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Hotel Management in the Digital Age:

Empirical Studies of Reputation Management and Dynamic Pricing

by

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Abstract

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Although a hotel's basic purpose of providing a temporary place of lodging has not changed fundamentally over the course of history, the industry has continuously evolved with the newest innovations in architecture, technology, and culture. The most recent evolution is the digitization of the hotel marketplace. This thesis investigates two areas heavily influenced by the digital marketplace – online reputation management and dynamic pricing.

The first study of this dissertation addresses one important facet of reputation management. How do managers' responses to online reviews alter the opinion of subsequent reviewers? By analyzing a dataset of approximately 17 million hotel reviews, we demonstrate that managers' responses can change the opinion of subsequent reviewers, but not always in a positive way. Responses to negative reviews generally improve subsequent opinion but responses to positive reviews can sometimes negatively influence subsequent opinion. A deep learning topic analysis of response and review texts reveals that tailored responses to positive reviews can actually negatively impact subsequent opinion. The findings in this study are shown to be consistent with the predictions of reactance theory.

The second study seeks to uncover the degree to which managers' pricing heuristics are optimal. Analyzing a year's worth of spot prices for a focal hotel and its two competitors in the Las Vegas market, we show that managers do not price optimally in two peculiar ways. First, managers are able to set close-to-optimal average prices during off-season but dramatically underprice during peak-season. This result is consistent with agency theory that suggests the observable binary outcome of selling out the hotel may attenuate managers' aggressiveness in setting prices. Second, managers, like untrained experimental subjects in prior literature, tend to make price changes that are too small. Furthermore, this study investigates the revenue gains due anticipating competitors' pricing behavior and mean reversion tendencies in online reviews.

Acknowledgments

Endless gratitude…

for my mother, whose love continues to provide me strength from heaven.

for my father, who will never stop challenging the way I see the world.

for my sister, who gives me so much hope for the future.

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Chapter 1

Hotel reputation management

The current research paradigm of social influence in customer satisfaction in the digital age focuses on peer effects in the expectation formation stage. We propose that the broad class of publicly observable service interactions can also have satisfaction externalities for customers who observe these interactions. We test the social influence of observable peer service interactions in the context of managers' response to online reviews. At the time of writing her review, a focal customer has already purchased and experienced the product or service. Even so, managers can still influence focal customers' post-consumption satisfaction through their responses to other customers' reviews. Through a novel natural-experiment, we find empirical evidence using a dataset of more than 17 million hotel reviews that publicly stated satisfaction is positively (negatively) influenced by managers' responses to negative (positive) reviews of previous customers. In addition, we apply latent Dirichlet allocation methods to model the tailoring of manager response to customer reviews. We find that response tailoring to negative (positive) reviews enhances (exacerbates) the positive (negative) effect on subsequent opinion.

1.1. Introduction

User generated content has become an essential piece of a consumer's decision-making toolbox. Nowhere is this more apparent than in the online consumer reviews of experiential products and services like hotels and restaurants. With the growing popularity of such sites as TripAdvisor.com and Yelp.com, consumers have tens of thousands of opinions at their disposal for every consumption choice, whether it is for lunch or a resort getaway. With the increased adoption of online review sites by consumers, managers have begun to use this traditionally one-sided platform to establish a voice for their businesses (Dholakia, Blazevic, Wiertz, & Algesheimer, 2009; Homburg, Ehm, & Artz, 2015). On many review platforms, managers are given a chance to respond to customer comments. Common sense suggests that responding to comments can act as a marketing tool for managers seeking to influence opinion of subsequent customers. While the practice has become standard in some industries as evidenced by the 40% response rate by hotels on TripAdvisor (based on our sample), there has been relatively scant academic literature on this topic. In this study, we seek to address a part of this important gap by analyzing the impact of manager responses on subsequent reviewer opinion.

While the current research is set in the online reviews domain, our study also extends the broader customer satisfaction literature. We view manager response to online reviews as an extension of a company's service interactions with its existing customers.

Thus, we frame our research as identifying the role of observing others' service interactions in augmenting the focal customer's own experiences in generating an overall level of satisfaction. Can observing a company's service interactions with another customer have an impact on the opinion of a customer who already has his or her own experiences to draw from? Fundamentally, this question extends the current paradigm of customer satisfaction that separates pre-purchase expectation formation using public information from post-consumption evaluation based on (dis)confirmatory private information (Oliver, 1980). We turn to an offline example to illustrate the intuition of how public information may enter post-consumption satisfaction in a service setting.

Consider the following scenario set in a restaurant. You are dining during a relatively busy service period surrounded by occupied adjacent tables. Your waiter has done a fine job of serving your table in a routine dining experience with no need to take exceptional actions. As you are finishing your meal and deliberating over the amount of tip to leave, your waiter expertly handles an adjacent table of fussy diners by replacing their slightly overcooked steaks. How might observing this adjacent customer's service interaction influence your tip? We speculate that observing this positive service recovery effort will influence you to leave a higher than expected tip because the waiter's otherwise unknown service capabilities are revealed. Despite the unsatisfactory food quality, the waiter goes above and beyond with service recovery efforts to satisfy customers. This example demonstrates the intuition that others' observable service interactions can add to a focal customer's overall evaluation of quality, leading to enhanced satisfaction when the observed service interaction is positive.

However, observed and experienced service interactions are not identical. Personal service experiences are composed of interactions with the firm meant for the focal consumer while observed experiences of peers are not. The difference in the intended target audience leads to the possibility that observed service interactions can be framed differently by the observer than the receiver. To illustrate this point, we turn to a second restaurant scenario. Your waiter has just received a handsome tip from an adjacent table and thanks the customers for their generous tip. While the customers who left the tip may perceive this interaction as an expression of genuine gratitude, the observer may frame the waiter's expression of gratitude as his or her tactic to influence the tips of the nearby diners. As a result, we speculate that the observing customers can be influenced to leave a lower than expected tip in this thought experiment. The alternative framing of the observer turns a positive interaction into a negative one, leading to a negative bias in the observer's satisfaction.

