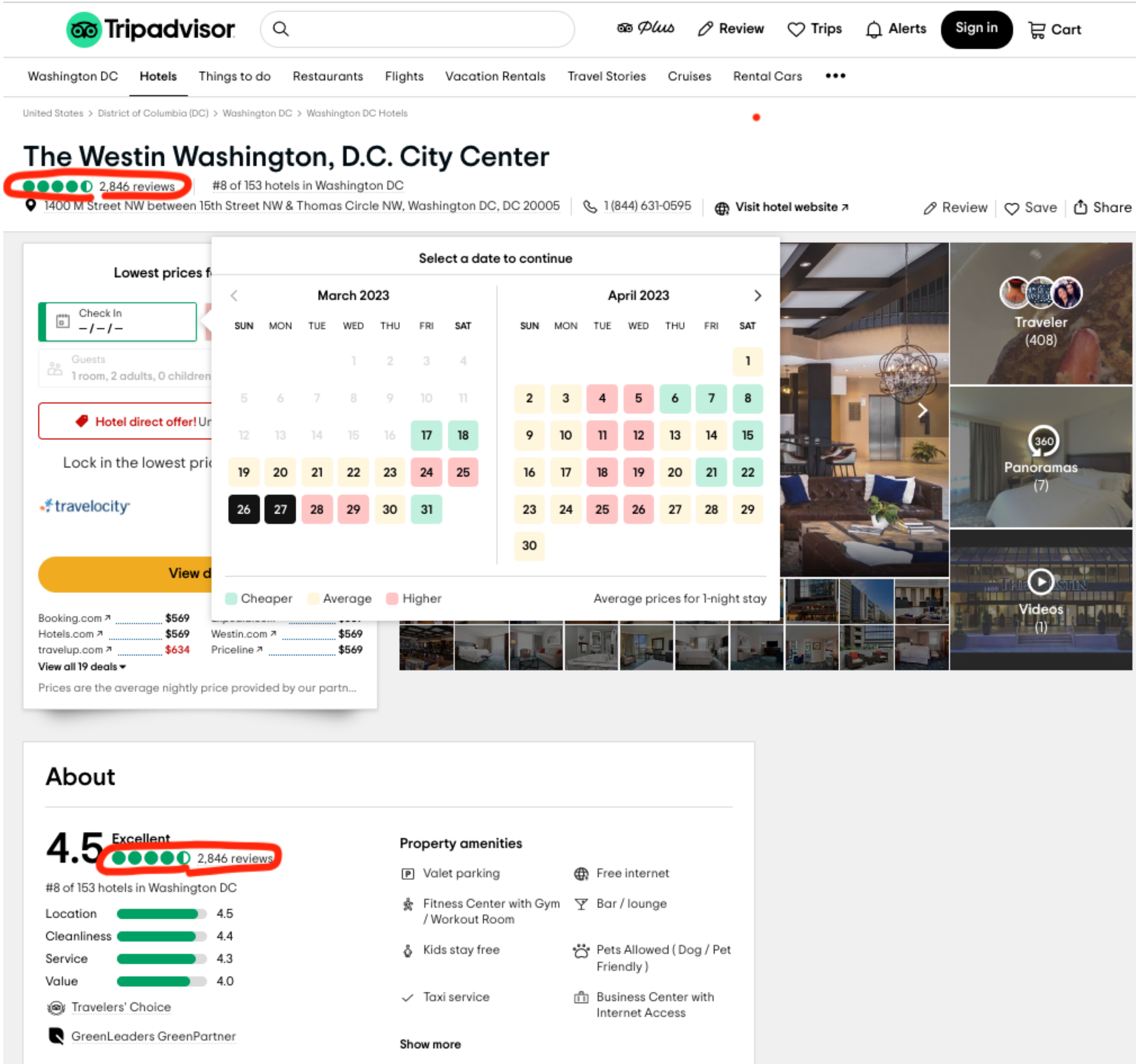

Figure 1.5: Hotel Page on Tripadvisor

- This picture is shown to users when they click open a specific hotel's page on Tripadvisor.
- The picture is taken in March 2023.

Table 1.5: Result - Regression discontinuity average effect (Bandwidth = 0.12)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
T(Round up)	0.003*	0.003**	0.003**	0.002*	0.006***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Rating	0.026***	0.073***	0.033***	-0.083***	0.059***	-0.010
	(0.004)	(0.021)	(0.002)	(0.013)	(0.004)	(0.024)
$Rating^2$		-0.007**		0.017***		0.010***
		(0.003)		(0.002)		(0.003)
hotel-fixed effect	yes	yes	yes	yes	yes	yes
market-year-month fixed effet	yes	yes	yes	yes	yes	yes
N	36618	36618	36618	36618	36618	36618
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Table uses the sample with ratings within 0.12 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

Table 1.6: Result - Regression discontinuity average effect (Bandwidth = 0.15)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
round_up	0.003*	0.003**	0.003***	0.002**	0.005***	0.005**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
accum_rating	0.027***	0.077***	0.028***	-0.095***	0.055***	-0.018
	(0.003)	(0.018)	(0.002)	(0.012)	(0.004)	(0.021)
accum_rating_sq		-0.007***		0.017***		0.010***
		(0.003)		(0.002)		(0.003)
hotel-fixed effect	yes	yes	yes	yes	yes	yes
market-year-month fixed effet	yes	yes	yes	yes	yes	yes
N	46446	46446	46446	46446	46446	46446
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Table uses the sample with ratings within 0.15 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

Table 1.7: Result - Regression discontinuity effect by 5-year periods (Bandwidth = 0.12)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
2000-2004 period×T(Round up)	-0.027*	-0.027*	-0.010	-0.010	-0.038**	-0.037**
	(0.015)	(0.015)	(0.010)	(0.010)	(0.017)	(0.017)
2005-2009 period×T(Round up)	-0.006	-0.005	0.006**	0.005**	0.000	0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
2010-2014 period×T(Round up)	-0.000	0.001	-0.002	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
2015-2019 period×T(Round up)	0.010***	0.011***	0.005***	0.004**	0.015***	0.015***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
2000-2004 period ×*Rating*	0.023**	-0.056	0.029***	0.045	0.052***	-0.011
	(0.010)	(0.066)	(0.006)	(0.042)	(0.011)	(0.076)
2005-2009 period ×*Rating*	0.014***	0.061**	0.024***	0.014	0.038***	0.075**
	(0.004)	(0.028)	(0.003)	(0.018)	(0.005)	(0.032)
2010-2014 period ×*Rating*	0.030***	0.159***	0.051***	0.052**	0.081***	0.211***
	(0.005)	(0.038)	(0.003)	(0.025)	(0.005)	(0.044)
2015-2019 period ×*Rating*	0.055***	0.304***	0.031***	-0.406***	0.085***	-0.103**
	(0.005)	(0.041)	(0.003)	(0.026)	(0.006)	(0.047)
2000-2004 period× $Rating^2$		0.011		-0.002		0.009
		(0.010)		(0.006)		(0.011)
2005-2009 period× $Rating^2$		-0.007*		0.002		-0.005
		(0.004)		(0.003)		(0.005)
2010-2014 period× $Rating^2$		-0.018***		0.000		-0.017***
		(0.005)		(0.003)		(0.006)
2015-2019 period× $Rating^2$		-0.034***		0.060***		0.026***
		(0.006)		(0.004)		(0.006)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
N	36618	36618	36618	36618	36618	36618
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Table uses the sample with ratings within 0.12 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

Table 1.8: Result - Regression discontinuity effect by 5-year periods (Bandwidth = 0.15)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
2000-2004 period×T(Round up)	-0.040***	-0.040***	-0.004	-0.004	-0.044***	-0.044***
	(0.013)	(0.013)	(0.008)	(0.008)	(0.015)	(0.015)
2005-2009 period×T(Round up)	-0.004	-0.004	0.003	0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)
2010-2014 period×T(Round up)	0.001	0.001	0.001	-0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
2015-2019 period×T(Round up)	0.008***	0.009***	0.004***	0.003**	0.012***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
2000-2004 period ×*Rating*	0.043***	-0.036	0.026***	0.023	0.070***	-0.013
	(0.009)	(0.060)	(0.006)	(0.038)	(0.010)	(0.069)
2005-2009 period ×*Rating*	0.012***	0.074***	0.019***	0.004	0.032***	0.078***
	(0.004)	(0.025)	(0.002)	(0.016)	(0.004)	(0.029)
2010-2014 period ×*Rating*	0.029***	0.126***	0.048***	0.021	0.077***	0.147***
	(0.004)	(0.033)	(0.003)	(0.021)	(0.005)	(0.038)
2015-2019 period ×*Rating*	0.051***	0.266***	0.022***	-0.394***	0.073***	-0.128***
	(0.004)	(0.035)	(0.003)	(0.022)	(0.005)	(0.040)
2000-2004 period× $Rating^2$		0.011		0.001		0.012
		(0.009)		(0.006)		(0.010)
2005-2009 period× $Rating^2$		-0.009**		0.003		-0.006
		(0.004)		(0.002)		(0.004)
2010-2014 period× $Rating^2$		-0.013***		0.004		-0.009*
		(0.004)		(0.003)		(0.005)
2015-2019 period× $Rating^2$		-0.029***		0.057***		0.027***
		(0.005)		(0.003)		(0.005)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
N	46446	46446	46446	46446	46446	46446
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Table uses the sample with ratings within 0.15 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

Table 1.9: Result - Test For Clustering Above Rounding Threshold

	density of 0.05-rating interval
1{ interval is just above rounding threshold}	0.008
	(0.006)
N	80
R-squared	0.01

a. Table shows the McCrary (2008) test described in Section 1.6

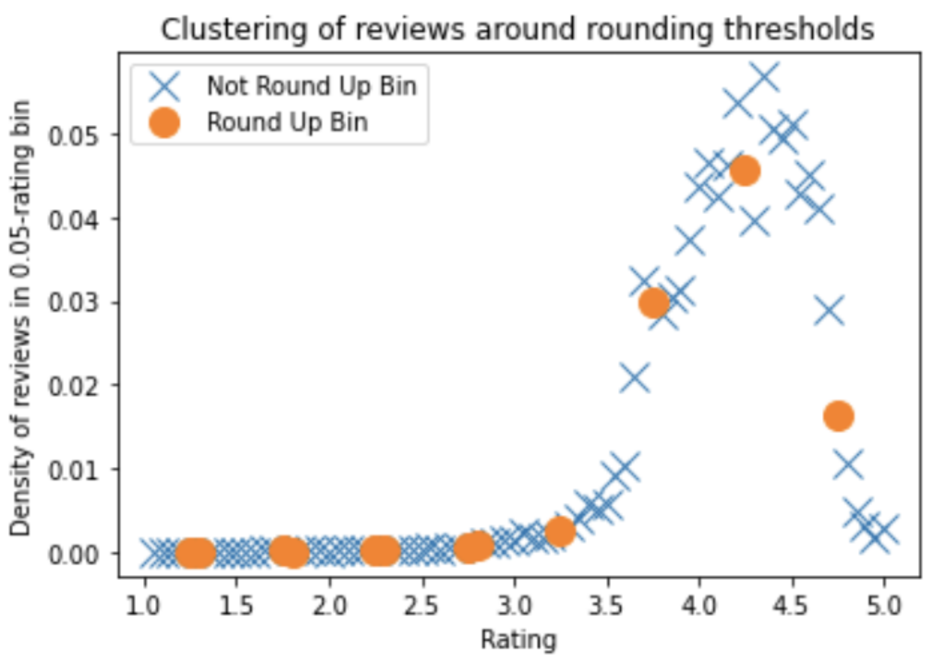

Figure 1.6: This figure shows that there is no bump in the density of reviews in rating bins near the rounding thresholds.

Chapter 2

The Welfare Impact of Tripadvisor Review Ratings: A Case Study of the Hotel Industry

2.1 Introduction

Over the past two decades, the rise of digitalization has brought about a significant transformation in the availability of information for consumers when shopping for experience goods. Online review platforms such as Yelp and Tripadvisor have emerged as prominent sources of information for consumers, allowing them to learn from other people's experiences and reducing the information asymmetry between consumers and firms. With this increased transparency, consumers are empowered to make more informed purchasing decisions. Additionally, online reputation has become a critical factor in the success of firms, as demonstrated in the previous chapter. As online reviews become increasingly prevalent, it is important to comprehend the value of public goods they generate for the economy, particularly in terms of their role in disclosing information about quality in consumer choices. Understanding this role in-depth will form the basis for evaluating the long-run impact of online reputation on the quality prevision of experience goods.

Consumers' purchasing decisions can be influenced by online reviews in two ways. The first way is by providing high-quality information that increases their willingness to pay. According to ComScore and Kelsey[1], more than 75% of consumers are willing to pay at least 20% more for hotel services that have received an "Excellent" comment or a 5-star rating compared to those with a "Good" comment or a 4-star rating. The second way online reviews affect purchase decisions is by providing match information that helps consumers understand the horizontal attributes of products. Since each consumer has different preferences for these attributes, match information enables them to better evaluate the level of compatibility with their requirements.

The focus of this chapter is on the quality of information presented in online reviews, with a particular emphasis on the impact of overall average ratings. Building on the previous chapter's findings, which demonstrated that Tripadvisor ratings have a causal effect on hotel bookings (measured by occupancy rate), this chapter aims to investigate the welfare implications of disclosing information about hotel quality through Tripadvisor review ratings. Specifically, I examine two research questions: (1) How does Tripadvisor review ratings influence consumers' choices of hotels by providing pre-purchase information on quality? and (2) What is the overall effect on welfare as a result of the disclosure of information through Tripadvisor review ratings? In other words, what would be the loss of welfare if Tripadvisor was not present, as opposed to the status quo? To answer these questions, I collected a monthly panel dataset containing hotels' room-night bookings, supplies, and average daily rates, as well as Tripadvisor review ratings from 2000 to 2016. Using this dataset, I estimate a structural model of hotel demand and supply, which accounts for both the imperfect information in consumer choices and hotels' capacity constraints. The structural model enables the quantification of the welfare impact. By simulating the market outcomes in counterfactual scenarios where online reviews were not available, I measure the welfare effect of

[1] https://www.comscore.com/Insights/Press-Releases/2007/11/Online-Consumer-Reviews-Impact-Offline-Purchasing-Behavior

removing online reviews from the status quo in 2016.

The data contains several distinct features that are well-suited to addressing my research questions. Firstly, it includes information on the quantity of room-night bookings and supplies for each property, which facilitates the identification of hotel demand and marginal cost and enables the analysis of the overall welfare that online reviews bring to the market. Secondly, the time span of the data ranges from when Tripadvisor was established as a platform to when it became a major source of travel information, enabling the examination of the effect of online reviews on consumer choices as their popularity grew over time. Thirdly, the panel data nature of the dataset and the available information on hotel characteristics allow for the separation of unobserved time-invariant quality characteristics from the observed ones, facilitating counterfactual experiments in this chapter.

This study provides two main contributions to the existing literature on the impact of online reviews on hotels' welfare. Firstly, it offers structural estimates of hotel demand while considering capacity constraints. Most prior research in the hospitality industry has concentrated on forecasting models. In contrast, this study employs a nested-logit demand model that accounts for consumers' choices in the presence of imperfect information and a supply model that incorporates increasing marginal costs as quantity approaches the capacity constraint. Additionally, both models control for hotel-fixed effects and market-year-month fixed effects. By allowing hotels to adjust markups more realistically in response to demand shocks, this model enhances the accuracy of the welfare estimates.

The structural model confronts the typical identification challenge of price endogeneity. Existing literature typically addresses this challenge by using supply-side instruments to estimate demand, and then using the supply model to recover marginal costs and simulate counterfactuals (Berry, 1994; Nevo, 2001; Lewis and Zervas, 2016). This study adopts an alternative identification approach proposed by MacKay and Miller (2023), which bypasses the challenge of finding explicit instrument variables that need to shift individual hotel's supply on a monthly level. The identification strategy exploits covariance restrictions between demand-side and supply-side structural error terms. Under such restrictions, the price parameter solves a quadratic equation in which the coefficients are functions of observables and the covariance of demand and cost shocks. To identify my supply-side model, I exploit the room-night bookings and supply data by additional moment conditions that require hotels to adjust markup based on competitors' occupancy rates.

The structural model estimates provide the answer to my first research question. I find favorable Tripadvisor ratings result in a significant increase in the number of room nights demanded by consumers, conditional on hotel-fixed effects and market-year-month fixed effects. Specifically, the results show that a 1-point increase in a hotel's rating is associated with a 5.5% rise in demand, measured by room-night bookings. Moreover, the effect of review ratings on hotel demand increased in magnitude and significance from 2000 to 2016, with the coefficients on the interactions between ratings and year periods rising from 2% in 2000-2005 to over 7% in 2011-2016.

Given demand estimates, I test the hypothesis of whether high-quality hotels respond to the effect of review ratings on demand by increasing their prices. If this is true, consumers would choose higher quality hotels less often than they would have without online reviews, decreasing the effect of information disclosure from reviews on consumer choices. The evidence from the data supports this hypothesis. For example, when quality is measured by the average rating as of December 2016 when most hotels have a substantial number of reviews, the average quality of hotels that consumers choose to stay in has decreased from 4.1 to 3.9 [2]. This suggests that consumers were choosing hotels whose quality is slightly below the ones they choose today. My reduced-form analysis on the relationship between prices and review ratings shows a 1-point increase in a hotel's rating is associated with a 1.3% measured by ADR, suggesting high-rated hotels are capturing some of the welfare generated by reviews.

The second contribution of this study is the quantification of the welfare impact of online

[2] I only look at hotels that have reviews in Dec 2016 here, not including those who exited the market before that month.

reviews relative to various alternative sources of pre-purchase information concerning hotel quality, providing insights into theoretical models of discrete choices under imperfect information. The welfare measure distinguishes between the ex-ante utility that consumers experience when making a purchase with limited information and the ex-post utility they experience after the purchase has been completed, as suggested by Train (2015). By introducing exogenous variations in priors about quality into the counterfactuals, this study compares the consumer surplus and overall welfare in 2016 under the existing review ratings and under these hypothetical quality beliefs.

In order to account for the role of prices in consumer decision-making and welfare, two types of price response are considered. The first approach involves keeping prices fixed as observed in the data. The differences in consumer choices solely stem from perceived quality under status-quo review ratings and counterfactual prior beliefs. The second approach posits that prices are adjusted in accordance with Bertrand Nash equilibrium, considering that hotels are subject to capacity constraints.

The welfare analysis results show the removal of review ratings has a negative impact on consumers. Furthermore, when prior knowledge is less accurate, the decrease in consumer surplus is more pronounced. This aligns with the theoretical predictions on consumer decision-making with imperfect information. The per-capita welfare loss ranges from \$0 to \$0.9 when prices are fixed and from \$2.2 to \$5.8 when prices adjust to equilibrium levels in the studied geographic markets. These findings emphasize the importance of review ratings in consumers' decision-making, particularly when pre-purchase information is limited.

The welfare impact for hotels shows hotels with higher quality than expected benefit from review ratings, resulting in increased producer surplus and revenue. Conversely, hotels with lower quality than expected experience the opposite. The net impact of the removal of Tripadvisor review ratings on revenue per room night ranges from -\$1.4 to -\$25.8, depending on pricing scenarios and consumers' prior beliefs about quality.

Overall, Tripadvisor ratings have a positive impact on total welfare when prices are adjusted under the Nash equilibrium. In markets where consumers possess relatively less prior knowledge about hotel quality, such as Miami Beach compared to Houston and Chicago's Central Business District, removing review ratings leads to a greater decline in consumer surplus and a more significant reduction in revenue per room night.

2.2 Literature Review

My study is related to two branches of literature. Firstly, it is linked to previous work on the impact of online reviews on sales through structural demand estimation. For instance, Lewis and Zervas (2016) found that a 1-point increase in a hotel's overall rating results in a 6.5% rise in demand, while Ghose, Ipeirotis, and Li (2009) incorporated textual mining in demand estimation and found that a 1-point increase in rating is linked with a 5% increase in sales. Koulayev (2014) utilized consumers' online search histories for hotels and estimated a nested-logit utility model. However, the study relied on clicking activities as indications of consumer preferences and focused on measuring the bias of price elasticity derived from the choice set generated by the search process, which was limited and subject to endogeneity issues related to preferences. Zhu and Zhang (2006) and Reimers and Waldfogel (2021). However, my demand estimation differs from these earlier studies in that I identify demand using an increasing marginal cost function that takes into account capacity constraints, which is relevant to brick-and-mortar businesses such as hotels and restaurants. These businesses bear an opportunity cost when they sell a unit because it can no longer be sold at a higher price to another customer. Failing to account for such price adjustments could result in unrealistic demand estimates. Similar techniques have also been explored in literature focusing on firms' entry and exit decisions, such as Farronato and Fradkin (2022), Ryan (2012), and Aguirregabiria and Ho (2012).

Second, my study is related to the existing work documenting the welfare effect of pre-purchase information from online platforms. These studies highlight the importance of online reviews and other digital information in shaping consumer behavior and decision-making. Zhang, Li, Cheng, and Lai (2017) develops a theoretical model that considers the impact of quality information and matches the information in online reviews. Their model suggests that while quality information reduces sellers' profits, it significantly enhances consumer welfare, while match information benefits sellers more than it harms consumers. The model also suggests that the inaccuracy of quality information has a negative impact on the welfare enhancement function of review information. Fang (2019) find online review platforms help consumers learn faster about restaurant quality, which leads to effects on restaurant revenues and survival rates. Farronato, Fradkin, Larsen, and Brynjolfsson (2020) study the impact of occupational licensing on a digital platform for residential home services. They find that the platform-verified licensing status of a professional is unimportant for consumer decisions relative to review ratings and prices. Reimers and Waldfogel (2021) compare the relative impacts of professional reviews and Amazon star ratings on consumer welfare in book publishing. They find star ratings on consumer surplus substantially larger than the effect of professional reviews.

An article closely related to my study is Lewis and Zervas (2016). However, there is a significant difference in their approach, as they assume a constant marginal cost and use supply-side moments to identify price coefficients by requiring marginal revenue to be equal in high and low seasons. This approach requires searching for equilibrium outcomes as the solution to the profit maximization problem subject to capacity constraints, which can lead to unstable solutions. Furthermore, my study expands on the counterfactual analysis by examining various scenarios of consumers' prior beliefs, which are dependent on exogenous changes in pre-purchase information available. This approach allows for a more comprehensive analysis of the welfare implications of online reviews in the hotel industry.

2.3 Data

The data utilized in this chapter is sourced from STR and Tripadvisor, which are the same sources used in Chapter 1. The combined data span from January 2000 to December 2016. It covers 513 hotel properties located in Miami Beach, Houston, and the Central Business District of Chicago (abbreviated as Chicago (CBD)), which represents approximately 60% of the total number of properties that were operational in the three geographic markets during the observation period covered by this study. It encompasses information on monthly performance as well as Tripadvisor review ratings. It is important to note that this sample does not incorporate motels, B&Bs, hostels, vocational rentals, Airbnb, or similar entities, They are assumed to be outside goods in this chapter. Any discrepancies between the data in this chapter and that of Chapter 1 are described below.

2.3.1 Data From STR

I received data on 587 hotels included in STR data. The STR data remains comprised of two distinct components. The first component is the monthly data that provides information on the performance of each individual property. The second component is the hotel characteristics data.