Based on our two examples, we argue that observing others' service interactions not only influence post-consumption evaluation of satisfaction, but the social nature of these interactions makes the additional information on service quality fundamentally different than primary information from personal experience due to the ambiguity of framing. Not every positive service interaction will be framed by observers as they are intended for the receiver.

Tying the online reviews scenario to the restaurant examples above, we suggest that managers' response to online reviews is an ubiquitous form of observable service interaction of peers that can influence the post-consumption stated satisfaction of customers. We see the analogy as follows. The scenario of a manager responding to a customer's negative review parallels the example of the waiter going above and beyond in his service recovery efforts. The scenario of a manager thanking customers for their positive reviews corresponds to the example of the waiter thanking a customer for a generous tip. In both scenarios, the subsequent review is analogous to the tip left by the focal diner. Our main findings are previewed by the analogy. We find evidence in a data rich environment that manager response to negative reviews (service recovery effort) can positively influence subsequent opinion (stated satisfaction) while response to positive reviews (expression of gratitude) can be detrimental to subsequent opinion.

We propose the following mechanisms to explain our results. When managers respond to negative reviews, subsequent reviewers are exposed to another instance of managers providing a valuable service interaction. This new information augments the customers' own experiences to improve his or her overall satisfaction with the service and product. In the second case, we propose that response to positive reviews can be framed by subsequent reviewers in such a way that is consistent with psychological reactance. Psychological reactance is the theory that individuals who perceive their freedoms to be threatened will take actions to regain those freedoms (Brehm, 1966). In our case, we hypothesize that subsequent reviewers see the response to positive reviews as an invasive action taken by managers to influence the perceptions of a community of customers, thereby threatening the community's goal of sharing personal experiences. As a result, these subsequent reviewers tend to bias their opinions downwards in a possibly subconscious act of defiance.

We contribute to the literature on online reviews by documenting the divergent impact of manager response to positive and negative reviews on subsequent reviewers' product evaluations. We also contribute to the satisfaction literature by demonstrating empirical evidence that observable peer customer service interactions can influence a focal customer's opinion and does so differently than personal experiences. This result suggests that future studies on service satisfaction should consider the impact of service externalities in addition to the dyadic interactions between a service provider and a focal customer. Furthermore, we show evidence of the moderating roles of branding (chain versus independent) and vertical positioning (price range) that are consistent with the proposed mechanisms. Finally, we provide additional evidence of our proposed mechanism through computational textual analysis of response tailoring. We view tailoring of a manager's response to a customer's complaint as an especially good customer service recovery effort. However, tailoring a response to a positive review can additionally influence an observer's propensity to frame the response as an advertising opportunity as opposed to a genuine expression of gratitude, thus leading to increased likelihood of psychological reactance. We find evidence supporting this hypothesis by demonstrating tailoring of responses to positive reviews increases the negative externality on subsequent opinion.

On the methodological front, in contrast to the existing electronic word of mouth (eWOM) literature, we contribute in two ways. First, we augment our analysis of numerical ratings with text topic identification using latent Dirichlet allocation (LDA) to bolster the causal mechanism suggested by reactance theory. The vast majority of eWOM literature ignores the rich information contained in actual review texts, choosing to analyze only the numerical data. Even when the prior literature uses text data, the text is usually converted to sentiment measures based on existing dictionaries trained on unrelated corpuses of documents such as Wikipedia. Notable exceptions include papers by Tirunillai and Tellis (2014) and Homburg, Ehm & Artz (2015). Using topic modeling techniques, we are able to address the important managerial issue of how to construct a manager response, specifically how and when to tailor responses to reviews. This type of insight can only be gained using LDA or other similarly nuanced topic modeling techniques.

Second, we rely on a novel identification strategy that our uniquely large dataset enables. Competing literature estimates the impact of manager response on subsequent opinion by leveraging cross-platform differences in manager response tendencies in a difference-in-differences (DD) setting. Specifically, by controlling for hotel quality with reviews from a second website that lacks manager responses, several working papers document a bump in ratings after managers begin to respond to reviews (Ye, Gu, & Chen, 2010; Proserpio & Zervas, 2015). This approach, while econometrically appealing as a standard causal argument, faces two shortcomings. First, DD disregards manager responses after the initial response. As a result, the estimated effect is not representative of all manager responses but rather represents the effect of a "regime change" from not responding to responding. However, it is not clear whether the observation of a first manager response is actually indicative of a regime change. Moreover, we cannot distinguish between the effects of responding to positive versus negative reviews given that most first responses are targeted at negative reviews. Second, this approach only addresses the confounding issue of changes in underlying quality, i.e. managers' response occurs contemporaneously with quality improvements which cause ratings to improve. The approach does not rule out the endogeneity issue of managers choosing to respond when faced with a period of site-specific random negative fluctuation in ratings. For example, if a hotel receives a string of bad reviews on TripAdvisor, managers may be more likely to respond to these reviews. Subsequently, average ratings return to the long run mean on TripAdvisor. The DD estimation method will identify this as a causal effect of manager response on subsequent ratings while the underlying mechanism could just be a natural mean-reverting process.

We propose a novel natural experiment approach in estimating the causal effect of manager response that addresses both issues with the DD approach. Using data from a single site, TripAdvisor, we analyze reviews that immediately follow a prior review that receives a response. By leveraging the timestamps attached to every manager response and reviewer rating, we are able to identify whether the previous review's response is visible to the immediate subsequent reviewer at the time of writing his or her own review. By comparing only reviews that follow a manager's response and identifying whether that response was visible, we eliminate alternative explanations related to the endogenous decision to respond. Additionally, our natural experiment allows us to incorporate all manager responses into our analysis, not just assuming that the first response is representative of a permanent regime change in the firm's policy. This way, we can analyze and establish the divergent effect of managers' response to positive reviews (MR-P) and managers' response to negative reviews (MR-N) on subsequent reviewer rating.