In the monthly performance data, in addition to the average occupancy rate, average daily rate (ADR) and revenue per available room (RevPAR), I also observe the total number of room nights sold and supplied in the month.

In the hotel characteristics data, I observe the following characteristics: (1) operation type, which indicates whether a hotel is owned or managed by a chain, a franchise, or an independent; (2) class type, which is an industry categorization which includes chain-affiliated and independent hotels. The class for a chain-affiliated hotel is the same as its chain scale. An independent hotel is assigned a class based on its ADR, relative to that of the chain-affiliated hotels in its geographic proximity. There are six class segments – Luxury, Upper-upscale, Upscale, Upper-midscale, Midscale, and Economy; (3) size type, which categorizes properties by the number of rooms. There are 5 size types – less than 75 rooms, 75-149 rooms, 150-299 rooms, 300-500 rooms, and greater than 500 rooms; (4) Location type, which is a hotel classification driven by the physical location. There are five location types – Urban, Suburban, Airport, Interstate/motorway, Resort, and Small Metro/Town. (6) coded identifiers for chain, owner, management company, and parent company, which can be used to group hotels by affiliated company; and (7) opening year of the hotel, which I use to calculate the hotel age.

There exist certain hotels for which performance data is missing, so I need to clean the data. I dropped any hotels that lack financial data for more than 3 consecutive months. As a result, the data is left with 513 hotels, which represents approximately 60% of the total number of hotels that were operational in the three markets during the observation period covered by this study. For any remaining gaps in the financial data, I leverage the k-nearest neighbor (KNN) algorithm to impute missing values.

KNN algorithm is known to make predictions with high accuracy and is also useful to impute missing values. The intuition is that similar instances are likely to have similar missing values. KNN works by finding the K nearest neighbors to a missing value and taking the average (for continuous variables) or mode (for categorical variables) of the values of those K nearest neighbors to fill in the missing value. In my specific case, the objective is to identify analogous observations using the other non-missing variables and subsequently use the average values of these analogous observations to fill in the gaps. For each geographic market and each month, I use all the available hotel characteristics and non-missing performance data as inputs to the algorithm. I test the algorithm performance by conducting a Kolmogorov-Smirnov test. The imputation process is shown to have no effect on the distributions of variables that contain missing values.

2.3.2 Data From Tripadvisor

Founded in 2000, Tripadvisor has become the largest travel site in the world with over 500 million reviews and 380 million monthly visits by 2017.[3] Consequently, my sample encompasses the entire span of Tripadvisor's existence, from its inception to its peak. I obtained all historical reviews for every hotel located within the three geographic markets by scraping data from the Tripadvisor website. Each review is rated using an integer scale of 1 to 5. For each hotel, I aggregated the individual review ratings to compute the average rating for each month, and subsequently calculated the cumulative average review ratings and review counts.

2.3.3 Summary Statistics

In a similar fashion to Chapter 1, I combined the STR data with Tripadvisor data, utilizing the hotel characteristics and detailed webpage information to effectuate the merging process.[4] The final dataset has 67,670 hotel-year-month observations with performance and review rating information. Within the STR data, there exist 35 hotels that do not match any listings on Tripadvisor. Figure 2.1 shows the total number of reviews and the average monthly review ratings on Tripadvisor in my sample.

In order to simplify the analysis without losing insights, I collapsed the 6 class segments offered by STR into three class groups. Specifically, I mapped the "Luxury" classification in STR to the Luxury group; the "Upper Upscale" and "Upscale" classifications in STR to the Upscale group; and the "Upper Midscale", "Midscale", and "Economy" classifications in STR to the Midscale/Economy group.

Table 2.1 provides a summary of the statistics for my sample. Of note, Houston is the most sizable market, with around 60% of the hotels in the sample being located there. Despite

[3] https://ir.tripadvisor.com/static-files/2a890757-de48-49b1-a564-dc7d914eed15

[4] Certain pieces of information, such as the hotel name, zip code, and the exact number of rooms listed on Tripadvisor, were removed post-merging in order to safeguard the identity of the hotels.

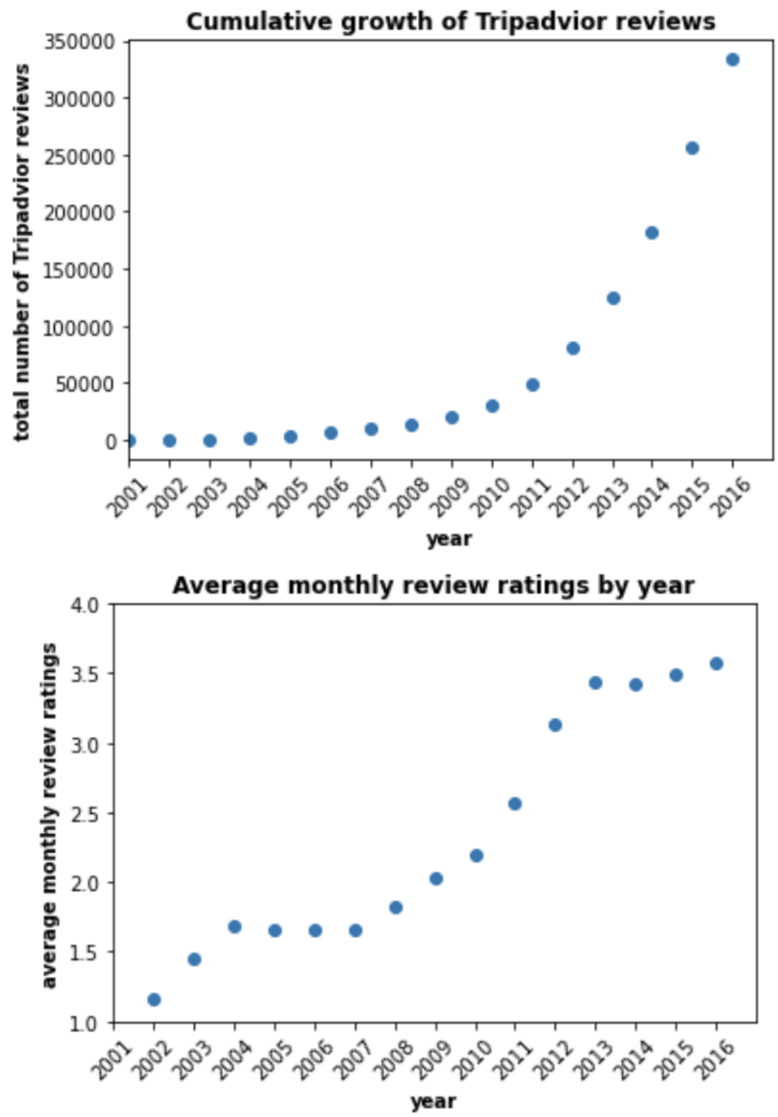

Figure 2.1: Tripadvisor review count (cumulative) and average ratings (monthly) over time

this, Houston only accounts for 24% of the reviews.

Ownership type and class vary across markets. For instance, 68.2% of the hotels in Miami Beach are independent, whereas only 2.6% of hotels in Houston are independent. In contrast, 71.1% of the hotels in Houston are franchises. Additionally, the percentage of chain-operated hotels in Chicago (CBD) exceeds that of Houston and Miami Beach. In terms of class, Houston has a significantly larger proportion of Midscale/Economy hotels, with 61.7% compared to 21.7% and 24.7% in Chicago (CBD) and Miami Beach, respectively. Furthermore, the capacity of the hotels varies depending on the market and class. On average, luxury hotels in Chicago (CBD) are larger compared to those in the other two markets. On the other hand, Midscale/Economy hotels tend to be smaller, with 90% of them having less than 150 rooms.

Table 2.1: Summary Statistics

		Chicago (CBD)	Houston	Miami Beach	All Markets
Number of reviews		209,550	100,456	112,850	422,856
Number of hotels on Tripadvisor		120	287	71	478
Number of hotels not on Tripadvisor		0	21	14	35
Number of hotel-month observations		16,312	43,865	7,493	67,670
Average hotel age by 2016		37	20	43	27
Average price (ADR)		$168.4	$89.5	$224.8	$123.4
% of hotels by Operation	*Chain*	35.0%	26.3%	15.3%	26.5%
	Franchise	45.0%	71.1%	16.5%	55.9%
	Independent	20.0%	2.6%	68.2%	17.6%
% of hotels by Class					
	Luxury	14.2%	2.3%	27.1%	8.8%
	Upscale	64.1%	36%	48.2%	44.6%
	Midscale/Economy	21.7%	61.7%	24.7%	46.6%
Average price (ADR) by Class					
	Luxury	$279.9	$222.2	$374.6	$308.9
	Upscale	$162	$117.7	$182.6	$143.1
	Midscale/Economy	$123.1	$68.5	$105.5	$76.7
Distribution of occupancy rate (%)					
	mean	72.2%	66.8%	72.5%	68.7%
	std	16.7%	15.7%	15.6%	16.1%
	min	1.8%	0.6%	5.4%	0.6%
	10 percentile	47.7%	45.7%	50.1%	46.6%
	25 percentile	61.9%	60%	63.8%	58.6%
	50 percentile	76.3%	68.3%	75.3%	70.8%
	75 percentile	85.1%	78.5%	84%	81.1%
	90 percentile	90.1%	85.9%	89.7%	87.9%
	max	100%	100%	100%	100%
Luxury count by size					
	75 rooms	1	0	5	6
	75-149 rooms	1	1	4	6
	150-299 rooms	4	3	7	14
	300-500 rooms	8	2	3	13
	500+ rooms	3	1	2	6
Upscale count by size					
	75 rooms	6	5	19	30
	75-149 rooms	11	43	13	67
	150-299 rooms	24	37	8	69
	300-500 rooms	25	20	1	46
	500+ rooms	11	6	0	17
Midscale/Economy count by size					
	75 rooms	3	66	15	84
	75-149 rooms	11	114	7	132
	150-299 rooms	11	9	1	21
	300-500 rooms	0	1	0	1
	500+ rooms	1	0	0	1

a. Classes are grouped based on the class segments provided by STR. Luxury is mapped with "Luxury" in STR; Upscale is mapped with "Upper Upscale" and "Upscale" in STR; Midscale and Economy are mapped with "Upper Midscale", "Midscale", and "Economy" in STR.

2.4 Theory: Pre-purchase Information and Consumer Welfare

Pre-purchase information is important for consumer choices of experienced goods because consumers are usually imperfectly informed about the true value of products when making decisions. The gap between the perceived attributes and the real attributes leads to the difference between ex-ante expected utility and ex-post realized utility. Pre-purchase information would be beneficial to consumers if it can help close this gap. This section illustrates a theory model as in Jin and Sorensen (2006) and Train (2015), and Reimers and Waldfogel (2021).

Consider an aggregated demand curve for a single product as shown in Figure 2.2. The

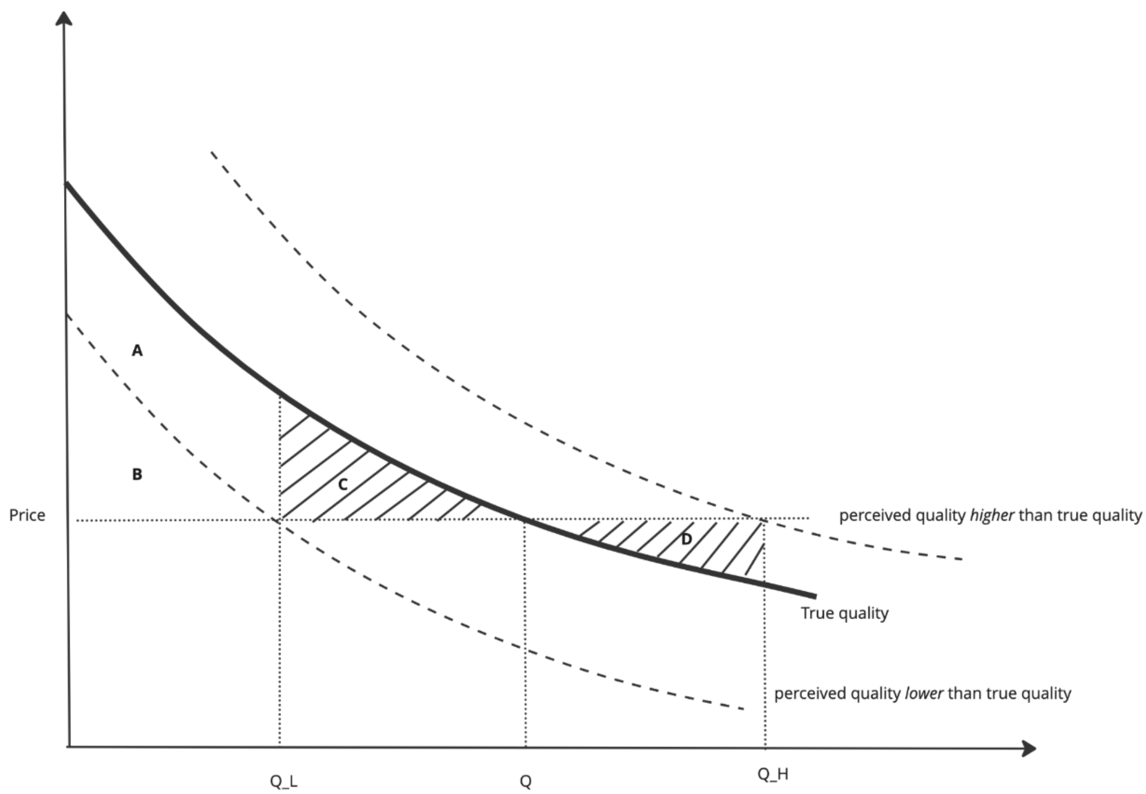

Figure 2.2: Ex-ante vs. Ex-post Utility and Consumer Welfare

solid line is the actual demand curve based on the true quality. When consumers' perceived quality is lower than the true quality, the ex-ante aggregate demand curve is the dashed line below the solid line. In this case, the quantity Q_L is less than the quantity under perfect information, which is Q. Because consumers would get ex-post utility given by the actual demand curve, the consumer surplus is the area $A + B + C$ under perfect information, but only $A + B$ when consumers expect the product quality to be less than what it truly is. The welfare loss from imperfect information is area C. In another case, when consumers' perceived quality is higher than the true quality, the ex-ante aggregate demand curve is the dashed line above the solid line and the. The quantity Q_H is larger than the quantity under perfect information, which is Q. Thus consumer surplus is the area $A + B + C$ less the area D. The welfare loss from imperfect information is area D. Pre-purchase information is valuable if it brings the ex-ante aggregated demand curve closer to the actual demand curve. In section 2.8.3, I conduct counterfactuals with different priors about quality and show how prior precision affects welfare.

The model only considers a single product, but the overall market welfare also depends on substitution among products. Consumers either buy too much of the "good" products or too little of the "bad" products. If the over-consumption of the "good" products exactly offsets the under-consumption of the "bad" products, the welfare effects would purely come from misallocation. Depending on whether the over-consumption of "good" products over-weighs the under-consumption of the "bad" products, there would be market expansion or shrinkage.

In the case of hotels, capacity constraints complicate the welfare effect of misallocation or market expansion further. The gain in market share for the "good" hotels is limited by their capacity. Moreover, the model does not account for price responses. If the "good" hotels gain market power to raise the price too high, there would be a negative effect on consumer surplus. In the proceeding section, I estimate a structural model which allows endogenous price changes and capacity constraints.

2.5 Hotel Demand

In order to model demand, I employed a one-level nested logit system. Within each market, consumers initially determine whether or not to make a hotel reservation and, if they decide to do so, choose a particular class group. Once the class group has been chosen, the consumer then proceeds to book a hotel within that group. The class groups utilized in this model are defined in Section 2.3.3, namely Luxury, Upscale, and Midscale/Economy. The utility consumer i gets from choosing hotel j in market m in time period t is given by

$$u_{i,j,t} = \alpha p_{j,t} + \gamma_{j,t} + \zeta_{i,g_{j\in G},t} + (1-\sigma)\epsilon_{i,j,t} \tag{2.1}$$

where t is the year-month time period; p_{jt} is price measured by the average ADR in the month; $\gamma_{j,t}$ captures the hotel's quality as described below; $\epsilon_{i,j,t}$ is distributed i.i.d extreme value type 1. $\zeta_{i,g_{j\in G},t}$ is the utility consumer i gets from the class g of hotel j or outside good. It is common to all hotels in the class $g \in G = \{\text{Luxury}, \text{Upscale}, \text{Midscale/Economy}, 0\}$. The outside good is the only product in group 0. Parameter $\sigma \in [0, 1)$ determines within class group correlations of utility levels. As σ approaches to zero, the within-group correlations of utility levels go to zero, and the model collapses to a standard logit system.

I assume that the consumers do not know the quality of the hotel but form their expectations based on a set of pre-purchase information $\mathbf{\Omega_{j,t}}$. I refer to this term as "perceived quality" and model it to take the following linear form:

$$\begin{aligned} E[\gamma_{j,t}|\mathbf{\Omega_{j,t}}] = {} & \phi_{1,t}(rating_{j,t} \times \mathbf{1}\{IsReviewed_{j,t}\}) \\ & + \phi_2 \mathbf{1}\{IsReviewed_{j,t}\} \\ & + h_j + \tau_t \times m_j + \xi_{j,t} \end{aligned} \tag{2.2}$$

where $rating$ is the cumulative average rating for hotel j by time period t; $\mathbf{1}\{IsReviewed_{j,t}\}$ is a dummy variable that indicates whether the hotel has been reviewed by time period t; h_j is the hotel-fixed effect, which controls for the time-invariant hotel-level quality; $\tau_t \times m_j$ is the market-year-month fixed effect, which controls for unobserved demand shocks (such as seasonal demand variation and time trends) contemporaneously affecting all hotels within a specific market; $\xi_{j,t}$ is a scalar latent variable, which captures other unobservable information about quality, for example, the change in consumers' perception of a brand or other word-of-mouth information.

The coefficients $\phi_{1,t}$ serve to capture the influence of review ratings on the perceived quality of the hotel, and are allowed to vary over time. This can be achieved through the implementation of a Bayesian model with Gaussian priors and signals, where the conditional variance in average ratings given quality decreases over time, resulting in consumers placing more significant emphasis on ratings over time. The coefficient ϕ_2 captures the effect of the presence of Tripadvisor reviews, which I assume is time-invariant.

Consumers maximize expected utility:

$$E[u_{i,j,t}|p_{j,t}, \mathbf{\Omega_{j,t}}, \zeta_{i,g_{j\in G},t}, \epsilon_{i,j,t}] = \alpha p_{j,t} + E[\gamma_{j,t}|\mathbf{\Omega_{j,t}}] + \zeta_{i,g_{j\in G},t} + (1-\sigma)\epsilon_{i,j,t}$$

The mean utility before the realization of $\zeta_{i,g_{j\in G},t} + (1-\sigma)\epsilon_{i,j,t}$ is denoted as $\delta_{j,t}$, which gets the following linear-form specification:

$$\begin{aligned} \delta_{j,t} &= \alpha p_{j,t} + E[\gamma_{j,t}|\mathbf{\Omega_{j,t}}] \\ &= \alpha p_{j,t} + E[\gamma_{j,t}|\{rating_{j,t,}, \mathbf{1}\{IsReviewed_{j,t}\}, h_j, \tau_t \times m_j, \xi_{j,t}\}] \end{aligned} \tag{2.3}$$

where the second line is the linear-form specification defined by equation (2.2).

In the nested logit demand system, the mean utility $\delta_{j,t}$ can be calculated in terms of market shares as the following

$$\delta_{j,t} = ln(s_{j,t}) - \sigma ln(s_{j,t|g_j\in G}) - ln(s_0) \tag{2.4}$$

where $s_{j,t}$ is the market share of hotel j in time period t, $s_{j,t|g_j\in G}$ is the market share of hotel j within the class group g_j in time period t, and $s_{0,t|g_j\in G}$ is the market share of hotels in classes other than g_j in time period t. They are defined as the following

$$s_{j,t} = \frac{q_{j,t}}{M_{m_j}}$$

$$s_{j,t|g_j \in G} = \frac{q_{j,t}}{Q_{g_j \in G,t}}$$

$$s_{0,t} = 1 - \frac{\Sigma_G Q_{g_j \in G,t}}{M_{m_j}}$$

where $q_{j,t}$ is the number of room-nights sold by hotel j in time period t, which is observed in my data; M_{m_j} is the market size that hotel j operates in, which is measured by the maximum number of room nights supplied by all the hotels in the market across all time periods in my data; and $Q_{g_j \in G,t}$ is the total number of room nights sold by hotel class g_j in market m during time period t, which is defined as $Q_{g_j \in G,t} = \Sigma_{k \in g_j} q_{k,t}$. As shown in Berry (1994), hotel j's market share in time period t is

$$s_{j,t} = \frac{e^{\delta_{j,t}/(1-\sigma)}}{D^{\sigma}_{g_j,t}[1 + \Sigma_G D^{1-\sigma}_{g_j,t}]} \tag{2.5}$$

where $D_{g_j,t} = \Sigma_{k \in g_j} e^{\delta_{k,t}/(1-\sigma)}$. Moreover, the elasticity of demand can be expressed as the following

$$\epsilon_{j,t} = \alpha p_{j,t}\left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} s_{j,t|g_j \in G} - s_{j,t}\right) \tag{2.6}$$

2.6 Hotel Supply

Each hotel competes with other hotels of the same class and hotels of different classes. I assume that the competition takes the form of a Bertrand Nash equilibrium.

One feature of the hotel industry is that hotels frequently confront capacity constraints. To optimize profit within the constraints of available rooms, hoteliers commonly employ strategies like revenue management or dynamic pricing, which take into account their inventory as well as sales forecast. For example, Farronato and Fradkin (2022) utilized the average daily prices and sales in hotel segments to demonstrate that prices exhibit a sharp increase as the number of rooms sold approaches the number of rooms available in the segment. One reason for this pricing pattern is akin to the dynamic pricing strategies adopted in the airline industry. Hortaçsu, Oery, and Williams (2022) shows airlines bear an opportunity cost when they sell a seat as it can no longer be sold at a higher price to another passenger. Thus, all else equal, greater demand generates higher marginal costs, inclusive of the opportunity cost. Hoteliers also face uncertainty about the actual level of demand when setting prices, increases in expected demand will increase the probability of hitting capacity constraints, thus increasing prices before realized demand reaches 100%.

I do not observe daily prices and bookings, only the monthly average ADR and monthly room nights sold by each hotel. Although identifying such a pricing pattern using monthly-level data is challenging, on average, hotels experience higher ADR during the month when they have a higher occupancy rate. This finding is supported by Figure 2.5 in the appendix, which illustrates the relationship between the deviation of the monthly occupancy rate and ADR from the yearly average price of the hotel and the deviation from the yearly average occupancy rate of the hotel. In addition, as Table 2.1 demonstrates, roughly 10% of the hotel-year-month observations in my dataset exhibit occupancy rates exceeding 88%, and there are some observations that achieve 100% occupancy rate. This outcome implies that my supply-side model needs to consider how prices increase as occupancy rates approach binding capacity constraints.

I adopt a similar approach as Farronato and Fradkin (2022) by estimating a marginal cost function that includes a constant term and an increasing term, which is triggered as soon as the hotel occupancy reaches at least 88%. The estimation of increasing marginal costs as production approaches capacity constraints was previously used by Fowlie, Reguant, and Ryan (2016) to estimate the cost structure of the cement industry.