1.2. Literature Review

At the heart of our current research is the idea that opinions are formed not only based on one's direct experiences but also the observed experiences of others. The literature on online reviews emphasizes social influence in the initial search stages of a customer's interaction with a product or service. This research framework implicitly or explicitly assumes, in a manner consistent with the broader expectation disconfirmation paradigm of the customer satisfaction literature (Anderson & Sullivan, 1993; Churchill & Surprenant, 1982; Oliver, 1980), that the pre-purchase expectations contain the only source of indirect information that matters up to the point of an individual deciding to share his or her opinions (Moe & Schweidel, 2012). However, there are many scenarios where attitude formation depends not only on expectations prior to experiential knowledge, but also on the direct observation of experiences of others. In social learning theory, Bandura (1977) emphasizes that learning "can occur through observation of modeled behavior and accompanying cognitive activities without extrinsic reinforcement." Framed in the context of learning about product or service quality, we can say that observing others' experiences with a product or service can augment the information gained from an individual's personal experiences. In this study, we test the hypothesis that the social component of service quality assessment continues well beyond the expectation formation stage as is typically assumed in the literature. In fact, we propose that even after a customer has ended his or her own interaction with the service provider, the customer can still be influenced by the passive observation of the service provider's interaction with other customers.

In order to test this hypothesis in a large empirical setting, we turn to the domain of electronic word of mouth (eWOM). eWOM has been a rich topic of research for marketing scholars. Early work primarily focused on documenting the robust impact of eWOM on sales in various categories. Perhaps more importantly, this rich area of study brought econometric causal inference arguments to the forefront of marketing research. Chevalier and Mayzlin (2006) use a differences-in-differences approach to establish the causal relationship between negative reviews and relative book sales on Amazon.com and BN.com. Luca (2011) exploits Yelp's rounding of aggregated ratings to the nearest half star in a regression discontinuity design framework to establish the effect of Yelp ratings on restaurant revenue and competition dynamics. Clemons et al. (2006) examine the hyper-differentiated craft beer industry to demonstrate the asymmetric impact of online reviews on high and low differentiated firms, suggesting that firms that offer greater product assortment will benefit more from eWOM. In the movies category, Liu (2006) examines the dynamic effects of WOM in the movie industry, correlating pre-release and post-release consumer sentiment and chatter volume with box-office revenues. Consistent with subsequent studies on movie WOM (Duan, Gu, & Whinston, 2008), Liu finds that the volume of WOM, rather than its valence, predicts subsequent sales. In the domain of our current study's travel focus, Ye et al. (2009) find a positive effect of online ratings on hotel sales on Ctrip, a Chinese online travel agent.

In light of the extensive evidence that eWOM can impact both online (Amazon, BN, Ctrip) and offline (Yelp, Ratebeer) sales across multiple categories, a stream of marketing literature has sprouted to examine how and why consumers use and contribute to online review forums. In a broad review, Berger (2014) argues that the social phenomenon of WOM serves five distinct functions for a participant: impression management, emotional regulation, information acquisition, social bonding, and persuasion. In our travel review context, we can expect all five of these factors to be at play. For example, sharing extremely detailed information about a trip may serve both the impression management and information acquisition functions. The sharer can expand their online identity as a travel expert while providing unique information to their peers. Travelers may share joyous opinions after a once in a lifetime travel experience or their extreme anger after a ruined vacation to regulate their emotional state, bond with others with similar experiences, and persuade future travelers in their purchasing decisions. All of these motivations for WOM exist to help build a community of likeminded consumers. In our case, TripAdvisor is such a community where members post reviews of their positive and negative experiences, contribute to forums to share travel knowledge, and seek expertise from their peers. Though we have extensively studied the members of eWOM communities, we know relatively little about how these members react when an outside entity such as managers interject in their conversations. Our study seeks to extend the academic knowledge on eWOM communities in this direction.

In an empirical study, Moe and Schweidel (2012) dive into some of the factors summarized by Berger that affect a consumer's decision on whether and what to post in an online product opinion forum. Moe and Schweidel propose a conceptual model of WOM incidence and evaluation that begins with formation of expectations by reading others' product reviews leading to a purchase decision followed by WOM incidence and evaluation decisions. The authors argue that individuals are more likely to contribute to public opinion in positive rating environments than negative ones, that less frequent posters exhibit bandwagon opinions, and frequent posters are motivated to present differentiated opinions in order to signal their expertise. In an earlier experimental study, Schlosser (2005) demonstrates that, conditioned on giving a public opinion, individuals are likely to adjust their opinion downwards given that others have rated the same product or experience negatively. Schlosser theorizes that others' negative opinions are more effective at altering a focal reviewer's opinion than positive ones because negative opinions are seen as more discerning and intelligent. Furthermore, Schlosser suggests that the social outcome of an individual's public opinion can influence the negativity bias, i.e. when a wider audience reads a poster's opinion, she/he is more likely to be influenced by others' negative opinions. The above examples from the literature illustrates some of the complex motivations that lead to the formation of eWOM but ignore the potential influence of observing service interactions between managers and other customers. We argue that a customer's post-purchase observation of others' service interactions can influence that focal customer's opinion of service quality.

One ubiquitous way in which managers' service interactions with other customers can be observed post-purchase is their public responses to online reviews. While manager response to reviews is a largely ignored phenomenon in academic research, the managerial motivations appear clear. By responding to reviewers, managers extend the duration of the service interaction and their sphere of influence. Managers may reply to negative reviews to address service complaints, manage impression, and reduce misinformation. On the other hand, managers may reply to positive reviews to demonstrate their appreciation of customers and humanize their brand. The downside to responding is that managers may appear flippant, overzealous, or insincere in their responses. Using data from Ctrip, Gu and Ye (2014) find that manager responses to negative reviews can increase the rating by the same individual at the same hotel in a future review. We view this as a positive customer service interaction that a subsequent reviewer might observe. However, the authors also find that individuals who do not receive a response to their initial negative review – but observe others who do receive a response – are more likely to post an even more negative review following a subsequent visit. The authors theorize that the former result is consistent with the prior literature on service recovery while the latter result can be explained in terms of peer-induced fairness theory. The latter result is of particular interest in our study as it is one of the few papers in any setting that documents the social influence of observing managers' interactions with *other* customers on a focal customers' opinion.

In a working paper, Proserpio and Zervas (2015) find a less ambiguous result at the firm level using TripAdvisor hotel reviews. Using methods similar to an earlier working paper by Ye et al. (2010), Proserpio and Zervas use Expedia reviews, which most hotels do not respond to, as a control for underlying hotel quality in their difference-in-differences identification of the effect of manager responses on subsequent reviewer opinion. The authors find that review ratings are higher in periods after the initial manager response than in periods prior to that response. The authors attribute this effect to a change in the distribution of reviewers between the pre and post response period, theorizing that manager response dissuades negative reviewers from leaving a review. While there is significant appeal in this identification approach, there are also several shortcomings. First, taking a single response as a policy change for a hotel fails to address the complexity of manager response policies. For an extreme example, if a manager has only responded to a single review, what is the theoretical causal link between that response and the ratings the hotel received 2 months later when the response is no longer easily visible to the reviewer? Moreover, the DD approach cannot test whether response to positive versus negative reviews have different effects on subsequent opinions since most initial responses are to negative reviews. Second, due to the cross-platform design, the authors are not able to take review order effects into account. If the two sites exhibit different review frequencies, one cannot compare the n^{th} review after a manager response across sites. This is critical in establishing a theoretical link because the order of review is essential in identifying the visibility of manager responses given that TripAdvisor and Expedia only display 10 reviews per page. If the manager response is not observable to subsequent reviewers, one cannot make any theoretical connections between the increased ratings to the incidence of a manager response. Third, despite controlling for underlying hotel quality, the DD approach cannot rule out the explanation that managers endogenously time their responses to site-specific random fluctuations in ratings which return to the long-run mean as a result of mean reversion tendencies in online ratings.

Despite the limitations of previous studies on manager response to online reviews, the findings of these studies are consistent with both lay theory and psychological foundations. For example, it is easy to imagine a consumer who is about to write a review to be reminded of a hotel's attentive service when spotting a manager's response on the hotel's TripAdvisor page. Alternatively, a theory that illuminates the positive effect of manager response is social exchange theory, which is founded on the premise that interactions between two parties can be characterized as an equitable exchange of various forms of capital, and the parties involved participate based on their analyses of costs and benefits (Emerson, 1976). In the case of manager response to online reviews, the managers' attentiveness can be seen as an expenditure of time and effort to be rewarded with a higher rating by the reviewer. This theory has tremendous intuitive appeal as it plays on the concept of an equilibrium outcome in which increasing number of hotels would adopt response behavior and average ratings increase overall in a mutually beneficial arrangement that reflects the observed empirical trends on TripAdvisor.

While the idea of manager response as having a positive effect on a hotel's reputation has tremendous appeal, both lay theory and the psychology literature may also suggest that the opposite can also be true. For example, one can imagine that a consumer who is not paying attention to what other reviewers have written may be drawn to a review that a manager has responded to. Given that managers tend to more frequently address negative reviews, this highlighting effect may introduce anchoring biases in subsequent reviewers. From a more theoretical perspective, White et al. (2008) offer reactance theory as an explanation for customers' negative attitudes towards firms that practice personalized customer communications. Psychological reactance is the theory that individuals will attempt to take actions to re-establish freedoms that are reduced, lost, or threatened (Brehm, 1966). In the manager response context, we can interpret a manager's intervention in an online review community as a threat to community members' freedom of expression. For example, if a reviewer wants to write a negative review but observes that the manager responds to negative reviews to address the individuals' complaints specifically, the reviewer may deem this as a threat to his/her freedom, and post an even more scathing review as a result.

While reactance for reviewers with negative experiences seems plausible, it does not appear immediately obvious that the effect might hold for positive reviews. However, going back to our restaurant example of the waiter who thanks an adjacent customer for leaving a generous tip and thereby causing the focal customers to view this action as manipulative, we can attribute the focal customer's propensity to leave a lower tip as a direct application of psychological reactance theory. Similarly, in the eWOM domain, imagine a reviewer who sees his motivation to express an opinion publicly as one grounded in his or her identity as a member of the TripAdvisor community who values the unfettered exchange of travel experiences. Assuming that a manager's response to positive reviews can influence travelers' choices and opinions, our hypothetical TripAdvisor member may take actions to offset the intentions of the manager by giving an artificially lower opinion than he or she would have otherwise given. As a result, an individual who would have given a five-star review may give four stars. Adding to the complexity of reactance in our context, White et al. (2008) find that reactance to direct managerial communication is attenuated when the utility from that communication is high. This nuance suggests that the reactance effect might actually be greater for responses to positive reviews, as the manager's response conveys less valuable information than in the case of negative reviews. Going back to our opening restaurant example, customers observing a waiter thanking an adjacent table for a large tip tend to frame this interaction as a manipulation tactic. We propose this negative framing is due to the relative unimportance of the interaction to the observer. Thus, consistent with White et al.'s finding, our hypothetical tipper experiences psychological reactance and leaves a lower tip. The theoretical tension in the plausible outcomes of manager response on subsequent reviews sets the stage for our current research. Our research resolves these tensions by demonstrating that observing MR-N and MR-P both affect stated satisfaction levels by augmenting a customer's personal experiences in a manner consistent with the reactance theory hypothesis. This result further cements our opening hypothesis that personal experiences and observed experiences of others contribute to the satisfaction evaluation in different ways due to the ambiguity in framing of observed experiences. The framing ambiguity is especially important when others' service interaction does not add informational value to the observer as is in the case of MR-P. In the following section, we describe the institutional insights and data that allows us to test our claims.

1.3. Empirical Setting

1.3.1. Institutional Insights

While the theoretical implications of our research are rooted in the general impact of observed peer service interactions on own quality perceptions in any service setting, we focus our analysis on TripAdvisor's online review community and the tourism industry. The choice of this context is both practical in terms of the ability to obtain publicly available data and substantively interesting due to the economic importance of both the firm and industry. According to the World Travel & Tourism Council (2015), tourism directly contributes $2.4 trillion and 105 million jobs to the global economy while its broader indirect impact on the global economy exceeds $7.6 trillion or 9.8% of the global economy. In the United States alone, there were over 52 thousand lodging properties with at least 15 rooms, over 4.9 million guestrooms, and approximately $163 billion in revenue in 2014 (American Hotel & Lodging Association, 2015). In such a large and diverse market, especially when purchases often need to be made sight-unseen, there is a tremendous need for online reviews to aid consumers in making informed purchase decisions.