Specifically, I assume the marginal cost for hotel j to take the following form:

$$\begin{aligned} c_{j,t} &= c_j + \mathbb{1}\{Occ_{j,t} > 0.88\} c_2 (q_{j,t} - \overline{q_j^{0.88}}) \\ &+ \tau_t \times m_j + \omega_{j,t} \end{aligned} \tag{2.7}$$

where $Occ_{j,t}$ is the average occupancy rate in time period t in fraction form[5]; $\overline{q_j^{0.88}}$ is the room nights sold by hotel j when its occupancy rate is 88%; $\tau_t \times m_j$ is the market-year-month fixed effect, and $\omega_{j,t}$ is the structural error, which is driven by the unobserved supply shocks. Under nested-Logit demand, the first-order condition for firms' profit maximization problem is the following:

$$c_{j,t} = p_{j,t} + \frac{s_{j,t}}{\frac{\partial s_{j,t}}{\partial p_{j,t}}} = p_{j,t} + \frac{1}{\alpha(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} s_{j,t|g_j \in G} - s_{j,t})} \tag{2.8}$$

2.7 Empirical Strategy

I use a three-step approach to estimate the demand and supply of hotels. In the first step, I estimate σ, the within-group correlations of utility levels, by regress $ln(s_{j,t}) - ln(s_{0,t})$ on $ln(s_{j,t|g_j \in G})$. The estimate $\hat{\sigma}$ is 0.54. In the second step, I estimate the price coefficient α in equation (2.3) and the increasing marginal cost in equation (2.7) by imposing covariance restriction on unobserved demand and cost shocks as MacKay and Miller (2023). In the third step, I use equation (2.3) and equation (2.4) and the estimates of α and σ to estimate the remaining coefficients in the demand model.

2.7.1 Within-group Share Endogeneity

In order to identify σ through the regression of $ln(s_{j,t}) - ln(s_{0,t})$ on $ln(s_{j,t|g_j \in G})$, it is necessary to understand the relationship between the number of hotels in each hotel class group and the corresponding share of the group. While seasonality in the hotel market is well-known, it is difficult to adjust for entry and exit based on seasonal demand for established hotels, and such a pattern was not observed in my data. Specifically, the number of operating hotels remained constant from the low season to the high season, conditional on the year.

To instrument for hotels' shares $s_{j,t|g_j \in G}$ within the class group, I explore the cross-sectional

[5] The occupancy rate in the data is percentages, for example, 88%. I translated it into fractions, for example, 0.88.

variations in the number of hotels available in each class group. Specifically, I use the number of hotels by ownership type within the class group for each hotel month[6]. Adopting the logic of BLP-type instruments, I also included terms involving the other hotels in the group, including the average age of other hotels in the group and the number of other hotels by size type in the group[7]. There are a total number of 8 instruments.

The results of the 2SLS estimation of σ are shown in Table 2.2.

Table 2.2: Result - within class-group correlations of utilities

	Second Stage	First Stage
$ln(s_{j,t\|g_j \in G})$	0.540***	
	(0.004)	
Number of Chain hotels in group		0.004*
		(0.003)
Number of Franchised hotels in group		0.031***
		(0.003)
Number of Independent hotels in group		-0.007***
		(0.002)
Average other hotel age in group		-0.008***
		(0.001)
Number of other hotels in group (less than 75 rooms)		-0.021***
		(0.003)
Number of other hotels in group (75-149 rooms)		-0.050***
		(0.003)
Number of other hotels in group (150-299 rooms)		-0.053***
		(0.002)
Number of other hotels in group (300-500 rooms)		-0.073***
		(0.004)
constant	-2.738***	-2.068***
	(0.019)	(0.024)
N	67,670	67,670
Adjusted R-squared	0.19	0.60

a. The dependent variable in the second stage is $ln(s_{j,t}) - ln(s_{0,t})$.

b. Groups are the class groups defined by the nested-logit demand model. There are three groups, i.e. Luxury, Upscale, and Midscale/Economy.

c. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

2.7.2 Price Endogeneity and Marginal Cost

In the hotel industry, the ability of hoteliers to adjust room rates based on both the uncertainty of demand and capacity constraints presents a challenge when attempting to identify demand and supply. This challenge is compounded in settings with imperfect competition,

[6]There are three ownership types, i.e. chain, franchised, and independent.

[7]There are 5 size groups, and I included 4 groups in my instruments.

where the endogeneity of prices results in an upward-sloping supply. As a result, the empirical relationship between prices and quantities does not represent a demand curve but rather a mixture of demand and supply. Researchers typically address this challenge by using supply-side instruments to estimate demand and subsequently leveraging the supply model to recover marginal costs and simulate counterfactuals. This approach is discussed in detail in Berry and Haile (2016).

There are two types of commonly used instruments in the literature, namely Hausman-type and BLP-type. Hausman-type instruments serve as proxies for marginal costs or other excluded cost shifters, while BLP-type instruments serve as the excluded shifters of firm markups. However, both types of instruments are challenging to identify in my setting. Firstly, Hausman-type instruments are difficult to apply because most variations in hotel prices are driven by correlated demand shocks. Since I control for market-year-month fixed effects in equation (2.3), valid cost instruments should shift individual hotels' marginal costs within a market time period. Unfortunately, such instruments are difficult to find. Secondly, common BLP-type instruments are based on the characteristics of competitors, but they do not vary significantly at the market-year-month level in my sample. Similar challenges were also encountered in Lewis and Zervas (2016) and Koulayev (2014).

In Lewis and Zervas (2016), the assumption of constant marginal cost is made, and the coefficient of price is estimated by enforcing a set of supply-side moments that require marginal revenues to be equal across the high and low seasons. However, this approach fails to account for the fact that hotel prices are typically higher during high seasons than during low seasons. In contrast, Koulayev (2014) sets on estimating demand by adding a rich set of controls.

I follow an approach developed in MacKay and Miller (2023) which exploits covariance restrictions between demand-side and supply-side structural error terms. The core intuition of their approach is that the supply side of the model dictates how prices respond to demand shocks, shaping the relative variation of quantities and prices in the data. As long as the supply-side model is identified, adding the covariance restriction exploits all of the price variations.

Specifically, I impose the following covariance restriction:

$$Cov(\xi_{j,t}, \omega_{j,t}) = 0 \tag{2.9}$$

where $\xi_{j,t}$ is the unobserved demand shocks in equation (2.2) and $\omega_{j,t}$ is the unobserved supply shocks in marginal cost function (2.7).

According to the corollary 1 in MacKay and Miller (2023), under this assumption and the function form of marginal cost as equation (2.7), the price coefficient α solves a quadratic equation as the following:

$$\begin{aligned} 0 = &(1 - \frac{Cov(p^*, g(q;c))}{Var(p^*)})\alpha^2 \\ &+ \left(\frac{Cov(p^*, \lambda)}{Var(p^*)} - \alpha^{OLS} + \alpha^{OLS}\frac{Cov(p^*, g(q;c))}{Var(p^*)} + \frac{Cov(\xi^{OLS}, g(q;c))}{Var(p^*)}\right)\alpha \\ &+ \left(-\alpha^{OLS}\frac{Cov(p^*, \lambda)}{Var(p^*)} - \frac{Cov(\xi^{OLS}, \lambda)}{Var(p^*)}\right) \end{aligned} \tag{2.10}$$

I compute the relevant components in this equation as the following:

The vector p^* are the residuals of a regression of prices p on the covariates in the demand specification, including the review ratings, full set of dummy variables for hotels, and market-time-month dummies. I follow MacKay and Miller (2023) to denote these covariates as matrix $\tilde{X}$. Therefore,

$$p^* = p - \tilde{X}[\tilde{X}'\tilde{X}]^{-1}[\tilde{X}'p] \tag{2.11}$$

MacKay and Miller (2023) shows the probability limit ($T \to \infty$) of the OLS estimate of α obtained from a regression of the mean utility δ on p and $\tilde{X}$ is

$$\alpha^{OLS} = \alpha - \frac{1}{\alpha}\frac{Cov(\xi, \lambda)}{Var(p^*)} + \frac{Cov(\xi, , g(q;c))}{Var(p^*)} + \frac{Cov(\xi, , \omega)}{Var(p^*)} \tag{2.12}$$

The corresponding OLS residuals are given by ξ^{OLS}.

λ comes from the first-order condition of the profit-maximization problem. In MacKay and

Miller (2023), it is defined by the markups. In my case, λ comes from equation (2.8) and it is defined as

$$\lambda_{j,t} \equiv \frac{1}{\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma} s_{j,t|g_j \in G} - s_{j,t}} \tag{2.13}$$

The vector $g(q;c)$ denotes the increasing marginal cost function, which depends on quantity and the cost parameters. It corresponds to my model as the following:

$$g(q_{j,t}; c_2) \equiv \mathbb{1}\{Occ_{j,t} > 0.88\} c_2 (q_{j,t} - \overline{q_j^{0.88}}) \tag{2.14}$$

where the right-hand side is defined by the marginal cost function in equation (2.7). In order to solve α via equation (2.10), I need to identify c_2 in the increasing marginal cost function. I adopt an instrument for $g(q_{j,t}; c_2)$, which assumes hoteliers know the overall occupancy rate of other hotels within the class group. The instrument is defined as the following:

$$z_{j,t} \equiv \frac{Q_{g_j \in G,t} - q_{j,t}}{S_{g_j \in G,t} - s_{j,t}} \tag{2.15}$$

where $Q_{g_j \in G,t}$ and $S_{g_j \in G,t}$ are the total number of room nights sold and supplied by the class group; $q_{j,t}$ and $s_{j,t}$ are the number of room nights sold and supplied by hotel j in time period t. I observe both bookings and room nights supplied in the data.

The intuition behind this instrument is that hoteliers set prices while monitoring the performance of competitors. When the occupancy rate of competitors in the same class group is high, there is a greater likelihood that the hotel will reach capacity constraints. However, the occupancy of competitors is not directly correlated with the marginal cost of the hotel. Formally, the instrument requires the following supply-side moment condition:

$$E[\omega_{j,t} z_{j,t}] = 0 \tag{2.16}$$

Because both my demand and marginal cost models control for hotel and market-year-month fixed effects, in practice, I translate equation (2.16) to the following moment condition using equation (2.7) and equation (2.8):

$$E\left[\left(p_{j,t} + \frac{\lambda_{j,t}}{\alpha} - g(q_{j,t}; c_2)\right) z_{j,t}\right] = 0 \tag{2.17}$$

I estimated the coefficients α and c_2 using the moment conditions given in equations (2.10) and (2.17). The resulting estimates were $\hat{\alpha} = -0.012$ and $\hat{c_2} = 0.08$, with standard errors of 0.003 and 0.002, respectively. To obtain these standard errors, I used bootstrapping, generating 500 random samples by drawing 90% of the observations from the data with replacement.

Given that the average price (measured by ADR) in the data is around $123 per room night, and market shares are small, the estimate of $\hat{\alpha} = -0.012$ suggests that the average elasticity is around -1.5. This result is consistent with the findings of Lewis and Zervas (2016) and is in line with the long-run elasticity of demand in the hospitality industry Corgel, Lane, and Woodworth (2012).

I estimate the remaining fixed effects in the marginal cost function using the first-order condition equation (2.8) with the estimates $\hat{\sigma}$, $\hat{\alpha}$, and $\hat{c_2}$ as the following:

$$p_{j,t} + \frac{1}{\hat{\alpha}(\frac{1}{1-\hat{\sigma}} - \frac{\hat{\sigma}}{1-\hat{\sigma}} s_{j,t|g_j \in G} - s_{j,t})} - \mathbb{1}\{Occ_{j,t} > 0.88\}\hat{c_2}(q_{j,t} - \overline{q_j^{0.88}}) \\ = c_j + \tau_t \times m_j + \omega_{j,t} \tag{2.18}$$

2.7.3 The effect of Tripadvisor ratings on demand

Given the estimates $\hat{\sigma}$ and $\hat{\alpha}$, I can re-write the expected quality by re-arranging eq(2.3) and eq(2.4) and get the following regression:

$$\begin{aligned} Q_{j,t} &= \phi_{1,t}(rating_{j,t} \times \mathbf{1}\{IsReviewed_{j,t}\}) \\ &+ \phi_2 \mathbf{1}\{IsReviewed_{j,t}\} \\ &+ h_j + \tau_t \times m_j + \tilde{\xi_{j,t}} \end{aligned} \tag{2.19}$$

where $Q_{j,t} \equiv ln(s_{j,t}) - \hat{\sigma} ln(s_{j,t|g_j \in G}) - ln(s_0) - \hat{\alpha} p_{j,t}$ which I refer as the "adjusted quality"; $\tilde{\xi_{j,t}}$ is a structural error, which represents the time-varying component affecting consumers' expected quality that is not attributed to review ratings. The parameters of interest are $\phi_{1,t}$, which captures the effect of Tripadvisor ratings on expected quality. I allow the effect to vary with the time periods defined by years. There are three periods – the 2000-2005 period, the 2006-2010 period, and the 2011-2016 period.

For this regression, a key concern is the endogeneity of review ratings. If consumers base their quality perceptions on word-of-mouth information, which is reflected in $\tilde{\xi_{j,t}}$, then there may be a correlation between review ratings and $\tilde{\xi_{j,t}}$, potentially leading to positive estimates of $\phi_{1,t}$ even if review ratings have no real impact on demand. To address this concern, I provide evidence and employ a regression-discontinuity approach in chapter 1, demonstrating that review ratings do in fact have a causal impact on hotel revenue and demand.

The results are in columns 1 to 3 in Table 2.3. All the estimates are statistically significant at the $p < 0.01$ level. The standard errors are clustered at the market-year level and hotel level. Column 1 shows the result assuming the ϕ coefficients are not time-varying. I find review ratings have a significant impact on hotel demand. On average, a 1-point increase in rating is associated with a 5.5% increase in room-night sales. This effect magnitude is close to Lewis and Zervas (2016), which studies the hotels in Arizona, California, Nevada, Oregon, and Washington from 2005 to 2014. They find a 1-point increase in Tripadvisor rating is associated with a 6.5% increase in room-night sales.

The effect of Tripadvisor ratings on room nights sold found in this chapter is larger compared to the result in chapter 1. Several factors may contribute to this difference. Firstly, unlike the reduced-form fixed effect approach in chapter 1, this chapter employs a structural model that accounts for price endogeneity and capacity constraints in estimating demand. When simulating the full equilibrium outcomes, some of the excess demand may not be realized in equilibrium quantity. Secondly, while the regression discontinuity approach in chapter 1 measures the effect of an exogenous 1-point lift in review ratings, this chapter measures the effect of perceived quality conveyed through review ratings, which includes the reputation and signaling effects of review ratings Sayfuddin and Chen (2021). Furthermore, there might be measurement errors in rating rounding calculations in chapter 1 and the differences in the samples and time periods between the two chapters, which may contribute to the difference. Column 2 shows the heterogeneous effects of review ratings by market. Hotels in Miami Beach experience a larger effect than the other two markets. A 1-point rating is associated with a 7.5% increase in room-night sales in Miami Beach, whereas the increases in Chicago (CBD) and Houston are 5.4% vs. 5.3% respectively.

Column 3 shows how the effect of review ratings changes over time by interacting ratings with yearly-period dummies. I find an increasing pattern in the effect of a 1-point rating on room-night sales. The effect increases from the 2000-to-2005 period which is 2%, to more recent years which is about 7.3%. Figure 2.3 visualizes the effect of Tripadvisor ratings and the number of reviews posted on Tripadvisor for the hotels in my sample during each time period. As the volume of reviews increases over time, we can observe a corresponding growth in the impact of review ratings.

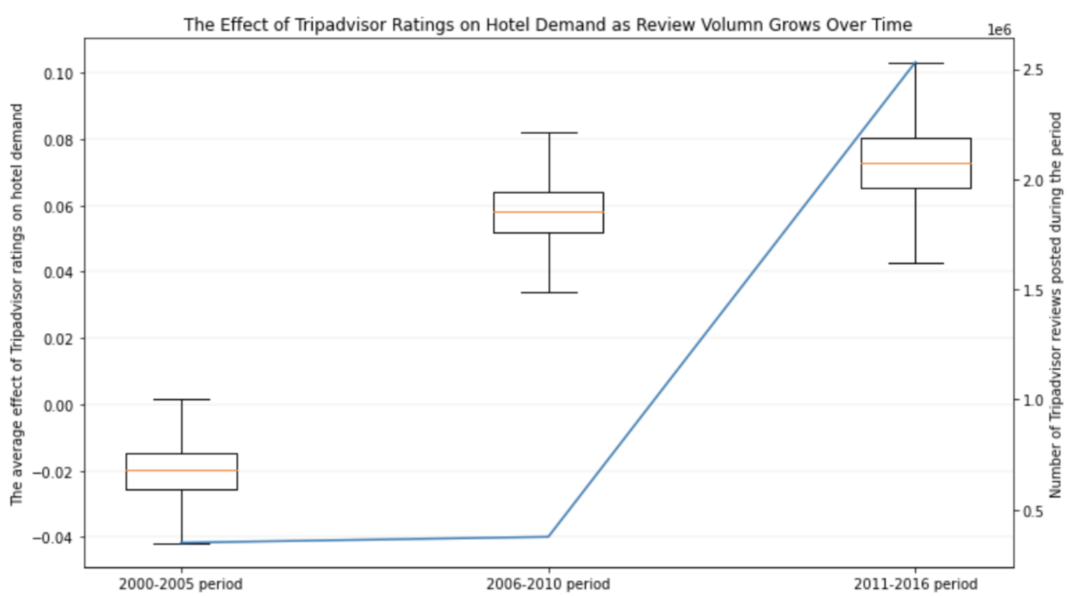

Figure 2.3: The effect of Tripadvisor ratings on hotel demand as review volume grows over time

a. The effect of rounding up is based on the result in Table 2.3 column 3.
b. The review count is based on the Tripadvisor reviews for the hotels in my sample.

Table 2.3: Result - Effect of Tripadvisor rating on sales and prices

	(1) $Q_{j,t}(1)$	(2) $Q_{j,t}(2)$	(3) $Q_{j,t}(3)$	(4) $\ln(ADR)_{j,t}(1)$	(5) $\ln(ADR)_{j,t}(2)$	(6) $\ln(ADR)_{j,t}(3)$
rating	0.055***			0.013**		
	(0.009)			(0.006)		
Chicago (CBD) $\times rating$		0.054***			0.017***	
		(0.011)			(0.001)	
Houston$\times rating$		0.053***			0.011***	
		(0.008)			(0.001)	
Miami Beach$\times rating$		0.075***			0.023***	
		(0.028)			(0.002)	
2000-2005 period$\times rating$			0.020**			0.006
			(0.008)			(0.005)
2006-2010 period$\times rating$			0.058***			0.015***
			(0.009)			(0.006)
2011-2016 period$\times rating$			0.073***			0.015**
			(0.011)			(0.006)
IsReviewed	-0.012***	-0.012***	-0.010***	-0.013	-0.014***	-0.011
	(0.003)	(0.003)	(0.003)	(0.023)	(0.004)	(0.023)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
N	67670	67670	67670	67670	67670	67670
Adjusted R-squared	0.96	0.96	0.96	0.97	0.97	0.97

a. In columns 1 to 3, dependent variables are $Q_{j,t} \equiv ln(s_{j,t}) - \hat{\sigma} ln(s_{j,t|g_j \in G}) - ln(s_0) - \hat{\alpha} p_{j,t}$, i.e. the LHS of equation (2.19).

b. In columns 4 to 6, dependent variables are the log of ADR.

b. N is the number of hotel-year-month observations.

c. Standard errors are double clustered at the market-year level and hotel level.

d. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

2.7.4 The effect of Tripadvisor ratings on price

Motivated by the findings in chapter 1, I test the hypothesis that higher ratings are associated with higher prices by conducting a reduced-form regression that is similar to equation (2.19). Specifically, I regress the logarithm of prices on the same set of right-hand-side variables as in equation (2.19).

$$\begin{aligned} \ln p_{j,t} &= \phi_{1,t}(rating_{j,t} \times \mathbf{1}\{IsReviewed_{j,t}\}) \\ &+ \phi_{2,t}\mathbf{1}\{IsReviewed_{j,t}\} \\ &+ h_j + \tau_t \times m_j + \nu_{j,t} \end{aligned} \tag{2.20}$$

where $\nu_{j,t}$ is the error term. This regression is "reduced-form" because prices are not derived from a model of optimization behaviors by hotels.

The results are in columns 4 to 6 in Table 2.3. Column 4 shows the average effect of review rating on price: a 1-point increase in review rating is associated with about a 1.3% increase in price for a room night, with a significant level at $p < 0.05$. This suggests that higher-quality hotels have gained pricing power after their quality was disclosed in online reviews, and although consumers are making better choices, these choices are moderately more expensive compared to if reviews were not considered. In line with the results from chapter 1, the impact of review ratings on prices is modest, indicating that hotels with better quality have limited ability to set "premium" prices, holding all other factors equal.

Column 5 shows the heterogeneous effects of review ratings on prices by Market. A 1-point increase in review ratings is correlated with a larger effect on hotel prices in Miami Beach than in the other two markets, suggesting hotels in Miami Beach are modestly more capable of exploiting their perceived quality through pricing. The larger effects on demand and price correlations match the fact that Miami Beach has a higher proportion of independent hotels and luxury hotels. As a popular vacation destination, hotels in Miami Beach also face a large percentage of potential customers being tourists, who may have less pre-existing information about the hotels.

Column 6 shows the result of interacting ratings with yearly-period dummies. There is an increase in the magnitude and significance of the price response in the 2006-to-2010 period and remained at a similar level since.

2.8 Counterfactuals

To assess the impact of Tripadvisor reviews on consumer welfare, I focus on the year 2016 and conduct counterfactual simulations where consumers are assumed to have no access to reviews. I then calculate the welfare differences between these counterfactual scenarios and the actual situation in 2016. Given that my previous empirical analyses demonstrate the significant effects of online reviews on both demand and prices, I consider two pricing scenarios in the counterfactual simulations. Under the first pricing scenario, prices are held constant and the welfare changes are driven solely by shifts in demand resulting from the change in consumers' perception of hotel quality. Under the second scenario, I allow prices to adjust based on profit maximization using the Bertrand Nash equilibrium outlined in section 2.6. To ensure an apples-to-apples comparison, I simulate the equilibrium outcomes for both the actual situation and the counterfactual scenarios.

2.8.1 Simulations without price responses

Recall that the quality of a hotel is $\gamma_{j,t}$. Under the status quo, my best estimates of consumers' perceived quality are the fitted values of the adjusted quality in equation (2.19). I compute these fitted values using the specification in column 3 in Table 2.3 with the actual review rating and the coefficient of the interaction between the 2011-2016 period and rating, which is 0.073. I denote these fitted values as $\gamma^s_{j,t}$. Therefore, the mean utility under the status quo is

$$\delta^s_{j,t} = \hat{\alpha} p_{j,t} + \gamma^s_{j,t} \tag{2.21}$$

In a world without online reviews, consumers can rely on other pre-purchasing information to infer hotel quality. I denote the counterfactual consumer's perceived hotel quality as $\gamma^c_{j,t}$ and define the counterfactual mean expected utility $\delta^c_{j,t}$ without price responses as

$$\delta^c_{j,t} \equiv \delta^s_{j,t} - (\gamma^s_{j,t} - \gamma^c_{j,t}) \tag{2.22}$$

As derived in the appendix, for a market and year-month time period, the change in consumer surplus from status quo to the counterfactual scenario is computed as the following

$$\begin{aligned} \Delta CS_{m,t} = -\frac{M}{\alpha}\Bigg[&\ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g} e^{\frac{\delta^s_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) - \ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g} e^{\frac{\delta^c_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) \\ &- \Sigma_j(\gamma^s_{j,t} - \gamma^c_{j,t})s^c_{j,t}\Bigg] \end{aligned} \tag{2.23}$$

where the first line captures the welfare change in log-sum terms from the status quo to the counterfactual from online reviews and the second line reflects the possibility that consumers would've chosen different hotels if they had no access to review ratings.