One of the largest players in the review platforms business is TripAdvisor. According to TripAdvisor's website (2015), the company boasts 340 million unique monthly visitors, 78 million members, and more than 225 million reviews for approximately 950,000 lodging options, 2.7 million restaurants, and 530,000 attractions. It has 24 branded websites that operate in 45 countries worldwide. In 2011, TripAdvisor introduced a mobile application with 190 million downloads to date. The scale of TripAdvisor offers the perfect laboratory to answer our research question. In order to frame our identification strategies, we draw upon some practical considerations of TripAdvisor's website design. For instance, reviews are by default shown in reverse chronological order, with each page showing the ten most recent reviews. Examining TripAdvisor's historic web designs using Internet Archive's Wayback Machine, the reverse chronological display of sets of 10 reviews per page has been a consistent hallmark of TripAdvisor's design. Understanding this website structure and the empirical fact that most consumers do not read past the first page of reviews (Pavlou & Dimoka, 2006), we focus our analysis on the most recent ten reviews at the time each new review is written. Furthermore, considering the reviewer has already visited the hotel at the time of writing a review, he or she is even less likely to scroll down the page to read additional reviews. In fact, unless the reviewer is actively seeking previous reviews prior to writing his or her own, he or she can only observe the first review and response, if it exists, at the time of writing the review (Figure 1-1) on both the mobile app and desktop site.

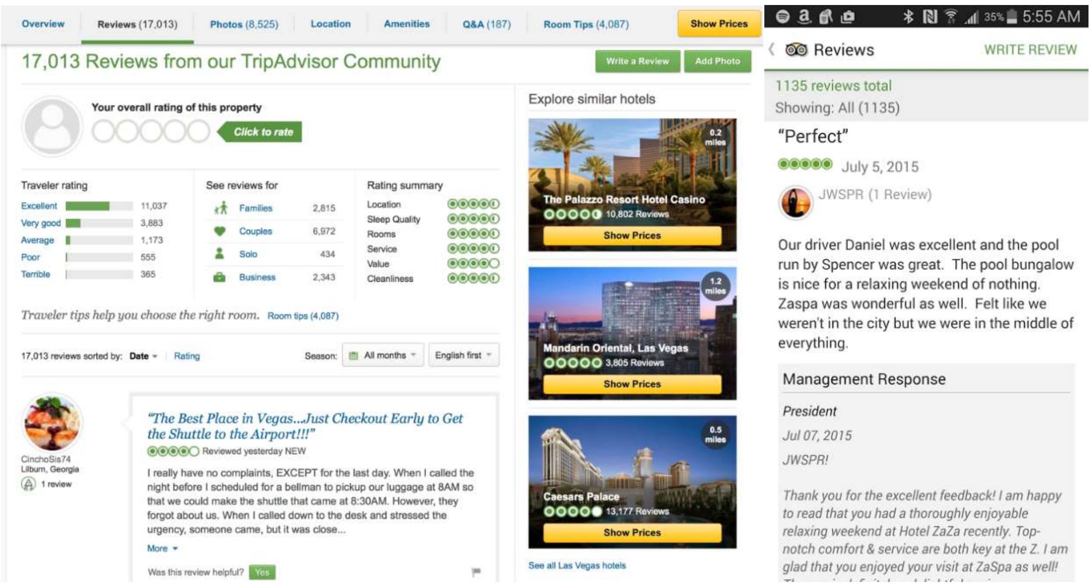


Figure 1-1 - TripAdvisor Design

The left screenshot shows the desktop version of TripAdvisor. The review button is on the top right of the page and the first review (and response if available) is visible. The right screenshot shows the mobile app. Again the "write a review" button is on the top right of the page and the first review and response is visible.

In the website's current iteration, upon clicking on the "write a review" button, consumers are presented with a survey style form and the texts of the three most recent reviews in the sidebar. From top to bottom of the form page, the reviewer is first asked to rate the property, title their review, compose their review text, and fill out some questionnaire items. After the review is submitted, it is vetted and posted usually within 24 hours by TripAdvisor. Upon final approval of the review, managers are then able to respond. The website publicly displays the date of both the initial submission of the review and the manager's response. Putting the pieces together, we can explain our strategy in identifying the causal impact of manager response on online reviews. Intuitively, an experimental researcher would exogenously assign subjects to one of two groups: a first group that is exposed to a manager response just prior to writing their reviews, and a second group that is not. In order to steer clear of confounding mean reversion of ratings that can affect DD approaches, our causal test replicates the perfect lab experiment described above by identifying two potential scenarios faced by each reviewer. In the first scenario, a hotel responds to a reviewer before the next reviewer writes a review. We call this the observable response scenario. In the second situation, the same hotel responds to a reviewer, but not before the next reviewer has written his or her review. We call this the unobservable response scenario. These two scenarios compare reviews following observable and unobservable responses for the same hotel, eliminating between-hotel differences, on the same site, eliminating confounding site differences, and after the manager response policy has been applied, eliminating manager response selection issues. In our case, managers may choose a policy to respond only after observing a randomly occurring sequence of negative reviews. If reviews are mean reverting, studies not addressing this type of behavior will bias their results towards finding a significant positive causal effect. We next describe the data collection process and descriptive statistics to document trends in online reviews and manager responses.