In order to calculate consumer surplus, it is necessary to simulate the counterfactual perceived hotel quality $\gamma^c_{j,t}$. This involves a two-step process. First, I simulate the counterfactual ratings $rating^c_{j,t}$ by allowing them to vary based on the pre-purchase information that would be available to consumers in the absence of reviews. The details of this process are explained in section 2.8.3. Then, using the same specification as in the status quo (equation (2.19)), I calculate $\gamma^c_{j,t}$ by substituting the simulated counterfactual ratings for the actual ratings. It should be noted that I assume the fixed effects and dummy variables are unchanged when computing $\gamma^s_{j,t}$ and $\gamma^c_{j,t}$. Therefore,

$$\gamma^s_{j,t} - \gamma^c_{j,t} = \hat{\phi_{1,t}}(rating_{j,t} - rating^c_{j,t}) \tag{2.24}$$

where $\hat{\phi_{1,t}}$ is the coefficient of the interaction between the 2011-2016 period and rating in Table 2.3, which is 0.073.

Given $rating^c_{j,t}$, I calculate the consumer surplus via equation (2.23) as the following

$$\begin{aligned}\Delta CS_{m,t} = -\frac{M}{\hat{\alpha}}\Bigg[&\ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g} e^{\frac{\delta^s_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) - \ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g} e^{\frac{\delta^c_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) \\ &- \Sigma_j \hat{\phi_{1,t}}(rating_{j,t} - rating^c_{j,t}) s^c_{j,t}\Bigg]\end{aligned} \tag{2.25}$$

where the last line is based on the assumption of counterfactual perceived quality in equation(2.24).

Given these estimated $rating^c_{j,t}$, I proceed to calculate the consumer surplus via eq(2.23) as the following

$$\begin{aligned}\Delta CS_{m,t} = -\frac{M}{\hat{\alpha}}\Bigg[&\ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g} e^{\frac{\delta^s_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) - \ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g} e^{\frac{\delta^c_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) \\ &- \Sigma_j \hat{\phi_{1,t}}(rating_{j,t} - rating^c_{j,t}) s^c_{j,t}\Bigg]\end{aligned} \tag{2.26}$$

where the last line is based on the assumption of counterfactual perceived quality in eq(2.24).

2.8.2 Simulations with equilibrium price responses

Given the marginal cost estimates and demand estimates $\hat{\alpha}$ and $\hat{\sigma}$, as well as the status quo and counterfactual perceived quality $\gamma^s_{j,t}$ and $\gamma^c_{j,t}$, I simulate the Nash equilibrium prices and market shares under both status quo and counterfactual scenarios. My approach is to find the equilibrium prices that solve the first-order conditions given by equation (2.8). Because the market shares in equation (2.8) are determined by the nested-logit demand system according to equation (2.5), the equilibrium prices $p_{j,t}^{StatusQuoEq}$ and $p_{j,t}^{CounterfactualEq}$ also enter the equation (2.8) via market shares as the following:

$$s_{j,t}^{StatusQuoEq} = \frac{e^{(p_{j,t}^{StatusQuoEq}+\gamma_{j,t}^{s})/(1-\sigma)}}{D_{g_j,t}^{\sigma}[1+\Sigma_G D_{g_j,t}^{1-\sigma}]}$$

$$s_{j,t}^{CounterfactualEq} = \frac{e^{(p_{j,t}^{CounterfactualEq}+\gamma_{j,t}^{c})/(1-\sigma)}}{D_{g_j,t}^{\sigma}[1+\Sigma_G D_{g_j,t}^{1-\sigma}]}$$

where $\gamma_{j,t}^{s}$ and $\gamma_{j,t}^{c}$ are the status quo and counterfactual perceived quality.

Table 2.4 demonstrates that the distributions of the simulated equilibrium prices under the status quo and the actual prices are highly similar, as does the scatter plot depicted in Figure 2.6 in the appendix.

With the equilibrium prices at hand, I can now calculate the change in consumer surplus

Table 2.4: Actual prices (ADR) and equilibrium prices (ADR) distributions under status quo

	Actual ADR \$	Equilibrium ADR \$ (Status Quo)
mean	141.57	141.42
std	96.12	94.87
min	34.08	31.45
25 percentile	85.24	85.28
50 percentile	119.55	119.23
75 percentile	170.74	170.29
max	1563.84	1556.55

from the status quo to the counterfactual scenario where reviews were not present. This change is computed as follows:

$$\Delta CS_{m,t} = -\frac{M}{\hat{\alpha}}\left[\ln\left(1+\Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta_{j,t}^{StatusQuoEq}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) - \ln\left(1+\Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta_{j,t}^{CounterfactualEq}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right)\right.$$
$$\left. - \Sigma_j s_{j,t}^{CounterfactualEq}\left(\hat{\phi_{1,t}}(rating_{j,t} - rating_{j,t}^c) + \hat{\alpha}(p_{j,t}^{StatusQuoEq} - p_{j,t}^{CounterfactualEq})\right)\right] \tag{2.27}$$

The second line again captures the cases when consumers would've chosen different hotels if they had no access to review ratings, which is determined by the relationship between the mean utilities under status quo and counterfactual in equilibrium:

$$\begin{aligned}\delta_{j,t}^{CounterfactualEq} &= \delta_{j,t}^{StatusQuoEq} - (\gamma_{j,t}^s - \gamma_{j,t}^c) - \hat{\alpha}(p_{j,t}^{StatusQuoEq} - p_{j,t}^{CounterfactualEq}) \\ &= \delta_{j,t}^{StatusQuoEq} - \hat{\phi_{1,t}}(rating_{j,t} - rating_{j,t}^c) - \hat{\alpha}(p_{j,t}^{StatusQuoEq} - p_{j,t}^{CounterfactualEq})\end{aligned} \tag{2.28}$$

2.8.3 Counterfactual ratings

To simulate the counterfactual ratings $rating_{j,t}^c$, I utilize a regression approach in which the actual review ratings are regressed on a set of variables that contribute to pre-purchase information about quality. The assumption is that consumers assess hotel quality based on these factors in the absence of online reviews.

According to the theoretical model presented in section 2.4, pre-purchase information is valuable to consumers if it accurately reflects the true quality of the product. The value of online reviews to consumers is dependent on how accurately they can assess product quality with alternative pre-purchase information in the absence of such reviews. In this section, I introduce the counterfactual scenarios where exogenous changes are made to the counterfactual ratings, affecting the accuracy of the perceived quality to varying degrees.

–***Baseline Scenario***– I assume that consumers possess full information on the time-invariant quality of all hotels, as well as the demand trends for each market-year-month. These counterfactual ratings are derived from the fitted values of the following regression using the actual Tripadvisor ratings in 2016:

$$rating_{j,t} = constant + h_j + \tau_t \times m_j + \varrho_{j,t} \tag{2.29}$$

where h_j is the hotel-level fixed effect and $\tau_t \times m_j$ is the market-year-month fixed effect, and $\varrho_{j,t}$ is the error term. The adjusted R-Squared of this regression is 0.72, implying the fixed effects explain about 72 percent variation in review ratings.

–***All-observable Scenario***– In contrast to the baseline scenario, it is possible that consumers might not observe all the time-invariant hotel-level factors. For example, if a hotel has an established reputation that is only known to the locals or a hotel provides delicious breakfast that is only known to repeat customers. Such information is not readily available to the public. I construct counterfactual ratings based on the hotel characteristics available in my data, including the operation type, class type, size type, location type, opening year, and identifiers for the chain, owner, management company, and parent company. I regress the actual ratings in 2016 on these characteristics together with the market-year-month fixed effects. The counterfactual ratings are the fitted values of this regression. The adjusted R-Squared of this regression is 0.53.

–***Partial-observable Scenario***– In this scenario, I assume that consumers can only access a limited subset of the available hotel characteristics. More precisely, I remove identifying information that consumers can use to recognize a particular group of hotels from the all-observable scenario. This includes chain identifier, parent company, owner, and management company identities. To obtain the counterfactual ratings, I use the fitted values of a regression of the actual 2016 ratings on the remaining hotel characteristics together with market-year-month fixed effects. The regression has an adjusted R-Squared of 0.34.

–***Average-rating Scenario***– Finally, I consider an extreme scenario by assigning a constant rating of 3.81, which is the average of all hotel-year-month ratings in 2016, to all hotels. This represents a case where consumers only have information about the average quality of all operating hotels but cannot distinguish individual qualities. The adjusted R-squared of

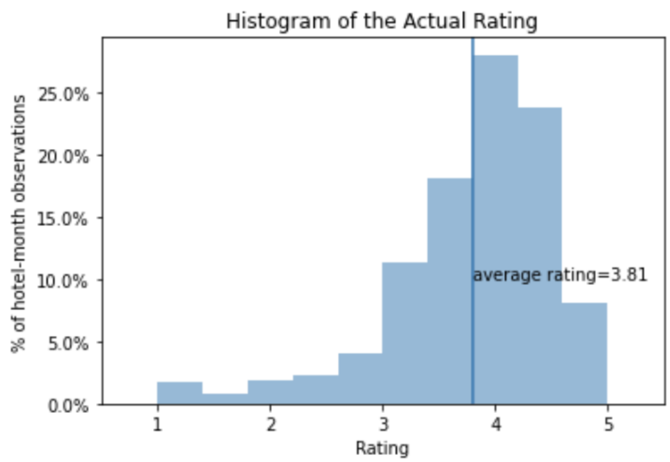

Figure 2.4: Average Ratings vs. Actual Ratings

the regression of the actual ratings in 2016 on the average rating and market-year-month fixed effects is 0.1. Figure 2.4 is the histogram of hotel-year-month ratings in the data. About 56% of the hotel ratings for a given year and month are within a 0.5 deviation from the average rating, which suggests that having information about the average rating can help consumers in obtaining a rough estimate of a hotel's quality. Appendix Figure 2.7 presents scatter plots that visualize the relationship between the counterfactual ratings and the actual ratings. The 45-degree line represents the perfect correlation between the two variables. As the prior knowledge of consumers about the quality of a hotel decreases, the fit of counterfactual ratings with respect to actual ratings also decreases.

2.9 Counterfactual Results

The aggregated welfare impacts from the removal of Tripadvisor review ratings in three markets in 2016 are presented in Tables 2.5 and 2.6 for two price-setting conditions, respectively. The columns indicate the counterfactual perceived quality under different priors. The removal of review ratings results in a decrease in consumer surplus under both fixed and equilibrium prices. Furthermore, the decrease in consumer surplus is greater when the accuracy of prior knowledge regarding quality deteriorates. The per-capita welfare loss resulting from the removal of review ratings under fixed prices and equilibrium prices ranges from \$0 to \$0.9 and \$2.2 to \$5.8, respectively, as the assumptions regarding prior knowledge of quality vary from baseline to average-rating.

In the baseline prior (column 1) and all-observable prior (column 2) scenarios, the absence of review ratings leads to a moderate decline in the overall market share of hotels in both fixed-price and equilibrium-price scenarios, ranging from 0.02% when prices are fixed to 0.16% when prices are adjusted in Nash equilibrium. However, when prices are fixed and under partial-observable prior (Table 2.5 column 3), the elimination of online reviews causes market expansion but further decreases consumer surplus due to the over-consumption of low-quality hotels.

For the hotels' producer surplus, in both pricing scenarios, the removal of review ratings has a negative welfare impact on hotels whose actual review ratings are better than what consumers would have anticipated and a beneficial welfare impact on hotels whose actual review ratings are worse than what consumers would have anticipated. Similar patterns exhibit in revenue and cost. On net, the per-room-night revenue loss of removing review ratings ranges from \$1.4 to \$19.3 and \$16.6 to \$25.8, under fixed-price and equilibrium-price scenarios respectively, as the assumptions regarding prior knowledge of quality vary from baseline to average-rating. Under fixed prices, the revenue decline for high-quality hotels is solely attributed to the reduction in the market share. However, in the equilibrium-price scenario, the revenue loss of high-quality hotels increases relative to the fixed-price scenario as they also lose the ability to set higher prices in accordance with their quality. The net change of the cost is generally negative, except when prices are adjusted according to Nash equilibrium and consumers only use observed characteristics to assess quality (Table 2.6 column 2). In this scenario, the cost savings in high-quality hotels does not compensate for the increase in costs experienced by hotels whose actual review ratings are below consumer expectations.

Lastly, the total welfare is computed based on the consumer surplus and producer surplus. The findings reveal an ambivalent outcome depending on pricing scenarios. In situations where prices are fixed, the removal of review ratings results in a net gain in welfare with the exception of scenarios with the average rating prior. On the other hand, when prices are adjusted in Nash equilibrium, the removal of review ratings leads to a decrease in total welfare across all prior beliefs. These results suggest that the availability of pre-purchasing information is beneficial when hotels have the capability to adjust prices based on the quality or if consumers were not able to differentiate hotel qualities absent reviews.

Table 2.7 and Table 2.8 present a breakdown of the impact of review ratings on welfare across different markets. Results indicate that removing review ratings leads to a decrease in consumer surplus in all three markets under both fixed and equilibrium prices. Moreover, a decrease in the accuracy of prior knowledge regarding quality leads to a larger reduction in consumer surplus across all markets. Interestingly, the reduction in consumer surplus per capita from the elimination of review ratings is less significant in the Chicago Central Business District but more pronounced in Miami Beach.

In Table 2.8, we observe that the per-room-night producer surplus of hotels in Miami Beach exhibits a stronger response to the removal of online reviews under both fixed and equilibrium prices. Additionally, hotels in Miami Beach experience a greater decline in revenue per room night compared to hotels in the other two markets. Specifically, under baseline conditions with fixed prices, hotels in Miami Beach experience a revenue loss of approximately \$3 per room night, while hotels in Houston and Chicago (CBD) lose \$1.8 and \$0.8, respectively. These findings align with the estimates presented in Table 2.3, columns 2 and 5, indicating that review ratings have a more significant impact on the quantity and prices of hotels in Miami Beach compared to those in Houston and Chicago (CBD).

Taken together, these findings underscore the importance of review ratings in markets where consumers possess relatively less prior knowledge about hotel quality, such as Miami Beach, a major travel destination.

Table 2.5: Welfare Effects of Removing Tripadvisor Reviews - Aggregated (Fixed Prices)

		(1) Baseline	(2) All-Observable	(3) Partial-Observables	(4) Average-rating
Change in Welfare (millions of $)		2.98	2.16	3.43	-4.22
Change in Consumer Surplus (millions of $)		-0.56	-0.91	-1.45	-2.66
Change in Producer Surplus (millions of $)	*net change*	3.54	3.07	4.87	-1.56
	Rating>Rating^c	-11.95	-18.28	-20.50	-22.93
	Rating<=Rating^c	15.49	21.35	25.37	21.37
Change in Revenue (millions of $)	*net change*	-4.28	-8.85	-13.18	-58.07
	Rating>Rating^c	-45.08	-63.92	-75.64	-104.39
	Rating<=Rating^c	40.80	55.06	62.46	46.32
Change in Total Cost (millions of $)	*net change*	-7.81	-11.93	-18.06	-56.51
	Rating>Rating^c	-33.12	-45.64	-55.14	-81.47
	Rating<=Rating^c	25.31	33.71	37.09	24.96
Average monthly change in total market share %		-0.02	-0.02	0.08	-0.31
Market Size (room nights)		2,955,406	2,955,406	2,955,406	2,955,406

a. This table shows the aggregate welfare impacts for three studied markets–Chicago (CBD), Houston, and Miami Beach by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 2.8.3.

c. Rating is the actual review rating for a hotel-year-month observation. *Rating^c* is the counterfactual rating.

d. Market size is measured by the maximum number of supply in terms of room nights across all years from all three markets.

2.10 Conclusion

In this chapter, I evaluated the impact of Tripadvisor ratings on consumer decision-making, and their value in the hotel industry as a source of information about quality. Using a structural model where consumers have imperfect information and hotels face capacity constraints, I find Tripadvisor ratings have a significant and positive impact on room nights demanded, with a 1-point increase in review rating leading to a 5.5% increase in room nights demanded. Additionally, a reduced-form analysis provides evidence that Tripadvisor ratings are positively correlated with prices.

The effects of review ratings on purchasing behavior have welfare consequences. By con-

Table 2.6: Welfare Effects of Removing Tripadvisor Reviews - Aggregated (Equilibrium Prices)

		(1) Baseline	(2) All-Observable	(3) Partial-Observables	(4) Average-rating
Change in Welfare (millions of $)		-38.85	-36.35	-30.36	-58.12
Change in Consumer Surplus (millions of $)		-6.65	-9.94	-14.40	-17.55
Change in Producer Surplus (millions of $)	*net change*	-32.20	-26.42	-15.96	-40.57
	$Rating > Rating^c$	-43.54	-41.35	-28.41	-45.34
	$Rating <= Rating^c$	11.35	14.94	12.45	4.77
Change in Revenue (millions of $)	*net change*	-49.81	-23.76	-25.01	-77.52
	$Rating > Rating^c$	-98.17	-70.32	-60.61	-98.13
	$Rating <= Rating^c$	48.37	46.56	35.60	20.61
Change in Total Cost (millions of $)	*net change*	-17.61	2.66	-9.05	-36.96
	$Rating > Rating^c$	-54.63	-28.96	-32.20	-52.79
	$Rating <= Rating^c$	37.02	31.62	23.15	15.84
Average monthly change in total market share %		-0.11	-0.16	-0.18	-0.53
Market Size (room nights)		2,955,406	2,955,406	2,955,406	2,955,406

a. This table shows the aggregate welfare impacts for three studied markets–Chicago (CBD), Houston, and Miami Beach by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 2.8.3.

c. Rating is the actual review rating for a hotel-year-month observation. $Rating^c$ is the counterfactual rating.

d. Market size is measured by the maximum number of supply in terms of room nights across all years from all three markets.

ducting counterfactual simulations under different prior beliefs about quality and comparing welfare with the status-quo ratings in 2016, I find Tripadvisor ratings are beneficial to consumers. As one would expect from the theory, the removal of review ratings results in a decrease in consumer surplus, with a greater decrease when the accuracy of prior knowledge deteriorates. The decrease in consumer surplus is moderate, especially when prices are fixed, indicating that consumers are reasonably good at distinguishing quality even in the absence of reviews. This is corroborated by the findings of Chapter 1, which indicate that the impact of exogenous changes in ratings on occupancy rates is also moderate.

Review ratings also benefit hotels with quality that is better than anticipated with higher producer surplus and revenue while the opposite is true for hotels with quality that is worse than anticipated. The per-room-night net revenue loss of removing review ratings ranges from \$1.4 to \$19.3 and \$16.6 to \$25.8, under fixed-price and equilibrium-price scenarios respectively.

Table 2.7: Welfare Effects of Removing Tripadvisor Reviews - By Market (Fixed Prices)

Welfare Effects Result - Fixed prices (by city)

	(1) Baseline	(2) All-Observables	(3) Partial-Observable	(4) Average-rating
Chicago (CBD)				
Change in Welfare (millions of $)	1.94	1.47	2.71	-2.06
Change in Consumer Surplus (millions of $)	-0.15	-0.22	-0.29	-0.57
Change in Producer Surplus (millions of $)	2.09	1.69	3.00	-1.49
Change in Revenue (millions of $)	-2.11	-3.27	-4.38	-24.04
Change in Total Cost (millions of $)	-4.20	-4.95	-7.37	-22.55
Average monthly change in total market share (%)	-0.03	-0.04	0.03	-0.44
Market Size (room nights)	1,210,161	1,210,161	1,210,161	1,210,161
Houston				
Change in Welfare (millions of $)	0.23	-0.35	-0.74	-3.60
Change in Consumer Surplus (millions of $)	-0.37	-0.58	-0.96	-1.88
Change in Producer Surplus (millions of $)	0.60	0.23	0.22	-1.72
Change in Revenue (millions of $)	-1.17	-3.62	-5.68	-21.78
Change in Total Cost (millions of $)	-1.77	-3.85	-5.90	-20.06
Average monthly change in total market share (%)	0.00	-0.03	0.07	-0.10
Market Size (room nights)	1,419,322	1,419,322	1,419,322	1,419,322
Miami Beach				
Change in Welfare (millions of $)	0.81	1.04	1.45	1.45
Change in Consumer Surplus (millions of $)	-0.04	-0.11	-0.20	-0.20
Change in Producer Surplus (millions of $)	0.85	1.16	1.65	1.65
Change in Revenue (millions of $)	-1.00	-1.96	-3.12	-12.25
Change in Total Cost (millions of $)	-1.85	-3.12	-4.78	-13.91
Average monthly change in total market share (%)	-0.04	0.00	0.08	-0.38
Market Size (room nights)	325,923	325,923	325,923	325,923

a. This table shows the welfare impacts in each of the three studied markets by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 2.8.3.

c. Market size is measured by the maximum number of supply in terms of room nights across all years in each market.

The overall effect on total welfare is largely contingent upon the ability of hotels to set prices in accordance with quality and whether consumers can differentiate quality. Review ratings lead to total welfare gains when high-quality hotels are able to exploit their perceived quality through pricing or consumers could not differentiate qualities absent reviews. Additionally, the welfare impact varies across three distinct studied markets, suggesting that market-specific conditions play an important role in affecting consumer choices and welfare, such as pre-existing knowledge about hotel quality.

There are many directions for future research. My empirical model assumes all consumers read review ratings when making purchasing decisions, but one could explore how the penetration of reviews affects their impact and the long-term effect of online reviews on hotel

Table 2.8: Welfare Effects of Removing Tripadvisor Reviews - By Market (Equilibrium Prices)

Welfare Effects Result - Equilibrium prices (by city)

	(1) Baseline	(2) All-Observables	(3) Partial-Observable	(4) Average-rating
Chicago (CBD)				
Change in Welfare (millions of $)	-3.96	-0.23	4.24	-3.41
Change in Consumer Surplus (millions of $)	-0.81	-0.95	-1.17	-1.92
Change in Producer Surplus (millions of $)	-3.16	0.72	5.41	-1.49
Change in Revenue (millions of $)	-6.69	-1.66	-1.14	-22.11
Change in Total Cost (millions of $)	-3.54	-2.38	-6.55	-20.12
Average monthly change in total market share (%)	-0.01	-0.17	-0.15	-0.57
Market Size (room nights)	1,210,161	1,210,161	1,210,161	1,210,161
Houston				
Change in Welfare (millions of $)	-3.59	-2.10	-2.91	-10.91
Change in Consumer Surplus (millions of $)	-2.93	-4.06	-7.28	-9.19
Change in Producer Surplus (millions of $)	-0.66	1.96	4.37	-1.72
Change in Revenue (millions of $)	-9.83	-2.26	3.60	-20.51
Change in Total Cost (millions of $)	-9.18	-4.22	-0.77	-9.53
Average monthly change in total market share (%)	-0.15	-0.23	-0.34	-0.35
Market Size (room nights)	1,419,322	1,419,322	1,419,322	1,419,322
Miami Beach				
Change in Welfare (millions of $)	-31.30	-34.02	-31.68	-4.80
Change in Consumer Surplus (millions of $)	-2.92	-4.92	-5.94	-6.45
Change in Producer Surplus (millions of $)	-28.38	-29.10	-25.74	1.65
Change in Revenue (millions of $)	-33.28	-19.84	-27.47	-34.90
Change in Total Cost (millions of $)	-4.90	9.26	-1.73	-7.31
Average monthly change in total market share (%)	-0.17	-0.07	-0.03	-0.67
Market Size (room nights)	325,923	325,923	325,923	325,923

a. This table shows the welfare impacts in each of the three studied markets by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 2.8.3.

c. Market size is measured by the maximum number of supply in terms of room nights across all years in each market.

demand and quality. It is possible for some low-quality hotels to improve their quality when online reviews play more important roles in consumer choices.