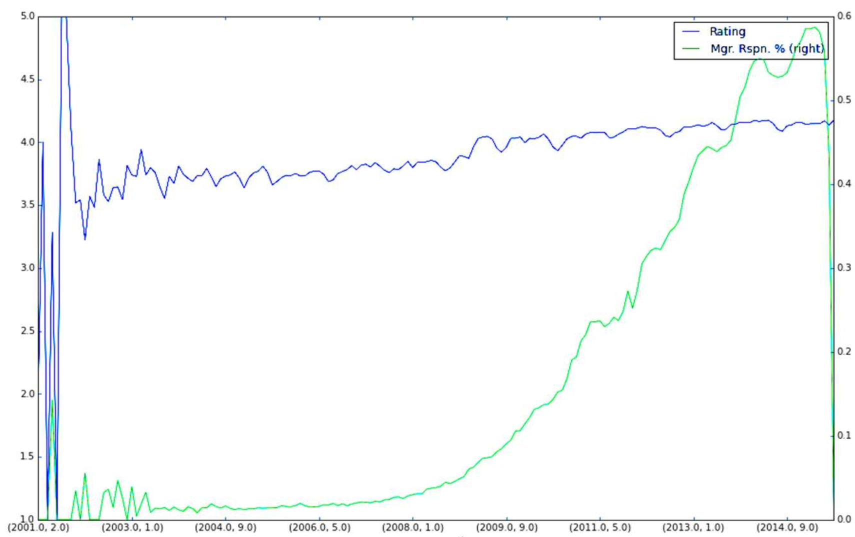
1.3.2. Data

In order to collect a representative sample of hotels on TripAdvisor, we strayed from the convention of previous studies to focus on a particular geographic region that may lead to local or regional biases. This, however, presents a challenge. It is not possible to randomly sample TripAdvisor's website. To get around this issue, we seeded our data collection by writing a crawler to collect all the reviews from 30 large hotels in Las Vegas. We chose Las Vegas because of the volume of reviews for Las Vegas hotels – many of which have over 10,000 reviews. From this initial seed collection, we then generated a list of all other reviews written by the 120,000 unique users in the seed dataset. Using this list of reviews, we compiled a list of over 60,000 hotels worldwide. We plot the resulting sample's longitude and latitude data in Figure 1-2. It is clear that our sample, though having a substantial North American and European bias that likely reflects TripAdvisor's site bias, covers almost the entire world.

Figure 1-2 - Geographic Coverage of Data
The plot above is generated from the longitude and latitude information in our raw data of over 60,000 hotels and nearly half a million total venues. Large blue dots represent high volume areas while smaller yellow dots represent low volume areas.

We end up with a raw dataset of 17,180,887 hotel reviews, more than 7.6% of TripAdvisor's entire database of 225 million reviews across all venue types (hotels, restaurants, B&B's, apartment rentals, activities, etc.). Although the data collected using our seeding method actually contained more reviews across the other venue types, we focus the current study on hotels due to the sparsity of manager response in non-hotel venues. Furthermore, our 65,099 hotels represent almost 7% TripAdvisor's total lodging sample, which includes smaller B&B's, campgrounds, and apartment rentals that we do not include. Writing the 17 million reviews are over 5.7 million unique users, representing 7.3% of all of TripAdvisor's members. This yields on average 3 hotel reviews per user and 264 reviews per hotel.

We find that reviewers on TripAdvisor are overwhelmingly positive and hotel managers respond to roughly 40% of all reviews. The mean rating is 4.09 while the median and 25th percentile rating is 4 out of a maximum of 5. Of course, given that these hotels are currently operating, we expect some positive survival bias as negatively rated hotels are more likely to close. Nonetheless, the overwhelming positivity on the site suggests that we should consider any rating below four a "negative" rating consistent with Gu and Ye (2014). Plotting the ratings and response rates, we establish that both are increasing in calendar time (Figure 1-3). Manager response percentage rises in especially dramatic fashion from nearly nonexistent to almost 60% by 2015. Clearly, manager response has developed into an industry norm over the past decade.



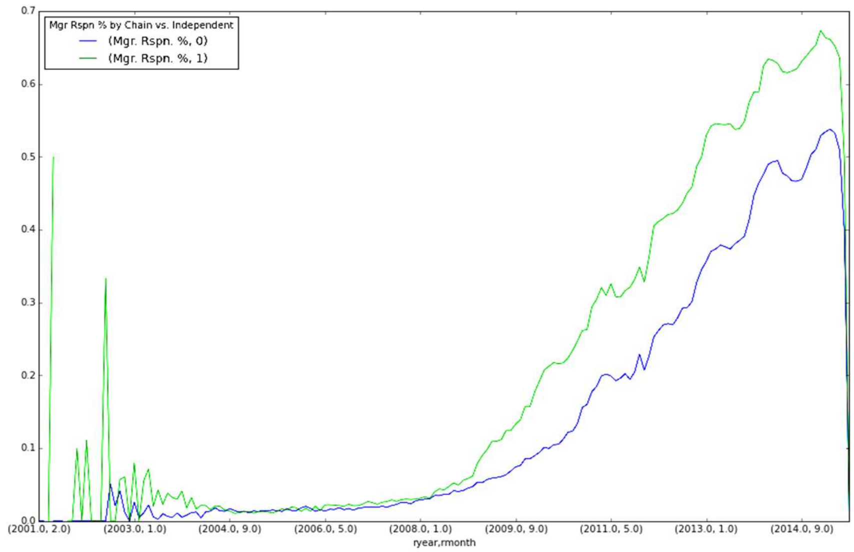


Figure 1-3 - Historical Review and Response Trends
Top panel: The above plot shows the time trend of monthly mean review ratings (blue, left axis) and average manager response % (green, right axis) over the time span of our dataset.
Bottom panel: Manager response rates by chain (green) and independent hotels (blue) over time. The graphical evidence clearly shows that chains are faster adopters than non-chains of manager response practices.

We show in Figure 1-4 that the adoption of manager response varies by the price range of the hotel, as defined by TripAdvisor's price range categories ($-$$$$). The hotels with no dollar amount information, generally located outside of the United States, are least likely to adopt manager response policies followed by the 1-dollar sign hotels. This is consistent with previously documented trend among Texas hotels on TripAdvisor (Proserpio & Zervas, 2015). The most expensive hotels are also less likely to respond when compared to mid-level properties. This is likely driven by the greater propensity for all managers to respond to negative reviews, of which expensive hotels generally lack.

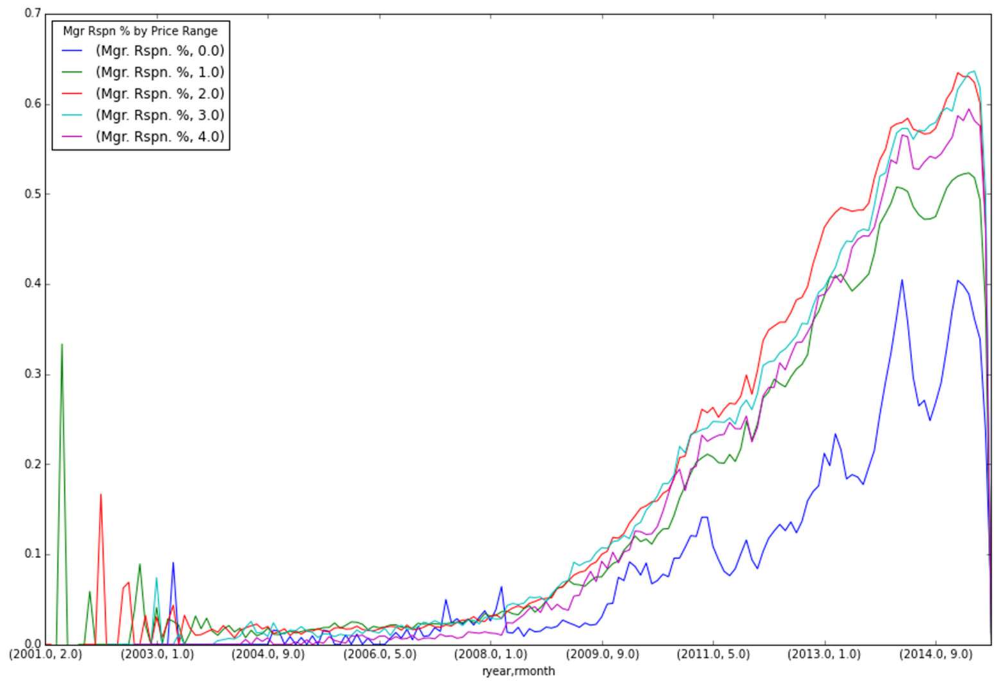


Figure 1-4 - Manager Response by Price Category
Hotels with no price information are least likely to respond to reviews. The lack of response to English reviews is driven by the propensity of these hotels to be located outside of North America.

There are also interesting differences between chain and independent hotels in their adoption patterns of manager response. In identifying hotel chains, we compiled a list of the world's largest hotel chains and their 136 sub-brands from each chain's website. We then matched the sub-brands' names to the venue names listed in our TripAdvisor raw data. In total, we matched 23,294 hotels from our list of 65,099 to chain brands, or about 36% of our data. We break down the total locations and guestrooms in Table 1-1. While Wyndham dominates the number of locations in our dataset, Hilton represents the largest number of guestrooms at nearly half a million. In the bottom panel of Figure 1-3, we show that chain hotels are much more likely to practice manager response than independent hotels, although chains and independents appear to adopt this practice around the same time and do not diverge in adoption rates until 2008. Among the top seven brands by room-count (there is a significant drop off in size between 7 and 8), Starwood is the chain that has most embraced manager response to online reviews, peaking recently at an astonishing 90% response rate.

Brand	Locations	Rooms	Avg Size
Wyndham Worldwide	3,564	330,336	93
Choice	3,219	266,197	83
Hilton Worldwide	3,045	493,685	162
Group Ihg	3,018	434,944	144
Marriott International	2,396	416,990	174
Best Western	2,026	167,103	82
Accor	1,455	224,145	154
Carlson Rezidor	812	115,526	142
Starwood Worldwide	773	213,271	276
La Quinta Inns	550	56,261	102
Premier Inn	508	46,453	91
Motel 6	497	46,680	94
Hyatt Corporation	387	102,421	265
Vantage Hospitality	281	17,070	61
Drury	123	15,098	123
Taj Palaces	119	13,069	110
Americinn	112	7,269	65
Fairmont Raffles	69	23,191	336
Millennium	60	15,708	262
Shangrila	55	19,423	353
Omni	34	13,425	395
Regent	34	4,385	129
Peninsula	25	5,109	204
Silverneedle	24	1,408	59
Banyan Tree	20	2,542	127
Shilo Inns	19	2,068	109
Mandarin Oriental	17	4,621	272
Oberoi	17	1,888	111
Home Inns	15	1,712	114
Loews	14	5,710	408
Ascott Limited	5	562	112
Intown	1	42	42

Table 1-1 - Chains Represented in Data

Diving deeper into antecedents of manager response, we look at the trend in response rates by review rating. Given that negative reviews have the greatest impact on sales (Chevalier & Mayzlin, 2006), one would expect to see higher response rates to negative reviews. However, the empirical evidence is not so straightforward. While the most extreme negative opinions received the most attention from managers in the early years of our dataset, managers begin to respond relatively infrequently to 1-star ratings after 2012. Rather, 2-star ratings represent the reviews most likely to receive a manager response. Furthermore, 4-star ratings have consistently received the least attention from managers. We speculate that this is because 4-star reviews represent the majority on TripAdvisor, and a policy to respond to these reviews means more resources need to be dedicated to construct responses. (Figure 1-5)