It is also worth mentioning that my findings are limited to numerical ratings and vertical differentiation. Since review ratings allow the aggregation of consumers' experiences into quality measures that deliver welfare benefits, one could examine the effect of textual content in reviews and the benefit of the match information in reviews.

2.11 Appendices

2.11.1 Derivation of welfare measures

The *actual utility* consumer i gets from choosing hotel j in market m in time period t is $u_{i,j,t}$. The *anticipated utility* is $w_{i,j,t}$. Let

$$d_{i,j,t} = u_{i,j,t} - w_{i,j,t}$$

be the difference between the actual and anticipated utility, such that $d_{i,j,t} > 0$ if the hotel is better than the consumer anticipated, and $d_{i,j,t} < 0$ if it is worse.

I assume the hotel that gives consumer i the *highest actual utility* is k^*, so the *highest actual utility* is $u_{i,k*,t}$. However, consumers are assumed to make choices based on the anticipated utility. Let's assume the hotel that gives consumer i the *highest anticipated utility* is j^*, which gives the *actual utility* $u_{i,j*,t}$. The utility loss due to the consumer's imperfect foreknowledge is then $u_{i,j*,t} - u_{i,k*,t}$.

Given my nested-logit demand specification in eq(1), we can derive the average consumer surplus loss for a consumer in market m as (Train (2015))[8]

$$\Delta CS_{m,t} = \frac{1}{\alpha}E[u_{k*,t}] - \frac{1}{\alpha}E[u_{j*,t}]$$

where

$$-\frac{1}{\alpha}E[u_{j*,t}] = -\frac{1}{\alpha}E[w_{j*,t} + d_{j*,t}]$$

Note that $E[w_{j*,t}]$ is the expectation of the maximum value of the *anticipated utility* and $E[d_{j,*}]$ is the expected difference between the actual and anticipated utility. In a world with online reviews, The *anticipated utility* is $w^c_{i,j,t}$ and the difference between the actual and anticipated utility is $d^c_{i,j,t}$. The average consumer surplus loss for a consumer in market m is

$$\Delta CS^c_{m,t} = \frac{1}{\alpha}E[u_{k*,t}] - \frac{1}{\alpha}E[u_{j^c*,t}]$$

[8] Because the coefficients on price and quality in eq(1) are the same for all consumers, so we can average over a population of consumers as such.

where $u_{j^c*,t}$ is the average actual utility from hotels that give consumers the highest anticipated utility without online reviews. So the welfare gain from having online reviews is

$$\begin{aligned}\Delta CS_{m,t} - \Delta CS^c_{m,t} &= \frac{1}{\alpha}E[u_{j^c*,t}] - \frac{1}{\alpha}E[u_{j*,t}] \\ &= -\frac{1}{\alpha}E[(w_{j*,t} - w_{j^c*,t}) + (d_{j*,t} - d_{j^c*,t})]\end{aligned} \tag{2.30}$$

The term $E[(w_{j*,t} - w_{j^c*,t})]$ can be derived from the nested-logit demand system as

$$E[(w_{j*,t} - w_{j^c*,t})] = \left[\ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta_j}{1-\sigma}})^{1-\sigma}\right) - \ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta^c_j}{1-\sigma}})^{1-\sigma}\right)\right]$$

In order to derive the term $E[(d_{j*,t} - d_{j^c*,t})]$, I assume the expected actual utility consumers get is the same as the expected anticipated utility under status-quo, i.e. with the presence of online reviews. Under this assumption, I have $d_{j*,t} = u_{j*,t} - w_{j*,t} = 0$. This assumption also implies that in the world without online reviews, consumers make choices according to $\delta^c_{j,t}$ but actually experience mean utility queal to mean utility $\delta_{j,t}$ under status quo. Therefore,

$$E[d_{j^c*,t}] = \Sigma_j s^c_{j,t}(\delta_{j,t} - \delta^c_{j,t}) \tag{2.31}$$

And the average change of consumer surplus from the status quo to the counterfactual scenario where reviews were not present is the following

$$\begin{aligned}\Delta CS_{m,t} - \Delta CS^c_{m,t} = -\frac{1}{\alpha}\Bigg[&\ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta_j}{1-\sigma}})^{1-\sigma}\right) - \ln\left(1 + \Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta^c_j}{1-\sigma}})^{1-\sigma}\right) \\ &- \Sigma_j s^c_{j,t}(\delta_{j,t} - \delta^c_{j,t})\Bigg]\end{aligned}$$

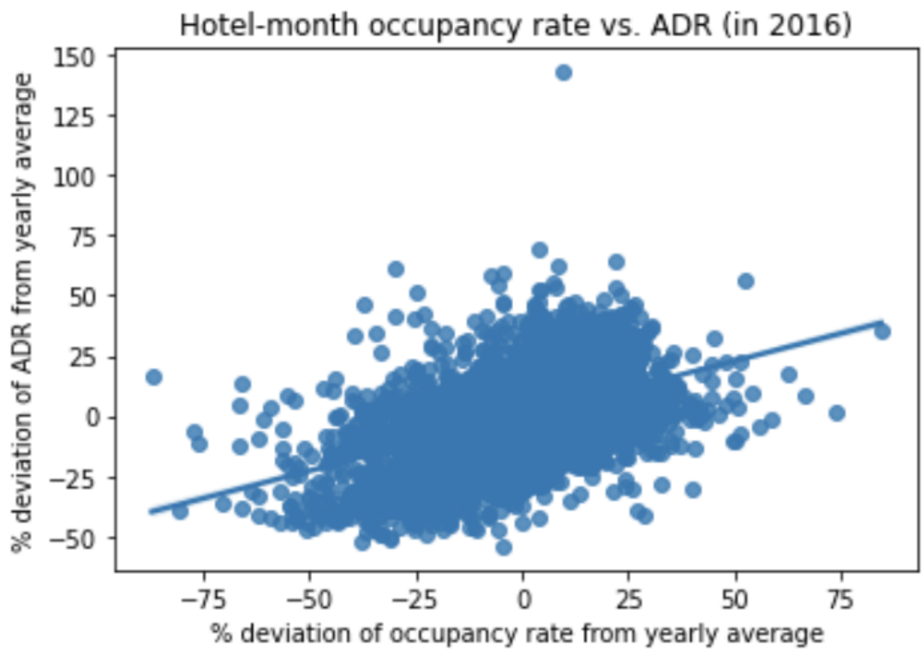

Figure 2.5: Relationship between the deviation of occupancy rate and ADR to yearly average

- Each scattered dot in this plot is a hotel-month observation.
- Horizontal axis is the percentage deviation of the occupancy rate to the yearly average occupancy rate of the hotel.
- Vertical axis is the percentage deviation of the ADR to the yearly average ADR of the hotel.
- The plot uses 2016 data.

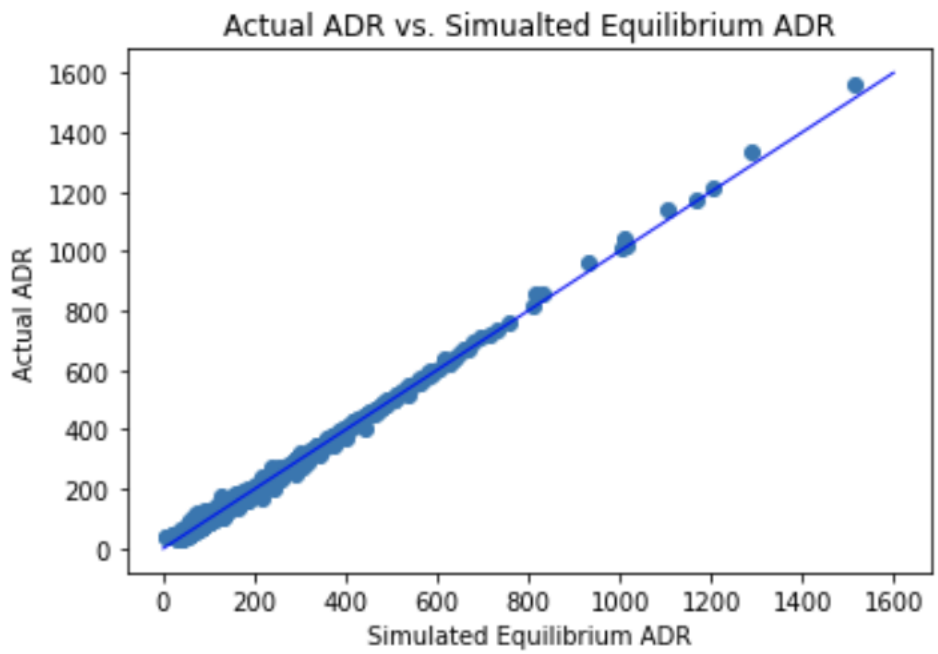

Figure 2.6: Counterfactual Pries vs. Actual Prices (ADR)

- This plot shows the actual ADR and simulated ADR under Bertrand Nash equilibrium in 2016.
- The ADR values are in dollars.

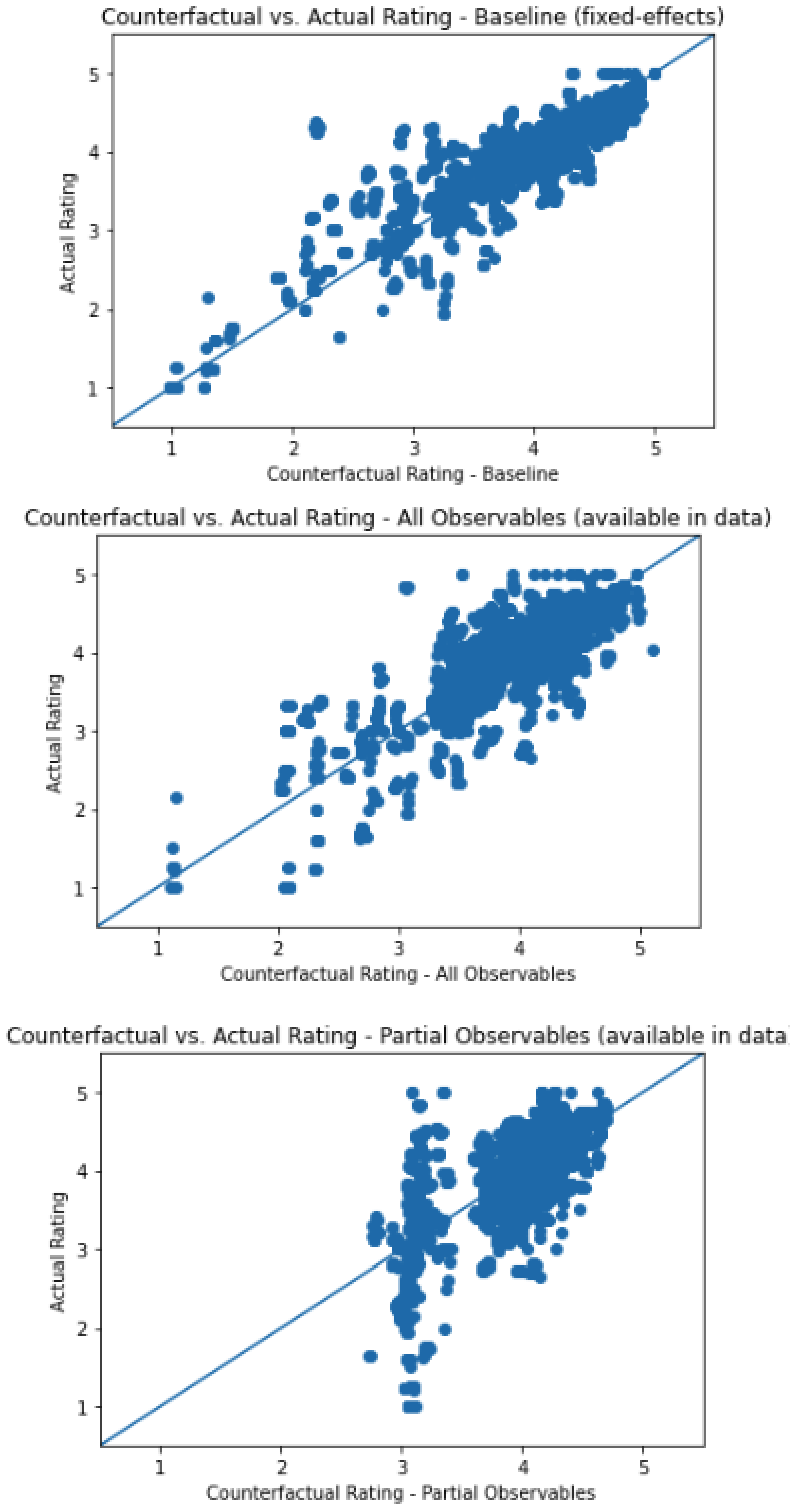

Figure 2.7: Counterfactual Ratings vs. Actual Ratings

Chapter 3

The Impact of Online Reviews on Hotel Quality Perception: The Added Value Beyond Brand

3.1 Introduction

In the competitive landscape of the hotel industry, developing a reputable image for quality is crucial for chain-affiliated companies. Brands serve as a quick and easy reference for consumers, allowing them to make informed purchasing decisions based on a reliable indicator of product quality. Despite the acknowledged importance of the quality reputation for chain-affiliated companies, a comprehensive examination of the impact of improved consumer information through online review ratings on the value of chain affiliation and overall social welfare has yet to be conducted. This study aims to fill this gap by providing insight into the extent to which online reviews and brand information inform consumer decision-making and contribute to welfare in the hotel industry.

In the hotel industry, chain affiliation refers to a system of ownership and management where a group of hotels is linked together under a common brand name, marketing strategy, and management structure. The chain-affiliated hotel properties are usually owned or managed by the same company or franchisee under a unified brand image. The trend of chain affiliation in the U.S. hotel industry has seen a marked increase over the past three decades. During the early 90s, chain affiliation was only present in about one-third of hotels, but now, over 60% of hotels belong to a chain (Sanford (2019)).

Given the importance of chain affiliation in the hotel industry, studying its relevance and influence in light of the growing impact of online reviews is crucial for several reasons. First, Both chain affiliation and online reviews are mechanisms aimed to mitigate information asymmetry in the hotel industry, shaping clear expectations of the hotel's quality. Online reviews offer consumers a wealth of information and opinions from other customers, as shown in prior chapters, that can impact their buying decisions. However, the information from online reviews and brand affiliation could be either substitutive or complementary. On one hand, consumers may resort more to online reviews as they gain popularity such that branding is less relevant in consumer choices. On the other hand, by providing up-to-date information about individual properties, online reviews might help consumers differentiate chain-affiliated hotels from independent hotels. Understanding the impact of online reviews on chain affiliation in consumer decision-making is crucial for assessing the value and benefits of these pre-purchase informational sources.

Second, the hospitality industry is highly competitive and chain affiliation can provide a competitive advantage for the affiliated hotels. By providing information about individual properties, online reviews can either enhance or reduce the competitive advantage of chain affiliation. When a chain receives a large number of positive online reviews, it can help to enhance its reputation and increase consumer confidence in the brand. This can lead to increased customer loyalty and ultimately a competitive advantage over rival chains. Moreover, when a chain consistently receives positive reviews across its locations, it can demonstrate to potential customers that they can expect a consistent level of quality no matter which location they choose. This can help to differentiate the chain from competitors in their operating markets. Conversely, when a chain receives a large number of negative online reviews or receives negative reviews for certain locations, it can demonstrate to potential customers that the quality of their experience may vary depending on the location. This can reduce consumer confidence in the brand and result in a loss of competitive advantage. Furthermore, the simple process of searching for information online can assist consumers in finding more choices, especially for independent hotels with limited offline reputations, potentially decreasing the competitive edge held by chains.

Third, although reputation for quality is a major source of a chain's value, reputation building is costly and time-consuming for chains. With the rise of online reviews, online reputation has been a growing concern in the hotel industry. Hotels invest large amounts of resources in developing their brand and reputation, both online and offline. Studying the impact of online reviews on chain affiliation is crucial for evaluating the value and welfare of these reputation-building mechanisms.

In this chapter, I examine three research questions: (1) Does the causal impact of Tripadvisor review ratings on hotel performance differ between chain-affiliated and independent hotels? (2) Do Tripadvisor review ratings have a differential effect on the demand for chain-affiliated hotels compared to independent hotels? (3) To what extent do Tripadvisor reviews provide value in the presence of brand affiliation, and what is the value of chain brands when Tripadvisor reviews are unavailable? These questions extend from Chapters 1 and 2.

To answer the first question, I use the regression discontinuity design from Chapter 1 to examine the effect of an exogenous lift in displayed ratings on the performance of chain-affiliated hotels versus independent hotels. Given that chain affiliation already signals quality, I expect rating rounding to have a weaker effect on chain-affiliated hotels than on independent hotels.

To answer the remaining two questions, I use the structural model and welfare measures from Chapter 2. I estimate the effect of ratings on hotel demand while allowing ratings to interact with dummies for chain-affiliated hotels. Then, I simulate the counterfactual market shares in three hypothetical scenarios where online reviews are not available, and perceived quality is based on information about chain-brand affiliation. I compute the welfare changes from the status-quo world in 2016 to the counterfactual scenarios under both fixed and Nash equilibrium prices. These welfare changes measure the value of Tripadvisor ratings when consumer preferences differ for chain-affiliated hotels versus independent hotels, as well as the value of chain brands when online reviews are not available.

My main findings are the following: (1) The round of Tripadvisor ratings has a modestly smaller effect on chain-affiliated hotels' revenue per available room (RevPAR) and average daily rate (ADR) compared to independent hotels. However, there is no significant difference in occupancy rates. (2) Tripadvisor ratings have smaller impact on the room nights demanded for chain-affiliated hotels relative to independent hotels, with a 1-point increase in review ratings associated with a 5.7% increase in room nights demanded by independent hotels, whereas the corresponding increase for chain-affiliated hotels is 4.8%. Moreover, this relative difference has been increasing from 2000 to 2016. (3) Online reviews still add value to consumers even with brand affiliation, and their removal results in a loss of consumer surplus. In my baseline scenario when consumers have full brand awareness, the removal of Tripadvisor ratings results in a loss in consumer surplus of about \$0.15 per capita when prices are fixed and \$3.99 per capita when prices are adjusted in Nash equilibrium. Whereas the further removal of brand information results in a loss in consumer surplus of about \$0.1 per capita when prices are fixed and \$0.08 per capita when prices are adjusted in Nash equilibrium. The effect on hotels' producer surplus depends on the pricing scenario. When prices are fixed, the removal of Tripadvisor ratings increases the producer surplus by about \$3 per room night when consumers have full-brand awareness, while the further removal of brand information increases the producer surplus by about \$0.3 per room night. When prices are adjusted in the Nash equilibrium, the removal of Tripadvisor ratings decreases the producer surplus by about $7 per room night when consumers have full-brand awareness, while the further removal of brand information decreases the producer surplus by about $0.2 per room night. Furthermore, when Tripadvisor reviews are absent, chain-affiliated hotels benefit from brand affiliation while independent hotels are harmed, in both fixed-price and equilibrium-price scenarios. When prices are fixed, the gain in producer surplus of chain-affiliated hotels is attributed to the gain in market shares. When prices are adjusted in Nash equilibrium, the gain in producer surplus of chain-affiliated hotels is attributed to the price responses.

3.2 Literature Review

This study relates to several branches of literature. First, it relates to research on the informational impact of chain affiliation. For example, Hollenbeck et al. (2019) shows the substitution between Tripadvisor rating and advertisement is stronger for independent hotels than for chains. Hollenbeck (2016) finds the premium in revenue for chain-affiliated hotels has declined by over 50% from 2000 to 2015. This decline is correlated with an increase in online reputation mechanisms. Luca (2011) finds the effect of Yelp review ratings is largely driven by independent restaurants while review ratings do not affect chain-affiliated restaurants. Waldfogel and Chen (2006) discovers that online information has a negative impact on brand preferences, finding that consumers who utilize price comparison websites are less likely to purchase from umbrella brands. Jin and Leslie (2003) finds that chain-affiliated restaurants develop reputations for good hygiene quality, which provides an incentive to maintain good hygiene, leading to better hygiene than non-chain restaurants on average. They also show that franchised chain restaurants tend to have lower hygiene quality than company-owned chain restaurants, suggesting they might have the tendency to free-ride on the chain's reputation.

Second, it relates to the literature on reputation building through branding, brand extension, and their role in signaling quality. Shapiro (1983), Milgrom and Roberts (1986) are among the early theoretical work on the use of branding for reputation building and as a signal for quality. Park, Jaworski, and MacInnis (1986) developed a framework to understand how brands can establish a reputation through product development and marketing communication. Maheswaran, Mackie, and Chaiken (1992) examines how brand names are utilized in consumer judgments about the quality and other attributes of new products associated with the brand. Recent theoretical work such as Moorthy (2012) and Miklós-Thal (2012) examines firms' incentives to link new products to existing brand names and the conditions under which brand extension can signal product quality.

There is also substantial evidence that supports the notion that consumers' expectations of quality persist across different products within the same brand. For example, Erdem (1998) finds a strong correlation between consumers' perceived quality for products within an umbrella brand. Bottomley and Holden (2001) finds the support for the model in Aaker and Keller (1990) that consumers evaluate brand extension based on the quality of the original brand. In recent years, studies on brand values and umbrella branding have shed further light on the topic, with works such as Goldfarb, Lu, and Moorthy (2009) measuring brand value in an equilibrium framework.

Third, this study relates to the research on chain affiliation. Kosová and Lafontaine (2012) synthesized a variety of empirical work and data on chains and franchised chains in retail and service sectors. There is also extensive work on vertical integration and franchising in the hotel industry. For example, Kosová, Lafontaine, and Perrigot (2013) studies the relationship between organizational form and performance within a major chain and how the firm's endogenous choice of organizational forms affects performance. Kalnins (2017) studies the use of pricing as quality signaling by hotel chains and Lin and Kim (2021) investigates the impact of hotel ownership structure changes on the magnitude of localized competition of different quality segment hotels. They find that the hotel ownership structure change from chain-affiliated to independent increases the number of neighboring economy hotels, whereas the change from independent to chain-affiliated increases the number of neighboring upper-upscale hotels. These studies implicitly recognize the importance of quality reputation effects as a primary source of value for chains without explicitly measuring them.

3.3 Data

In this chapter, I use both datasets from Chapter 1 and Chapter 2. Chapter 1's data is used for causal analysis and Chapter 2's data is used for the structural model and counterfactual analysis. Both datasets are combined property-month-level financial performance data from Smith Travel Research (STR), and the entire historical records of Tripadvisor reviews for hotels in the STR sample. I observe the geographic market for each hotel. Hotel identities are masked in both datasets. Figure 3.1 shows the observed metrics in each dataset.

	Financial performance metrics	**Tripadvisor review variables**	**Time span**	**Number of hotels**	**Number of hotel-month**
Chapter 1	Average Occupancy rate, Average ADR, Average RevPAR	Average rating Review count Average cumulative rating Cumulative review count	Janurary 2000 to December 2019	1,188	173,686
Chapter 2	Average Occupancy rate, Average ADR, Average RevPAR, Monthly room-night bookings, Monthly room-night supply		Janurary 2000 to December 2016	513	67,670

Figure 3.1: Datasets Summary

3.3.1 Variables for Chain Affiliation

Because I examine the varying impact of online reviews on chain-affiliated and independent hotels in this chapter, I further explain the context and relevant variables included in my data pertaining to this chapter's analyses.[1].

[1]The details about the definitions of variables can be found on STR website: https://str.com/data-insights/resources/glossary

I observe the chain scale in both datasets [2]. For chain-affiliated hotels, every hotel is classified into one of six major chain scales, including luxury, Upper Upscale, Upscale, Upper Midscale, Midscale, and Economy. Chain-affiliated hotels include chain- owned or managed and franchise hotels. Independent hotels belong to a stand-alone scale category as "Independent".

In Chapter 2's dataset, I also observe the affiliated brand for chain and franchise hotels. The brand names are masked as coded identifiers. For every hotel, the chain scale remains fixed and does not change over time. There are 100 affiliated chain brands in Chapter 2's data. The largest brand has 19 affiliated properties in my sample. About 10% of these chain brands have affiliated hotels operating in all three markets covered by Chapter 2's data. It is worth noting that the market coverage of brands is based on my sample. For example, a brand with affiliated hotels operating in only one market in my sample might have affiliated hotels operating in other markets that are not observed in my sample.

Table 3.1 shows the number of markets covered by the affiliated brands in my sample. Table 3.2 shows the number of chain-affiliated hotels by the market coverage of their affiliated brands in my sample. There are 116 (27.4%) chain-affiliated hotels that are affiliated brands having hotels operating in three markets under the same brand name in my sample.

Table 3.1: Brand coverage by the number of markets in Chapter 2's sample

Number of markets (with operating hotels affiliated with the brand)	**Number of affiliated brands**
3	10
2	33
1	57

a. The market coverage of brands is based on my sample only. For example, a brand with affiliated hotels operating in only one market in my sample might have affiliated hotels operating in other markets that are not observed in my sample.

[2] In Chapter 2's data, I observe operation type and class type. When combined, the two variables contain chain scale information.

Table 3.2: Number of Chain-affiliated hotels by affiliated brand coverage in three markets in Chapter 2's sample

	Chicago (CBD)	Houston	Miami Beach	Total
Affiliated with Brand operating in 3 Markets	30	75	11	116
	31.3%	25.0%	40.7%	27.4%
Affiliated with Brand operating in 2 Markets	27	113	11	151
	28.1%	37.7%	40.7%	35.7%
Affiliated with Brand operating in 1 Markets	19	112	5	136
	19.8%	37.3%	18.5%	32.2%
Total	96	300	27	423

a. The table displays the number of chain-affiliated hotels, grouped by the number of markets in which their affiliated brand has operating hotels under the same brand name.
b. The market coverage of brands is based on my sample only. For example, a brand with affiliated hotels operating in only one market in my sample might have affiliated hotels operating in other markets that are not observed in my sample.
c. The percentages indicate the percentage of chain-affiliated hotels in each market with their brand coverage. For example, 40.7% of chain-affiliated hotels in Miami Beach are affiliated with brands having hotels operating in 3 markets under the same brand name.

3.3.2 Summmary Statistics

Table 3.3 and Table 3.4 present the summary statistics of Chapter 1 and Chapter 2's data breaking down by chain-affiliated and independent hotels.

Table 3.3: Summary Statistics for Chapter 1's data

		N	Mean	Std	Median	Min	25th pct	75th pct	Max
Occupancy rate (%)	**All Hotels**	**173,686**	**71.2**	**16.6**	**73.4**	**0.4**	**60.7**	**84.1**	**100.0**
	Chain	149,757	71.1	16.2	73.0	0.4	60.8	83.6	100.0
	Independent	23,929	71.9	19.0	75.9	2.1	59.9	87.1	100.5
ADR	**All Hotels**	**173,686**	**126.1**	**90.7**	**105.7**	**12.9**	**70.9**	**152.0**	**2552.6**
(average daily rate) ($)	*Chain*	149,757	118.2	83.9	101.4	12.9	68.9	140.3	2552.6
	Independent	23,929	175.5	113.2	156.2	17.0	98.3	224.9	921.7
RevPAR	**All Hotels**	80281	**93.7**	**76.6**	**73.4**	**0.3**	**43.7**	**116.2**	**1711.0**
(revenue per available room) ($)	*Chain*	149,757	87.3	70.3	69.9	0.3	42.6	106.0	1711.0
	Independent	23,929	134.1	99.0	118.4	1.2	59.7	184.7	831.2
Average review rating	**All Hotels**	**115,111**	**3.9**	**1.0**	**4.0**	**1.0**	**3.5**	**4.5**	**5.0**
	Chain	100,460	3.9	1.0	4.0	1.0	3.5	4.5	5.0
	Independent	14,651	4.0	0.8	4.2	1.0	3.8	4.6	5.0
Average review count	**All Hotels**	**115,111**	**28.2**	**81.6**	**8.0**	**2.0**	**2.0**	**24.0**	**2226.0**
	Chain	100,460	22.7	60.3	6.0	2.0	2.0	20.0	1386.0
	Independent	14,651	66.3	160.2	16.0	2.0	6.0	50.0	2226.0

a. The sample size N for occupancy rate, ADR, and RevPAR include all 1,188 hotels in my sample.
b. The sample size N for Review rating, and Review count include all 849 hotels that have listings on Tripadvisor.
c. Each observation is a hotel-month.

Compared to chain-affiliated hotels, independent hotels have higher average occupancy rates, average daily rates (ADR), and revenue per available room (RevPAR) in both samples. However, they have lower room nights booked and supplied as shown in Chapter 2's

Table 3.4: Summary Statistics for Chapter 2's data

		N	Mean	Std	Min	25th pct	50th pct	75th pct	Max
Occupancy rate	**All Hotels**	**67,670**	**68.7**	**16.1**	**0.6**	**58.6**	**70.8**	**81.1**	**100.0**
(%)	*Chain-affiliated*	58,536	68.7	15.9	0.6	58.6	70.6	80.9	100.0
	Independent	9,134	69.0	17.7	1.8	58.1	72.0	82.5	100.0
ADR	**All Hotels**	**67,670**	**123.5**	**88.2**	**19.0**	**71.8**	**107.1**	**149.7**	**1,763.7**
(average daily rate) ($)	*Chain-affiliated*	58,536	113.3	68.6	19.0	67.6	100.9	140.0	1,004.6
	Independent	9,134	188.7	150.1	25.5	112.8	152.7	211.3	1,763.7
RevPAR	**All Hotels**	**67,670**	**86.8**	**67.5**	**0.3**	**43.1**	**70.7**	**109.7**	**1,167.9**
(revenue per available room) ($)	*Chain-affiliated*	58,536	79.9	57.2	0.3	40.7	66.3	100.9	790.2
	Independent	9,134	131.4	102.1	2.6	71.3	110.0	159.8	1,167.9
Bookings	**All Hotels**	**67,670**	**4,649**	**5,586**	**7**	**1,745**	**2,905**	**5,469**	**60,261**
(room nights)	*Chain-affiliated*	58,536	4,822	5,743	7	1,843	2,978	5,656	60,261
	Independent	9,134	3,536	4,294	62	1,246	2,274	4,552	40,944
Supply	**All Hotels**	**67,670**	**6,622**	**7,385**	**62**	**2,700**	**4,030**	**8,036**	**62,589**
(room nights)	*Chain-affiliated*	58,536	6,858	7,571	62	2,880	4,092	8,716	62,589
	Independent	9,134	5,109	5,834	237	1,860	3,660	6,960	46,624
Monthly Review Rating	**All Hotels**	**64,438**	**3.7**	**1.0**	**1.0**	**3.3**	**4.0**	**4.3**	**5.0**
(Cummulative average)	*Chain-affiliated*	55,999	3.7	1.0	1.0	3.2	4.0	4.3	5.0
	Independent	8,439	3.9	0.7	1.0	3.6	4.0	4.4	5.0
Monthly Review Count	**All Hotels**	**64,438**	**7**	**13**	**0**	**1**	**1**	**6**	**272**
	Chain-affiliated	55,999	6	12	0	1	1	5	229
	Independent	8,439	12	18	0	2	7	15	272

a. Occupancy rate, ADR, and RevPAR are the monthly average occupancy rate, average daily rate, and revenue per available room.

b. Bookings and Supply are the total numbers of room nights sold and supplied each month.

c. Monthly Review Rating is the cumulative average rating by the month.

d. Monthly Review Count is the number of reviews received in the month.

e. Monthly Review Ratings and Count do not include hotels that are not listed on Tripadvisor.

sample (Table 3.4), which is likely due to their disproportionate representation in luxury and upscale class segments, and their smaller average size, as indicated in Table 3.5. Moreover, independent hotels on average receive more monthly reviews on average and have higher cumulative average review ratings than chain-affiliated hotels.

Over the years, there has been a steady increase in the number of reviews posted on Tripadvisor. Figure 3.2 in the appendix illustrates the changes in cumulative average review ratings and occupancy rates following Tripadvisor's establishment in Chapter 2's data. The vertical axes on the right-hand side represent the number of reviews posted on Tripadvisor annually, while those on the left-hand side show the average cumulative review ratings and occupancy rates for chain-affiliated and independent hotels. Prior to 2009, independent hotels had lower average cumulative review ratings and occupancy rates than chain-affiliated hotels. However, after 2009, the opposite trend emerged, suggesting that the growth of Tripadvisor reviews has given independent hotels an advantage in terms of ratings and occupancy rates.

3.4 Causal impact of Tripadvisor ratings for chain-affiliated vs. independent hotels

I extend the analysis in Chapter 1 by looking at the heterogenous effect of Tripadvisor ratings on chain-affiliated vs. independent hotels. The goal is to examine whether chain affiliation affects the causal impact of Tripadvisor ratings on hotel financial performance.

Table 3.5: Hotel count by operation type in Chapter 2's data

		Chain-affiliated	**Independent**	**All hotels**
Hotel count by Class type				
	Luxury	25	20	45
	Upscale	182	47	229
	Midscale/Economy	216	23	239
Hotel count by Size type	*75 rooms*	78	42	120
	75-149 rooms	180	25	205
	150-299 rooms	86	18	104
	300-500 rooms	56	4	60
	500+ rooms	23	1	24
Hotel count total		423	90	513

a. Class types are based on the class segments provided by STR. Luxury is mapped with "Luxury" in STR; Upscale is mapped with "Upper Upscale" and "Upscale" in STR; Midscale and Economy are mapped with "Upper Midscale", "Midscale", and "Economy" in STR.

3.4.1 Fixed-effect regression

Using the fixed-effect model in Chapter 1, I interact the $Rating_{j,t}$ and $\mathbf{1}\{IsReviewed\}$ with the dummy variable for chain-affiliation as the following:

$$\begin{aligned} y_{j,t} = &\beta_1 Rating_{j,t} + \delta_1 Rating_{j,t} \times \mathbf{1}\{Chain\}_j \\ &+ \beta_2 \mathbf{1}\{IsReviewed\}_{j,t} + \delta_2 \mathbf{1}\{IsReviewed\}_{j,t} \times \mathbf{1}\{Chain\}_j \\ &+ year_t \times \mathbf{1}\{Chain\}_j + h_j + \tau_t \times m_j + \epsilon_{j,t} \end{aligned} \tag{3.1}$$

The coefficients δ_1 and δ_2 measure the relative impact of Tripadvisor ratings on chain-affiliated hotels' performance compared to independent hotels' performance, holding all other factors equal. A negative and statistically significant value of δ_1 indicates that the correlation between ratings and performance is weaker for chain-affiliated hotels compared to independent hotels. To further control for unobserved year trends among chain-affiliated hotels independent of reviews, I include interactions between the chain-affiliation dummy and year in a separate specification.

Table 3.6 shows the estimates of the specification in equation (3.1). The results indicate that the overall average ratings do not have a significant differential effect on chain-affiliated hotels. This implies that, after controlling for consumers' underlying quality, chain affiliation is not significantly correlated with hotel performance. This finding aligns with those of Luca (2011), where the authors reveal that the positive effect of Yelp ratings on restaurants' revenue is driven by independent restaurants, and ratings do not influence restaurants with chain affiliation.

3.4.2 Regression discontinuity design

Although the fixed-effect model shows no significant differences in the correlations between overall average ratings and performance for chain-affiliated hotels versus independent hotels, it is possible that chain-affiliated hotels may respond differently to exogenous rating changes

Table 3.6: Result - Fixed-effect regressions with chain-affiliation using Chapter 1's sample

	(1) ln_Occ_jt (I)	(2) ln_Occ_jt (II)	(3) ln_ADR_jt (I)	(4) ln_ADR_jt (II)	(5) ln_RevPAR_jt (I)	(6) ln_RevPAR_jt (II)
Rating	0.036*	0.035*	0.032**	0.038**	0.067***	0.073***
	(0.020)	(0.020)	(0.016)	(0.016)	(0.022)	(0.022)
Chain×*Rating*	-0.009	-0.007	-0.001	-0.009	-0.010	-0.017
	(0.022)	(0.021)	(0.017)	(0.017)	(0.024)	(0.024)
IsReviewed	0.103	0.102	0.131**	0.119*	0.234***	0.221**
	(0.081)	(0.079)	(0.063)	(0.062)	(0.090)	(0.090)
Chain×*IsReviewed*	0.053	0.051	0.038	0.025	0.091	0.076
	(0.086)	(0.084)	(0.066)	(0.065)	(0.096)	(0.096)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
chain-year fixed effects	no	yes	no	yes	no	yes
N	173686	173686	173686	173686	173686	173686
N (Chain)	149757	149757	149757	149757	149757	149757
N (non-Chain)	23929	23929	23929	23929	23929	23929
Adjusted R-squared	0.58	0.58	0.97	0.97	0.92	0.92

a. Columns indicate the dependent variables in fixed-effect regressions 3.1, namely the log of occupancy rate, ADR, and RevPAR.
b. N is the sample size. Each observation is a hotel-year-month.
c. Standard errors are double clustered at market-year-month level and hotel level.
d. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

than independent hotels. In the regression discontinuity framework, rounding up review ratings is essentially a signal of quality increase that is independent of the underlying reputation of quality. It is plausible that consumers may react more strongly to quality increase signals for independent hotels than for chain-affiliated hotels, due to a lack of prior information or an existing reputation for independent hotels. To test this hypothesis, I examine the heterogeneity of the treatment effect in Chapter 1 equation (3) by adding an interaction between rating and chain dummy. The regression is as the following:

$$\begin{aligned} y_{jt} = &\lambda T_{j,t} + \eta T_{j,t} \times \mathbf{1}\{Chain\}_j + \phi Rating_{j,t} + \delta Rating_{j,t} \times \mathbf{1}\{Chain\}_j \\ &+ year_t \times \mathbf{1}\{Chain\}_j + h_j + \tau_t \times m_j + \varepsilon_{jt} \end{aligned} \tag{3.2}$$

The coefficient η is of interest as it represents the difference in the effect of a 0.5-bubble increase in Tripadvisor displayed rating on performance for chain-affiliated hotels compared to independent hotels, which is not explained by the underlying perceived quality of the hotel. If η is significantly negative, it implies that the impact of review ratings on chain-affiliated hotels' performance is smaller compared to independent hotels. The coefficient λ measures the average effect of a 0.5-bubble increase in Tripadvisor displayed rating on performance for independent hotels. Therefore, the sum of λ and η is the conditional average treatment effect (CATE) of rating rounding for chain-affiliated hotels.

In my main specification, the sample of hotel-year-month observations is restricted to those that are within 0.1, in terms of the average rating, of a rounding threshold. As robustness checks, I consider alternative bandwidths of 0.12 and 0.15. I demonstrate that the results are not influenced by the choice of bandwidth as shown in the appendix.

Table 3.7 shows the heterogenous impacts of Tripadvisor ratings on chain-affiliated hotels and independent hotels. As shown in columns 1 and 2, despite an exogenous lift in Tripadvisor rating, there is no significant difference in the changes in the occupancy rate between chain-affiliated hotels and independent hotels, conditional on the underlying rating. However, positive and statistically significant coefficients of rating suggest that the changes in occupancy rate are still associated with customers' perceived quality. In terms of ADR, as shown in columns 3 and 4, the effect of Tripadvisor ratings on chain-affiliated hotels is significant and smaller than that on independent hotels, although the differences in effect size are moderate, with a 0.2% to 0.4% effect size for chain-affiliated hotels and 1.2% to 1.4% effect size for independent hotels. Regarding RevPAR, as shown in columns 5 and 6, the effect of Tripadvisor ratings on chain-affiliated hotels is significantly less than that of independent hotels. For chain-affiliated hotels, a 1-point increase in Tripadvisor rating leads to a 0.8% to 1% smaller effect on RevPAR compared to independent hotels.

3.5 The demand of chain-affiliated vs. independent hotels

Although the previous section's analysis found no significant effect on chain-affiliated hotels' occupancy rates due to rating rounding, indicating that chains have relatively little

Table 3.7: Result - Regression discontinuity heterogeneous effect by chain affiliation (Bandwidth = 0.1)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
T(Round up)	0.007	0.007	0.007***	0.006***	0.011	0.010
	(0.006)	(0.006)	(0.002)	(0.002)	(0.008)	(0.008)
Chain $\times T$(Round up)	-0.001	-0.001	-0.005***	-0.005***	-0.004**	-0.005***
	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Rating	0.093***	0.161**	0.082***	-0.072	0.175***	0.089
	(0.011)	(0.077)	(0.007)	(0.049)	(0.013)	(0.088)
Chain$\times$*Rating*	-0.077***	-0.093	-0.054***	0.012	-0.132***	-0.081
	(0.012)	(0.080)	(0.008)	(0.051)	(0.014)	(0.091)
$Rating^2$		-0.010		0.022***		0.012
		(0.010)		(0.007)		(0.012)
Chain$\times$ $Rating^2$		0.002		-0.009		-0.007
		(0.011)		(0.007)		(0.012)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
chain-year fixed effects	yes	yes	yes	yes	yes	yes
N	30705	30705	30705	30705	30705	30705
N (Chain)	26905	26905	26905	26905	26905	26905
N (non-Chain)	3800	3800	3800	3800	3800	3800
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Regression model uses the sample with ratings within 0.1 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

uncertainty about quality, Tripadvisor ratings still have a significant positive effect on hotels' financial performance overall, as shown in Chapter 1. This suggests that the impact of Tripadvisor ratings is largely driven by independent hotels. As a result, the increased availability of information about independent hotels could lead to a higher expected utility for consumers choosing to stay in independent hotels, potentially increasing the perceived value of independent hotels over chain-affiliated hotels. Therefore, Tripadvisor has the potential to not only shift demand between independent hotels but also increase the overall value proposition of independent hotels relative to chain-affiliated hotels.

To examine whether Tripadvisor review ratings have shifted the demand for chain-affiliated hotels relative to independent hotels, I use the structural model estimated in chapter 2 by allowing review ratings to have differential effects on the perceived quality for chain-affiliated hotels and independent hotels. Specifically, I use the same estimates of the within-class-group correlations of utility levels σ and price coefficient α, and estimate the following specification for the adjusted quality, which is defined as $Q_{j,t} \equiv ln(s_{j,t}) - \hat{\sigma} ln(s_{j,t|g_j \in G}) - ln(s_0) - \hat{\alpha} p_{j,t}$:

$$\begin{aligned} Q_{j,t} = {} & \phi_{1,t} rating_{j,t} \times \mathbf{1}\{IsReviewed_{j,t}\} \\ & + \eta_t rating_{j,t} \times \mathbf{1}\{IsChain_j\} \times \mathbf{1}\{IsReviewed_{j,t}\} \\ & + \phi_2 \mathbf{1}\{IsReviewed_{j,t}\} \\ & + h_j + \tau_t \times m_j + \tilde{\xi_{j,t}} \end{aligned} \tag{3.3}$$

where $rating_{j,t}$ is the cumulative average rating on Tripadvisor for hotel j by year-month t; $\mathbf{1}\{IsChain_j\}$ is a dummy variable that indicates whether the hotel is chain-affiliated; $\mathbf{1}\{IsReviewed_{j,t}\}$ is a dummy variable that indicates whether the hotel has been reviewed by year-month t; h_j is the hotel-fixed effect and $\tau_t \times m_j$ is the market-year-month fixed effect; and $\tilde{\xi_{j,t}}$ is a structural error, which represents the time-varying component affecting consumers' perceived quality that is not attributed to review ratings.

The coefficient $\phi_{1,t}$ represents the impact of Tripadvisor ratings on the expected quality of independent hotels, and its value varies across the three-year periods considered in the study: 2000-2005, 2006-2010, and 2011-2016. The coefficient η_t reflects the effect of Tripadvisor ratings on the expected quality of chain-affiliated hotels relative to independent hotels. If η_t is negative and statistically significant, it suggests that Tripadvisor ratings have a weaker impact on the expected quality of chain-affiliated hotels compared to independent hotels. The value of η_t also varies across the yearly periods. Therefore, the effect of Tripadvisor ratings on the expected quality of chain-affiliated hotels can be calculated as $\phi_{1,t} + \eta_t$. Because the adjusted quality $Q_{j,t}$ is also equal to $ln(s_{j,t}) - \hat{\sigma} ln(s_{j,t|g_j \in G}) - ln(s_0) - \hat{\alpha} p_{j,t}$, and the market shares are small, I can also interpret $\phi_{1,t}$ and η_t as the effect of Tripadvisor ratings on room nights demanded, all else equal.

To ensure that the results are not biased due to the possibility of chain hotels experiencing a downward trend before the popularity of Tripadvisor, I include the interactions between chain-affiliation dummies and yearly-period dummies in a separate specification as a robustness check. Additionally, similar to chapter 2, I replace the dependent variable in equation (3.3) with the natural logarithm of $p_{j,t}$ to examine if Tripadvisor ratings have differential effects on the prices of chain-affiliated hotels versus independent hotels.

Table 3.8 presents the results of the analysis. In columns 1 and 4, it can be observed that the effects of Tripadvisor ratings are, on average, smaller for chain-affiliated hotels relative to independent hotels. Specifically, a 1-point increase in review ratings is associated with a 5.7% increase in room nights demanded by independent hotels, whereas the corresponding increase for chain-affiliated hotels is 4.8%. Similarly, a 1-point increase in review ratings is associated with a 1.6% rise in ADR of independent hotels, while the corresponding increases for chain-affiliated hotels' ADR are 1.2%. Columns 2 and 3 of Table 3.8 illustrate the differential effects of Tripadvisor ratings on room-night demand across yearly periods. The effects of Tripadvisor ratings have been increasing for independent hotels, and the relative differences in effects on chain-affiliated hotels have also been increasing. From 2000 to 2005, a 1-point increase in review ratings was associated with a 2.6% increase in room nights demanded by independent hotels, while the corresponding increase for chain-affiliated hotels was 2%. In contrast, from 2011 to 2016, a 1-point increase in review ratings was associated with a 7.5% to 8.1% increase in room nights demanded by independent hotels, whereas the corresponding increase for chain-affiliated hotels was 5.9% to 6.3%. This result indicates that Tripadvisor ratings have a positive effect on room-night demand overall, but the effect is more substantial for independent hotels compared to chain-affiliated hotels. Additionally, the relative effects have grown larger over time, with independent hotels experiencing a more significant increase in room nights demanded relative to chain-affiliated hotels.

Similarly, columns 5 and 6 of Table 3.8 demonstrate the varying impacts of Tripadvisor ratings on ADR (Average Daily Rate) across different years. In the case of independent hotels, the effect of a 1-point increase in Tripadvisor ratings on ADR increased from 0.7% during

2000-2006 to 1.8% during 2006-2010 and remained constant during 2011-2016. On the other hand, for chain-affiliated hotels, the effect of Tripadvisor ratings on ADR has been comparably smaller than that of independent hotels during 2006-2010 and has remained constant since then.

Overall, the results show the additional information in review ratings has differential effects on the expected quality, thus room-night demanded chain-affiliated versus

Table 3.8: Result - differential effect of Tripadvisor ratings on chain-affiliated hotels vs. independent hotels

	(1) Q_jt (I)	(2) Q_jt (II)	(3) Q_jt (III)	(4) ln_ADR_jt (I)	(5) ln_ADR_jt (II)	(6) ln_ADR_jt (III)
Rating	0.057***			0.016***		
	(0.003)			(0.001)		
Chain×*Rating*	-0.009***			-0.004***		
	(0.002)			(0.001)		
2000-2005 period×*Rating*		0.026***	0.026***		0.007***	0.008***
		(0.003)	(0.003)		(0.001)	(0.001)
2006-2010 period×*Rating*		0.062***	0.062***		0.018***	0.017***
		(0.003)	(0.003)		(0.001)	(0.001)
2011-2016 period×*Rating*		0.075***	0.081***		0.019***	0.019***
		(0.003)	(0.003)		(0.001)	(0.001)
Chain ×2000-2005 period × *Rating*		-0.006**	-0.006**		0.000	-0.000
		(0.003)	(0.003)		(0.001)	(0.001)
Chain ×2006-2010 period × *Rating*		-0.012***	-0.011***		-0.004***	-0.002**
		(0.002)	(0.003)		(0.001)	(0.001)
Chain ×2011-2016 period × *Rating*		-0.016***	-0.018***		-0.004***	-0.004***
		(0.002)	(0.003)		(0.001)	(0.001)
IsReviewed	-0.121***	-0.104***	-0.104***	-0.020***	-0.018***	-0.019***
	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.004)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
Chain $\times yearly - period$	no	no	yes	no	no	yes
N	67670	67670	67670	67670	67670	67670
Adjusted R-squared	0.97	0.97	0.97	0.97	0.97	0.97

a. Columns indicate the dependent variables in regressions 3.3, namely the adjusted quality $Q_{j,t}$ and the log of $ADR_{j,t}$.

b. N is the sample size. Each observation is a hotel-year-month.

c. Standard errors are double clustered at the market-year level and hotel level.

d. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

3.6 The value of Tripadvisor ratings and brand affiliation

In this section, I conduct counterfactual experiments to compare the welfare of the 2016 status-quo world, where consumers had access to both chain-brand affiliation and Tripadvisor reviews, with hypothetical scenarios where only chain-brand affiliation information was available. To measure the impact of online reviews and brand reputation on consumer behavior and welfare, I introduce exogenous changes in review ratings based on the availability of brand information. Like in Chapter 2, I simulate counterfactual outcomes under both fixed prices and Nash equilibrium prices. However, I differ from before in that I use the estimates of 2011-2016 period rating coefficients found in Table 3.8, column 2, to simulate hotel demand.

Based on the welfare measure as shown in Chapter 2, when prices are fixed, the change in consumer surplus for each market year month from the status-quo review ratings to the counterfactual review ratings are calculated as the following:

$$\Delta CS_{m,t} = -\frac{M}{\hat{\alpha}}\Bigg[\ln\left(1+\Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta^s_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) - \ln\left(1+\Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta^c_{j,t}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right)$$
$$- \Sigma_j\hat{\phi_{1,t}}(rating - rating^c_{j,t})s^c_{j,t} - \Sigma_j\hat{\eta_t}(rating - rating^c_{j,t})s^c_{j,t}\times \mathbf{1}\{IsChain_j\}\Bigg] \quad (3.4)$$

where the last line is based on the assumptions on the counterfactual perceived quality, which depends on the coefficients of the review ratings in 2011-2016 period, that is $\hat{\phi_{1,t}} = 0.075$, and $\hat{\eta_t} = -0.016$ and counterfactual ratings of hotel quality.

Similarly, when prices are adjusted based on Nash equilibrium, the change in consumer surplus for each market-year-month from the status-quo review ratings to the counterfactual review ratings is calculated as the following:

$$\Delta CS_{m,t} = -\frac{M}{\hat{\alpha}}\Bigg[\ln\left(1+\Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta_{j,t}^{StatusQuoEq}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right) - \ln\left(1+\Sigma_{g\in G}(\Sigma_{j\in g}e^{\frac{\delta_{j,t}^{CounterfactualEq}}{1-\hat{\sigma}}})^{1-\hat{\sigma}}\right)$$
$$- \Sigma_j s_{j,t}^{CounterfactualEq}\left(\hat{\phi_{1,t}}(rating_{j,t} - rating_{j,t}^{c}) + \hat{\alpha}(p_{j,t}^{StatusQuoEq} - p_{j,t}^{CounterfactualEq})\right)$$
$$- \Sigma_j s_{j,t}^{CounterfactualEq}\hat{\eta}_t(rating - rating_{j,t}^{c}) \times \mathbf{1}\{IsChain_j\}\Bigg] \tag{3.5}$$

The equilibrium prices and market shares are simulated using the hotel demand estimates in Table 3.8, column 2.

3.6.1 Counterfactual ratings

I use the same methodology as in Chapter 2 to simulate the counterfactual ratings $rating_{j,t}^{c}$. Specifically, I regress the actual review ratings on a set of variables that contribute to brand recognition absent reviews and use the fitted values as the counterfactual ratings. I consider three counterfactual scenarios as the following.

–***Baseline Scenario***– I use the same counterfactual ratings in the Baseline scenario in Chapter 2. That is, I assume consumers possess full information on the time-invariant quality of all hotels, as well as the demand trends for each market-year-month. Comparing the welfare in this scenario with the status-quo world in 2016, I can measure the welfare impact of Tripadvisor ratings in providing information about quality that cannot be identified through hotel identity, which incorporates chain-affiliation and market-year-month time trends. It is important to note that the simulation varies from the baseline scenario in Chapter 2 since it is based on the estimates found in 3.8, column 2. That is, consumers treat chain-affiliated hotels and independent hotels differently conditional on ratings.

–***Partial-observable Scenario***– Same as the Partial-observable Scenario in Chapter 2. That is, I assume that consumers can only access a limited subset of the available hotel characteristics, including the dummy variable indicating whether the hotel is chain-affiliated or independent, class type, size type, location type, and opening year. I regress the actual ratings in 2016 on these characteristics together with the market-year-month fixed effects. The counterfactual ratings are the fitted values of this regression.

–***Partial-with-brands Scenario***– In addition to the hotel characteristics featured in the Partial-observable Scenario, I have incorporated chain-brand identifiers for chain-affiliated hotels in the regression of ratings. This means that I assume consumers also take note of the brand affiliation of each chain-affiliated hotel. By comparing the welfare shift from the status quo to this scenario with the welfare shift from the status quo to the partial-observable scenario, I can measure the values of associating with a chain brand.

Table 3.9 displays the count of hotel-year-month observations categorized by whether the actual review rating is higher or lower than the counterfactual rating for each counterfactual scenario. When the actual rating surpasses the counterfactual rating, it indicates that the quality perceived by consumers through current review ratings is greater than what they would have predicted in the counterfactual scenario and vice versa. As the amount of pre-purchase information decreases from columns 1 to 3, the number of observations with the actual review rating higher than the counterfactual rating also increases, suggesting the removal of pre-purchase information lower consumers' expectations about quality in general. However, this trend does not hold for independent hotels. For independent hotels, the removal of brand information from column 2 to column 3 increases consumers' expectations about quality, as more independent hotels have actual ratings higher than counterfactual ratings when brand information is available compared to when it is removed.

Appendix Figure 3.3 shows scatter plots that visualize the relationship between the counterfactual ratings and the actual ratings. The 45-degree line represents the perfect correlation between the two variables.

Table 3.9: Compare actual ratings with counterfactual ratings

		(1) **Baseline**	(2) **Partial-with-brands**	(3) **Partial-observable**
Total number of hotel-year-month obs		5597	5597	5597
hotel-year-month with *Rating>Rating*[c]	**Overall**	2209 *39.5%*	2632 *47.0%*	2713 *48.5%*
	Chain-affiliated	1889 *33.8%*	2196 *39.2%*	2329 *41.6%*
	Independent	320 *5.7%*	436 *7.80%*	384 *6.90%*
hotel-year-month with *Rating<=Rating*[c]	**Overall**	3388 *60.5%*	2965 *53.0%*	2884 *51.5%*
	Chain-affiliated	2939 *52.5%*	2632 *47.0%*	2499 *44.6%*
	Independent	449 *8.0%*	333 *5.9%*	385 *6.9%*

a. The first row shows the total number of hotel-year-month observations in 2016.

b. The second row shows the number of hotel-year-month observations where actual ratings are greater than the counterfactual ratings under each counterfactual scenario.

c. The percentages are the percentage of hotel-year-month observations among total, i.e. 5597 observations..

3.6.2 Counterfactual Results

Table 3.10 and 3.11 shows the aggregated welfare impacts from the removal of Tripadvisor review ratings in all three markets in 2016 under fixed prices and equilibrium prices, respectively. Table 3.10 and 3.11 in the appendix break down the welfare impacts by three geographic markets. The columns indicate the counterfactual perceived quality under different priors based on brand recognition. In order to measure the value of Tripadvisor ratings to the value of chain affiliation, I compare column 1 which indicates the welfare impact of removing Tripadvisor ratings in the baseline scenario with the differences between columns 2 and 3, which indicate the values of associating with a chain brand.

For consumers, the value of chain-affiliated brands relative to Tripadvisor reviews is modest. The removal of Tripadvisor ratings results in a loss in consumer surplus of about \$0.15 per capita when prices are fixed and \$3.99 per capita when prices are adjusted in Nash equilibrium, as shown in column 1 [3]. The removal of hotel-fixed effects while keeping the chain-affiliated brands, results in a loss in consumer surplus of about \$0.24 per capita when prices are fixed and \$4.86 per capita when prices are adjusted in Nash equilibrium, as shown in column 2. Additionally, further removing the affiliated-brands results in a loss in consumer surplus of about \$0.34 per capita when prices are fixed and \$4.94 per capita when prices are adjusted in Nash equilibrium, as shown in column 3.

For hotels, the removal of pre-purchase information has a negative welfare impact on hotels whose actual review ratings are better than what consumers would have anticipated and a beneficial welfare impact on hotels whose actual review ratings are worse than what consumers would have anticipated. The overall effect on producer surplus depends on whether the gains of "bad" hotels overweigh the loss of "good" hotels from the removal of pre-purchase information.

When prices are fixed, any changes in welfare are attributed solely to shifts in market shares. Table 3.10 indicates that in the baseline scenario, chain-affiliated hotels have a 0.15% higher total market share than the status quo, while independent hotels have a 0.24% lower total market share than the status quo. This suggests that review ratings benefit independent hotels but harm chain-affiliated hotels in terms of market shares. Conversely, when comparing columns 2 and 3, the total market share of chain-affiliated hotels decreases by 0.32% when brand information is removed, while the total market share of independent hotels increases by 0.15% when brand information is removed. This suggests that brand affiliation benefits chain-affiliated hotels but hurts independent hotels in terms of market shares absent reviews. Consequently, chain-affiliated hotels experience the most significant gain in revenue and producer surplus in the baseline scenario among all three counterfactual scenarios, while independent hotels experience the most significant gain in revenue and producer surplus in the partial-observable scenario among all three counterfactual scenarios. This result implies

[3] I use the total changes in consumer surplus divided by market size measured by room nights to calculate the per capita welfare change for consumers. For example, when prices are fixed, the consumer surplus loss from the removal of Tripadvisor ratings is calculated as $\frac{0.49*1000000}{\text{market size}} = \frac{0.49*1000000}{2955406} \approx 0.15$ based on column 1 in Table 3.10

that when prices are fixed, review ratings hurt chain-affiliated hotels even when consumers have full brand awareness, while brand information harms independent hotels when review ratings are not available.

When prices are adjusted based on Nash equilibrium, changes in welfare are attributed to both shifts in market shares and price responses. Table 3.11 shows that, in terms of market shares, the removal of review ratings increases the total market share of chain-affiliated hotels by 0.35% and decreases the total market share of independent hotels by 0.82%. This suggests that review ratings benefit independent hotels but harm chain-affiliated hotels in terms of market shares. Conversely, when comparing columns 2 and 3, the total market share of chain-affiliated hotels increases by 0.91% when brand information is removed, while the total market share of independent hotels decreases by 0.93% when brand information is removed. This suggests that brand affiliation benefits independent hotels but hurts chain-affiliated hotels in terms of market shares in the absence of reviews. However, because of price responses, brand affiliation still benefits chain-affiliated hotels in terms of producer surplus when reviews are not available. As shown in columns 2 and 3 in Table 3.11, the producer surplus of chain-affiliated hotels decreases when brand information is removed, while the producer surplus of independent hotels increases when brand information is removed. Finally, as in the fixed-price scenario, review ratings hurt chain-affiliated hotels in terms of total market share and producer surplus, even when consumers have full brand awareness, as shown in column 1.

Overall, for hotels, the values of Tripadvisor ratings relative to chain brands are the following. When prices are fixed, the removal of Tripadvisor ratings increases the producer surplus by about \$3 per room night when consumers have full-brand awareness, while the removal of brand information increases the producer surplus by about \$0.3 per room night when reviews are not available. When prices are adjusted in the Nash equilibrium, the removal of Tripadvisor ratings decreases the producer surplus by about \$7 per room night when consumers have full-brand awareness, while the removal of brand information decreases the producer surplus by about $0.2 per room night when reviews are not available.

Furthermore, when consumers have full brand awareness (i.e., when comparing the baseline scenario to the status quo), chain-affiliated hotels benefit from the removal of Tripadvisor ratings in both fixed-price and Nash equilibrium scenarios, while independent hotels only benefit from the removal of Tripadvisor ratings when prices are fixed and are negatively impacted by the removal of Tripadvisor ratings when prices are adjusted in Nash equilibrium. This result suggests that if prices are adjusted in Nash equilibrium, online reviews benefit independent hotels when consumers have full brand awareness.

3.7 Conclusion

This chapter examines the impact of Tripadvisor review ratings on the performance and demand of chain-affiliated and independent hotels, as well as the value of Tripadvisor ratings in the presence of brand affiliation. The evidence demonstrates that the rounding of Tripadvisor ratings has a modestly smaller effect on the revenue and average daily rate of chain-affiliated hotels compared to independent hotels, but there is no significant difference in occupancy rates. Furthermore, Tripadvisor ratings have a smaller effect on the demand for chain-affiliated hotels compared to independent hotels, and the relative difference has been increasing over time, suggesting Tripadvisor ratings have increased the preferences for independent hotels relative to chain-affiliated hotels. Consequently, when consumers have full brand awareness, Tripadvisor ratings still bring value to consumers and benefit independent hotels if prices are allowed to adjust in Nash equilibrium. When Tripadvisor reviews are not available, brand affiliation benefits chain-affiliated hotels while hurting independent hotels.

In conclusion, my findings suggest that online reviews continue to play a vital role in shaping consumer perceptions of quality, even in the presence of brand awareness. Online reviews

Table 3.10: Welfare Effects of Removing Tripadvisor Reviews - Aggregated (Fixed Prices)

		(1) Baseline	(2) Partial-with-brands	(3) Partial-observable
Change in Welfare (millions of $)		8.64	8.24	8.91
Change in Consumer Surplus (millions of $)		-0.45	-0.72	-1.01
Change in Producer Surplus (millions of $)	*net change*	9.09	8.96	9.92
	Rating>Rating^c	-9.14	-15.59	-15.55
	Rating<=Rating^c	18.23	24.55	25.47
Change in Revenue (millions of $)	*net change*	17.67	11.90	10.46
	Rating>Rating^c	-31.35	-48.63	-53.73
	Rating<=Rating^c	49.02	60.54	64.19
Change in Total Cost (millions of $)	*net change*	8.58	2.95	0.55
	Rating>Rating^c	-22.21	-33.04	-38.18
	Rating<=Rating^c	30.79	35.99	38.72
Market Size (room nights)		2955406	2955406	2955406
Change in Producer Surplus (millions of $)				
net change	*Chain-affiliated*	6.05	3.81	4.47
	Independent	3.04	5.15	5.44
Rating>Rating^c	*Chain-affiliated*	-8.28	-14.35	-14.26
	Independent	-0.85	-1.24	-1.29
Rating<=Rating^c	*Chain-affiliated*	14.33	18.17	18.73
	Independent	3.90	6.38	6.74
Change in Revenue (millions of $)				
net change	*Chain-affiliated*	11.29	3.08	1.40
	Independent	6.38	8.83	9.06
Rating>Rating^c	*Chain-affiliated*	-27.50	-42.69	-47.25
	Independent	-3.85	-5.94	-6.48
Rating<=Rating^c	*Chain-affiliated*	38.79	45.77	48.65
	Independent	10.22	14.77	15.54
Change in Total Cost (millions of $)				
net change	*Chain-affiliated*	5.25	-0.73	-3.07
	Independent	3.33	3.68	3.62
Rating>Rating^c	*Chain-affiliated*	-19.22	-28.34	-32.99
	Independent	-2.99	-4.71	-5.19
Rating<=Rating^c	*Chain-affiliated*	24.46	27.60	29.92
	Independent	6.33	8.39	8.80
Average monthly change in total market share (%)	all hotels	-0.03	-0.00	0.05
	Chain-affiliated	0.15	0.05	-0.27
	Independent	-0.24	0.11	0.26

a. This table shows the aggregate welfare impacts for three studied markets–Chicago (CBD), Houston, and Miami Beach by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 3.6.1.

c. Rating is the actual review rating for a hotel-year-month observation. *Rating*^{c} is the counterfactual rating.

d. Market size is measured by the maximum number of supply in terms of room nights across all years from all three markets.

e. Average monthly change in total market share is the change of the total market share (in percentages) for all hotels (or all chain-affiliated hotels or all independent hotels) averaged over 12 months in 2016.

Table 3.11: Welfare Effects of Removing Tripadvisor Reviews - Aggregated (Equilibrium Prices)

		(1) **Baseline**	(2) **Partial-with-brands**	(3) **Partial-observable**
Change in Welfare (millions of $)		-32.55	-36.91	-37.66
Change in Consumer Surplus (millions of $)		-11.79	-14.35	-14.60
Change in Producer Surplus (millions of $)	*net change*	-20.76	-22.56	-23.06
	Rating>Rating^c	-31.95	-40.50	-35.63
	Rating<=Rating^c	11.19	17.94	12.57
Change in Revenue (millions of $)	*net change*	-14.60	-24.85	-26.07
	Rating>Rating^c	-34.43	-61.96	-50.73
	Rating<=Rating^c	19.83	37.11	24.66
Change in Total Cost (millions of $)	*net change*	6.15	-2.30	-3.01
	Rating>Rating^c	-2.48	-21.46	-15.10
	Rating<=Rating^c	8.64	19.16	12.09
Market Size (room nights)		2955406	2955406	2955406
Change in Producer Surplus (millions of $)				
net change	*Chain-affiliated*	5.84	3.96	2.06
	Independent	-26.60	-26.52	-25.12
Rating>Rating^c	*Chain-affiliated*	-11.40	-14.39	-12.08
	Independent	-20.55	-26.11	-23.55
Rating<=Rating^c	*Chain-affiliated*	17.25	18.36	14.14
	Independent	-6.05	-0.41	-1.57
Change in Revenue (millions of $)				
net change	*Chain-affiliated*	20.38	3.29	8.96
	Independent	-34.98	-28.15	-35.04
Rating>Rating^c	*Chain-affiliated*	-21.08	-37.26	-22.33
	Independent	-13.35	-24.70	-28.41
Rating<=Rating^c	*Chain-affiliated*	41.46	40.55	31.29
	Independent	-21.63	-3.44	-6.63
Change in Total Cost (millions of $)				
net change	*Chain-affiliated*	14.54	-0.67	6.91
	Independent	-8.38	-1.63	-9.92
Rating>Rating^c	*Chain-affiliated*	-9.68	-22.87	-10.25
	Independent	7.19	1.41	-4.85
Rating<=Rating^c	*Chain-affiliated*	24.21	22.20	17.15
	Independent	-15.58	-3.03	-5.07
Average monthly change in total market share (%)	all hotels	-0.16	-0.13	-0.13
	Chain-affiliated	0.35	-0.62	0.29
	Independent	-0.82	0.24	-0.69

a. This table shows the aggregate welfare impacts for three studied markets–Chicago (CBD), Houston, and Miami Beach by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 3.6.1.

c. Rating is the actual review rating for a hotel-year-month observation. *Rating^c* is the counterfactual rating.

d. Market size is measured by the maximum number of supply in terms of room nights across all years from all three markets.

e. Average monthly change in total market share is the change of the total market share (in percentages) for all hotels (or all chain-affiliated hotels or all independent hotels) averaged over 12 months in 2016.

provide detailed up-to-date information about the quality of individual properties that can help consumers make informed decisions, further emphasizing the importance of a strong online presence for hotels in today's digital age.

Future research could explore how the value of chain affiliation and online reviews changes over time as online review penetration increases. This could involve modeling different types of consumers based on their preferences for brands or online reviews, and conducting counterfactual experiments to assess welfare under varying levels of online review usage. Additionally, future research could explore the effects of review text on the matching process between consumers and hotels and compare its impact to that of horizontal brand preferences.

3.8 Appendices

Table 3.12: Result - Regression discontinuity heterogeneous effect by chain affiliation (Bandwidth = 0.12)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
T (Round up)	0.005	0.005	0.007***	0.006***	0.011*	0.012*
	(0.005)	(0.005)	(0.002)	(0.002)	(0.006)	(0.006)
Chain $\times T$(Round up)	-0.001	-0.001	-0.005***	-0.005***	-0.005***	-0.005***
	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Rating	0.090***	0.182***	0.081***	-0.137***	0.171***	0.045
	(0.010)	(0.070)	(0.007)	(0.045)	(0.012)	(0.080)
Chain$\times$*Rating*	-0.072***	-0.117	-0.055***	0.064	-0.126***	-0.053
	(0.011)	(0.073)	(0.007)	(0.047)	(0.012)	(0.084)
$Rating^2$		-0.013		0.030***		0.018
		(0.010)		(0.006)		(0.011)
Chain$\times$ $Rating^2$		0.006		-0.016**		-0.010
		(0.010)		(0.006)		(0.011)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
chain-year fixed effects	yes	yes	yes	yes	yes	yes
N	36618	36618	36618	36618	36618	36618
N (Chain)	31936	31936	31936	31936	31936	31936
N (non-Chain)	4682	4682	4682	4682	4682	4682
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Regression model uses the sample with ratings within 0.12 neighborhood around rounding thresholds.

b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.

c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.

d. N is the sample size. Each observation is a hotel-year-month.

f. Standard errors are double clustered at market-year-month level and hotel level.

g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

Table 3.13: Result - Regression discontinuity heterogeneous effect by chain affiliation (Bandwidth = 0.15)

	(1) ln_Occ_jt (1)	(2) ln_Occ_jt (2)	(3) ln_ADR_jt (1)	(4) ln_ADR_jt (2)	(5) ln_RevPAR_jt (1)	(6) ln_RevPAR_jt (2)
T (Round up)	0.004	0.004	0.007***	0.006***	0.011***	0.011***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)
Chain $\times T$(Round up)	-0.001	-0.001	-0.006***	-0.006***	-0.006***	-0.005***
	(0.006)	(0.006)	(0.001)	(0.002)	(0.002)	(0.002)
Rating	0.090***	0.182***	0.081***	-0.137***	0.171***	0.045
	(0.010)	(0.070)	(0.007)	(0.045)	(0.012)	(0.080)
Chain$\times$*Rating*	-0.072***	-0.117	-0.055***	0.064	-0.126***	-0.053
	(0.011)	(0.073)	(0.007)	(0.047)	(0.012)	(0.084)
$Rating^2$		-0.013		0.030***		0.018
		(0.010)		(0.006)		(0.011)
Chain$\times$ $Rating^2$		0.006		-0.016**		-0.010
		(0.010)		(0.006)		(0.011)
hotel-fixed effects	yes	yes	yes	yes	yes	yes
market-year-month fixed effects	yes	yes	yes	yes	yes	yes
chain-year fixed effects	yes	yes	yes	yes	yes	yes
N	46446	46446	46446	46446	46446	46446
N (Chain)	40552	40552	40552	40552	40552	46446
N (non-Chain)	5894	5894	5894	5894	5894	5894
Adjusted R-squared	0.69	0.69	0.97	0.97	0.94	0.94

a. Regression model uses the sample with ratings within 0.15 neighborhood around rounding thresholds.
b. *Rating* is the underlying overall review rating, which is calculated as cumulative average ratings.
c. T(Round up) is the treatment dummy indicating whether the rating is rounded up.
d. N is the sample size. Each observation is a hotel-year-month.
f. Standard errors are double clustered at market-year-month level and hotel level.
g. Significance levels are denoted by asterisks (* p<0.1, ** p<0.05, *** p<0.01).

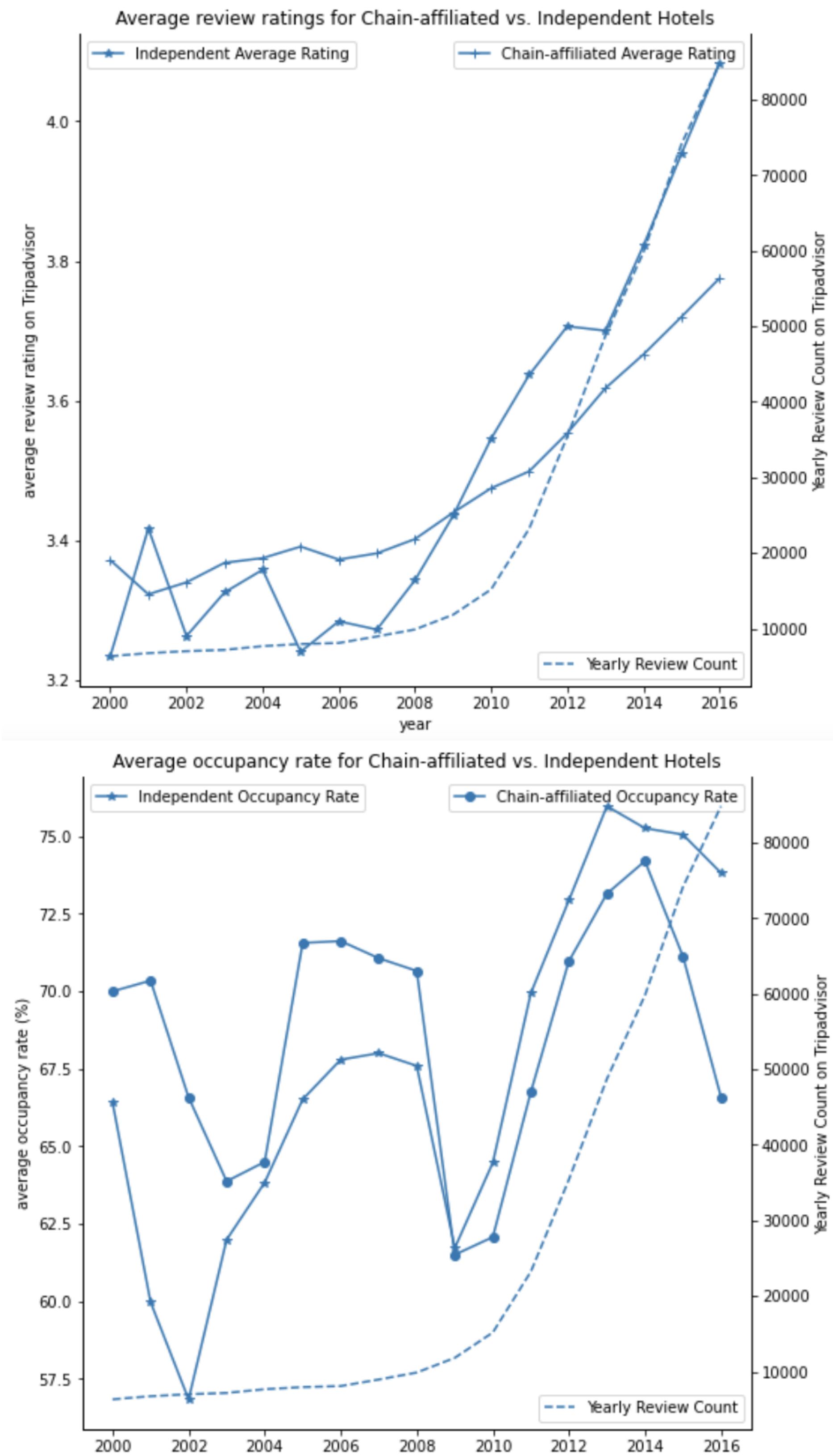

Figure 3.2: Review ratings and occupancy rate after Tripadvisor in Chapter 2's sample

Table 3.14: Welfare Effects of Removing Tripadvisor Reviews - By Market (Fixed Prices)

	(1) **Baseline**	(2) **Partial-Observable + Chain Brands**	(3) **Partial-Observable**
Chicago (CBD)			
Change in Welfare (millions of $)	1.32	1.93	1.88
Change in Consumer Surplus (millions of $)	-0.12	-0.21	-0.22
Change in Producer Surplus (millions of $)	1.44	2.14	2.10
Change in Revenue (millions of $)	-1.99	-3.14	-3.75
Change in Total Cost (millions of $)	-3.42	-5.28	-5.85
Average monthly change in total market share (%)	-0.03	-0.02	0.03
Market Size (room nights)	1210161	1210161	1210161
Houston			
Change in Welfare (millions of $)	1.83	1.37	1.30
Change in Consumer Surplus (millions of $)	-0.29	-0.40	-0.62
Change in Producer Surplus (millions of $)	2.12	1.78	1.92
Change in Revenue (millions of $)	4.61	2.36	1.23
Change in Total Cost (millions of $)	2.48	0.58	-0.68
Average monthly change in total market share (%)	-0.01	-0.01	0.06
Market Size (room nights)	1419322	1419322	1419322
Mia**mi Beach**			
Change in Welfare (millions of $)	5.48	4.94	5.73
Change in Consumer Surplus (millions of $)	-0.05	-0.11	-0.17
Change in Producer Surplus (millions of $)	5.53	5.04	5.90
Change in Revenue (millions of $)	15.05	12.68	12.98
Change in Total Cost (millions of $)	9.52	7.64	7.08
Average monthly change in total market share (%)	-0.05	0.03	0.07
Market Size (room nights)	325923	325923	325923

a. This table shows the welfare impacts in each of the three studied markets by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 3.6.1.

c. Market size is measured by the maximum number of supply in terms of room nights across all years in each market.

Table 3.15: Welfare Effects of Removing Tripadvisor Reviews - By Market (Equilibrium Prices)

	(1) **Baseline**	(2) **Partial-Observable + Chain Brands**	(3) **Partial-Observable**
Chicago (CBD)			
Change in Welfare (millions of $)	-7.24	-6.87	-6.15
Change in Consumer Surplus (millions of $)	-2.43	-2.82	-2.92
Change in Producer Surplus (millions of $)	-4.81	-4.05	-3.24
Change in Revenue (millions of $)	6.32	3.67	4.54
Change in Total Cost (millions of $)	11.14	7.72	7.78
Average monthly change in total market share (%)	-0.06	-0.05	-0.02
Market Size (room nights)	1210161	1210161	1210161
Houston			
Change in Welfare (millions of $)	7.37	2.46	0.54
Change in Consumer Surplus (millions of $)	-4.66	-5.85	-5.98
Change in Producer Surplus (millions of $)	12.03	8.31	6.53
Change in Revenue (millions of $)	11.08	5.34	3.56
Change in Total Cost (millions of $)	-0.95	-2.98	-2.97
Average monthly change in total market share (%)	-0.31	-0.36	-0.33
Market Size (room nights)	1419322	1419322	1419322
Miami Beach			
Change in Welfare (millions of $)	-32.67	-32.49	-32.05
Change in Consumer Surplus (millions of $)	-4.70	-5.67	-5.70
Change in Producer Surplus (millions of $)	-27.97	-26.82	-26.35
Change in Revenue (millions of $)	-32.01	-33.86	-34.18
Change in Total Cost (millions of $)	-4.04	-7.04	-7.83
Average monthly change in total market share (%)	-0.10	0.03	-0.05
Market Size (room nights)	325923	325923	325923

a. This table shows the welfare impacts in each of the three studied markets by comparing the counterfactuals to the status quo in 2016.

b. Columns indicate how the counterfactual ratings are calculated based on section 3.6.1.

c. Market size is measured by the maximum number of supply in terms of room nights across all years in each market.

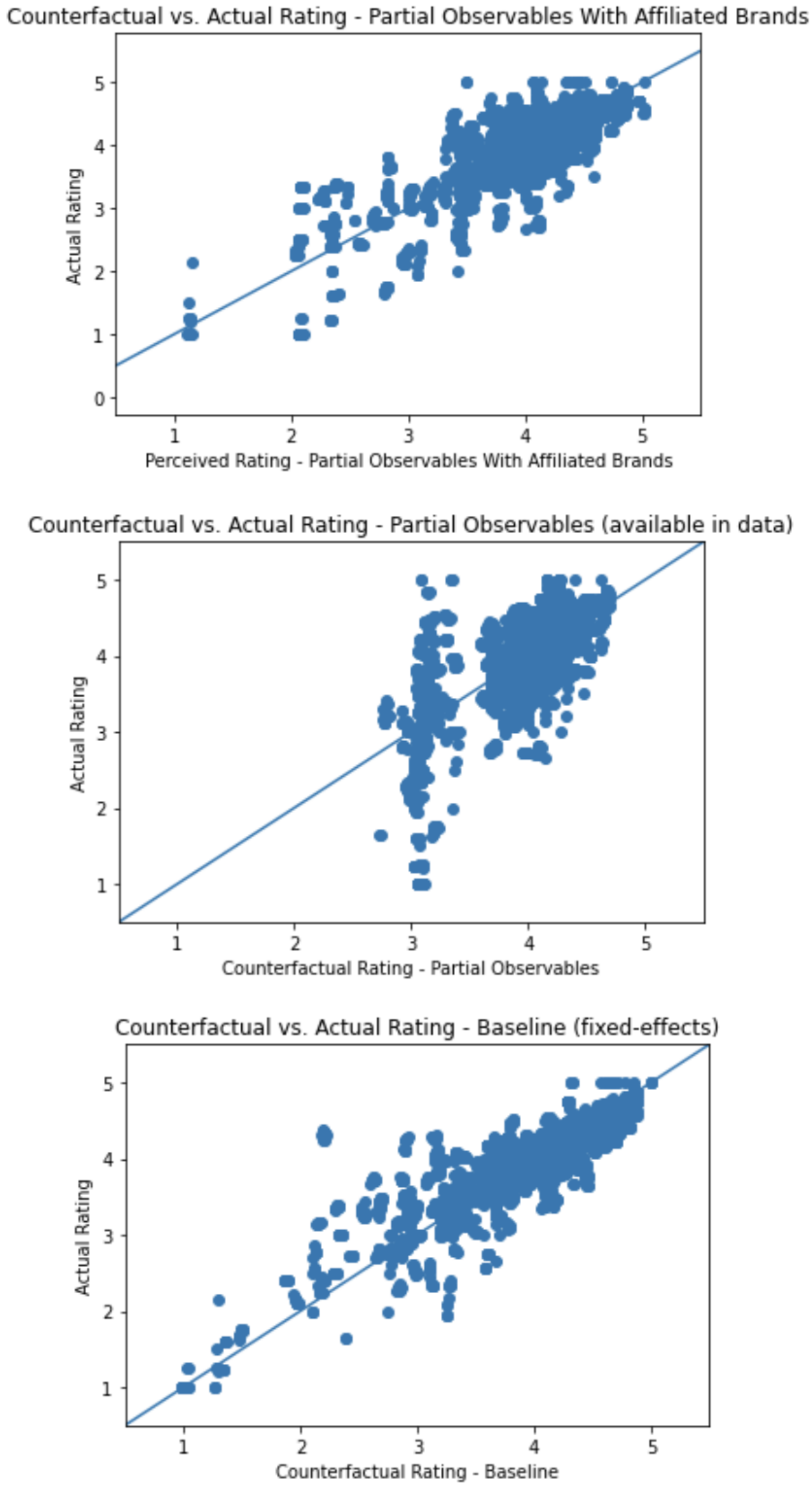

Figure 3.3: Counterfactual Ratings vs. Actual Ratings

Bibliography

Aaker, D. A. and K. L. Keller (1990). Consumer evaluations of brand extensions. *Journal of marketing 54*(1), 27–41.

Aguirregabiria, V. and C.-Y. Ho (2012). A dynamic oligopoly game of the us airline industry: Estimation and policy experiments. *Journal of Econometrics 168*(1), 156–173.

Anderson, C. (2012). The impact of social media on lodging performance.

Anderson, M. and J. Magruder (2012). Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *The Economic Journal 122*(563), 957–989.

Bar-Isaac, H., S. Tadelis, and F. Zettelmeyer (2008). Recommendations, reputation, and responsiveness in online marketplaces. *Journal of Political Economy 116*(3), 694–721.

Berry, S. and P. Haile (2016). Identification in differentiated products markets. *Annual review of Economics 8*, 27–52.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, 242–262.

Blal, I. and M. C. Sturman (2014). The differential effects of the quality and quantity of online reviews on hotel room sales. *Cornell Hospitality Quarterly 55*(4), 365–375.

Bottomley, P. A. and S. J. Holden (2001). Do we really know how consumers evaluate brand extensions? empirical generalizations based on secondary analysis of eight studies. *Journal of marketing research 38*(4), 494–500.

Chevalier, J. A. and D. Mayzlin (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research 43*(3), 345–354.

Corgel, J., J. Lane, and M. Woodworth (2012). Hotel industry demand curves. *The Journal of Hospitality Financial Management 20*(1), 85–95.

Cui, G., H.-K. Lui, and X. Guo (2012). The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce 17*(1), 39–58.

Dickstein, M. J. (2011). Efficient provision of experience goods: Evidence from antidepressant choice. *Job Market Paper, Harvard University*.

Duan, W., B. Gu, and A. B. Whinston (2008). Do online reviews matter?—an empirical investigation of panel data. *Decision support systems 45*(4), 1007–1016.

Erdem, T. (1998). An empirical analysis of umbrella branding. *Journal of Marketing Research 35*(3), 339–351.

Fang, L. (2019). The effects of online review platforms on restaurant revenue, survival rate, consumer learning and welfare. Technical report, Working paper.

Farronato, C. and A. Fradkin (2022). The welfare effects of peer entry: The case of airbnb and the accommodation industry. *American Economic Review 112*(6), 1782–1817.

Farronato, C., A. Fradkin, B. Larsen, and E. Brynjolfsson (2020). Consumer protection in an online world: An analysis of occupational licensing. Technical report, National Bureau of Economic Research.

Fowlie, M., M. Reguant, and S. P. Ryan (2016). Market-based emissions regulation and industry dynamics. *Journal of Political Economy 124*(1), 249–302.

Ghose, A., P. Ipeirotis, and B. Li (2009). The economic impact of user-generated content on the internet: Combining text mining with demand estimation in the hotel industry. In *Proceedings of the 20th workshop on information systems and economics (WISE)*.

Gibbs, C., D. Guttentag, U. Gretzel, L. Yao, and J. Morton (2018). Use of dynamic pricing strategies by airbnb hosts. *International Journal of Contemporary Hospitality Management*.

Goldfarb, A., Q. Lu, and S. Moorthy (2009). Measuring brand value in an equilibrium framework. *Marketing Science 28*(1), 69–86.

Hollenbeck, B. (2016). Online reputation mechanisms and the decreasing value of brands.

Hollenbeck, B., S. Moorthy, and D. Proserpio (2019). Advertising strategy in the presence of reviews: An empirical analysis. *Marketing Science*.

Hortaçsu, A., A. Oery, and K. R. Williams (2022). Dynamic price competition: Theory and evidence from airline markets. Technical report, National Bureau of Economic Research.

Hu, N., L. Liu, and J. J. Zhang (2008). Do online reviews affect product sales? the role of reviewer characteristics and temporal effects. *Information Technology and management 9*, 201–214.

Jin, G. Z. and P. Leslie (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *The Quarterly Journal of Economics 118*(2), 409–451.

Jin, G. Z. and A. T. Sorensen (2006). Information and consumer choice: the value of publicized health plan ratings. *Journal of health economics 25*(2), 248–275.

Kalnins, A. (2017). Pricing variation within dual-distribution chains: The different implications of externalities and signaling for high-and low-quality brands. *Management Science 63*(1), 139–152.

Kosová, R. and F. Lafontaine (2012). Much ado about chains: A research agenda. *International Journal of Industrial Organization 30*(3), 303–308.

Kosová, R., F. Lafontaine, and R. Perrigot (2013). Organizational form and performance: Evidence from the hotel industry. *Review of Economics and Statistics 95*(4), 1303–1323.

Koulayev, S. (2014). Search for differentiated products: identification and estimation. *The RAND Journal of Economics 45*(3), 553–575.

Lewis, G. and G. Zervas (2016). The welfare impact of consumer reviews: A case study of the hotel industry.

Lin, S.-C. and Y. R. Kim (2021). Heterogeneous effects of hotel ownership structure changes on localized market competition using multilevel mixed-effect analyses. *Managerial and Decision Economics 42*(4), 808–820.

Lu, Q., Q. Ye, and R. Law (2014). Moderating effects of product heterogeneity between online word-of-mouth and hotel sales. *Journal of electronic commerce research 15*(1), 1.

Luca, M. (2011). Reviews, reputation, and revenue: The case of yelp. com. harvard business school nom unit working paper 12-016, 1-40.

MacKay, A. and N. Miller (2023). Estimating models of supply and demand: Instruments and covariance restrictions. *Harvard Business School Strategy Unit Working Paper* (19-051).

Maheswaran, D., D. M. Mackie, and S. Chaiken (1992). Brand name as a heuristic cue: The effects of task importance and expectancy confirmation on consumer judgments. *Journal of consumer psychology 1*(4), 317–336.

Mayzlin, D., Y. Dover, and J. Chevalier (2014). Promotional reviews: An empirical investigation of online review manipulation. *The American Economic Review 104*(8), 2421–2455.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics 142*(2), 698–714.

Miklós-Thal, J. (2012). Linking reputations through umbrella branding. *Quantitative marketing and economics 10*, 335–374.

Milgrom, P. and J. Roberts (1986). Price and advertising signals of product quality. *Journal of political economy 94*(4), 796–821.

Moorthy, S. (2012). Can brand extension signal product quality? *Marketing science 31*(5), 756–770.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica 69*(2), 307–342.

Park, C. W., B. J. Jaworski, and D. J. MacInnis (1986). Strategic brand concept-image management. *Journal of marketing 50*(4), 135–145.

Pokryshevskaya, E. and E. Antipov (2020). Robust regression discontinuity estimates of the causal effect of the tripadvisor's bubble rating on hotel popularity. *Higher School of Economics Research Paper No. WP BRP 63.*

Reimers, I. and J. Waldfogel (2021). Digitization and pre-purchase information: the causal and welfare impacts of reviews and crowd ratings. *American Economic Review 111*(6), 1944–71.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica 80*(3), 1019–1061.

Sanford, W. (2019). The shifting scene of independent hotels in america.

Sayfuddin, A. and Y. Chen (2021). The signaling and reputational effects of customer ratings on hotel revenues: Evidence from tripadvisor. *International Journal of Hospitality Management 99*, 103065.

Schuckert, M., X. Liu, and R. Law (2015). Hospitality and tourism online reviews: Recent trends and future directions. *Journal of Travel & Tourism Marketing 32*(5), 608–621.

Shapiro, C. (1983). Premiums for high quality products as returns to reputations. *The quarterly journal of economics 98*(4), 659–679.

Train, K. (2015). Welfare calculations in discrete choice models when anticipated and experienced attributes differ: A guide with examples. *Journal of choice modelling 16*, 15–22.

Vermeulen, I. E. and D. Seegers (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism management 30*(1), 123–127.

Waldfogel, J. and L. Chen (2006). Does information undermine brand? information intermediary use and preference for branded web retailers. *The Journal of Industrial Economics 54*(4), 425–449.

Wang, W., F. Li, and Z. Yi (2019). Scores vs. stars: A regression discontinuity study of online consumer reviews. *Information & Management 56*(3), 418–428.

Yang, Y., S. Park, and X. Hu (2018). Electronic word of mouth and hotel performance: A meta-analysis. *Tourism management 67*, 248–260.

Ye, Q., R. Law, and B. Gu (2009). The impact of online user reviews on hotel room sales. *International Journal of Hospitality Management 28*(1), 180–182.

Zhang, T., G. Li, T. Cheng, and K. K. Lai (2017). Welfare economics of review information: Implications for the online selling platform owner. *International Journal of Production Economics 184*, 69–79.

Zhu, F. and X. Zhang (2006). The influence of online consumer reviews on the demand for experience goods: The case of video games. *ICIS 2006 proceedings*, 25.

Zhu, F. and X. Zhang (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of marketing 74*(2), 133–148.