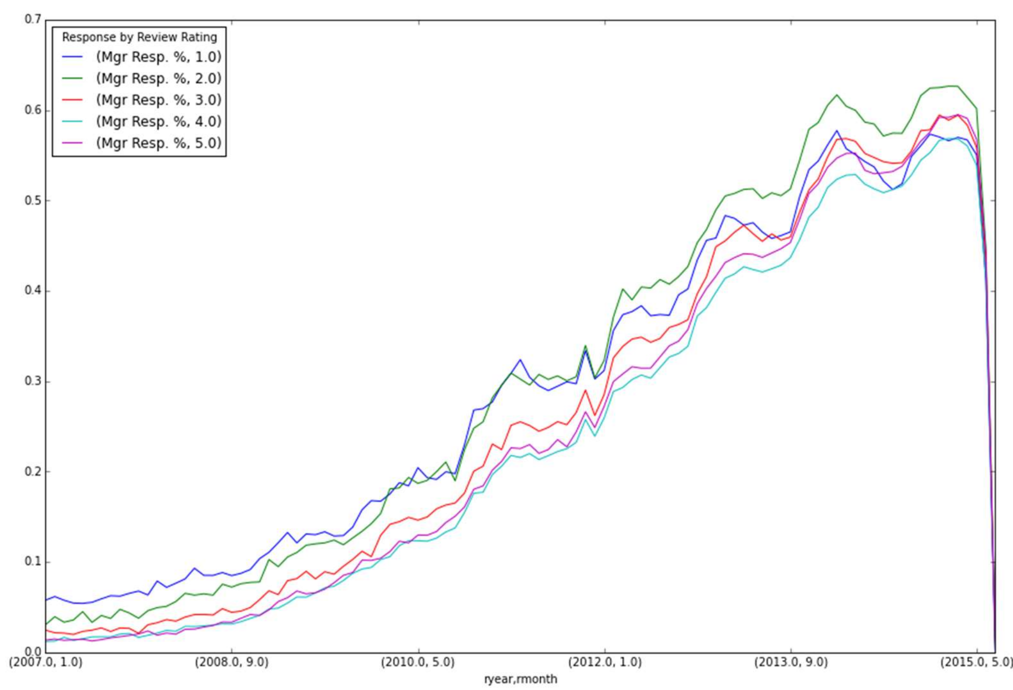


Figure 1-5 - Manager Response by Review Rating
Manager response % by review rating. 1 star ratings have become the least responded to review despite being the formerly most responded to rating.

Based on the above descriptive statistics, it is clear that manager response policies are quite heterogeneous across firms and time. As a result, we need to control for or eliminate response policy heterogeneity and endogeneity to ratings in order to estimate the causal impact of manager response on subsequent ratings. Next, we examine the descriptive statistics around the initial manager response using the centering approach prescribed by Proserpio and Zervas (2015) to identify pre and post response periods. We observe the downward spike that is Ashenfelter's dip (Ashenfelter, 1978), but it appears that the subsequent ratings do not return to pre-Ashenfelter's dip levels as is documented in a sample using Texas hotels (Proserpio & Zervas, 2015). However, subsequent months may indeed appear to be higher due to the continuation of pre-intervention time trends in ratings. To further investigate the model free evidence of a potential positive impact of manager response on subsequent opinion, we turn to the review order domain as opposed to the calendar time domain, i.e. comparing the N reviews before and after the initial response.

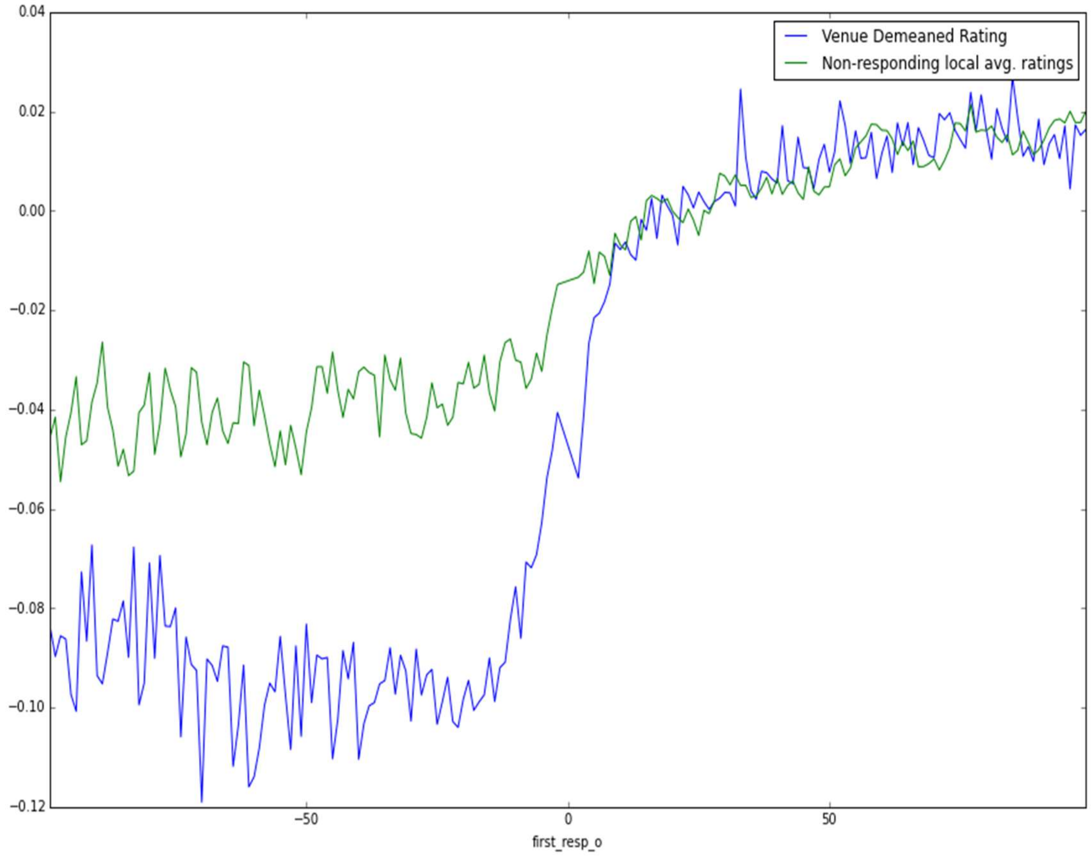


Figure 1-6 - Responding vs. Non-responding Hotel Ratings
First response centered, review ordered, venue-demeaned average ratings and matched average ratings of local firms that never adopt a response policy. This figure seems to show that after the mangers begin responding to reviews, the two time series converge.

In the review order domain, we want to compare the pre and post response reviews with a control group of hotels that never respond in the timeframe of our dataset. To do this, we first compute the hotel-demeaned ratings for the treated group of reviews (both before and after the first manager response). Then, we compute average hotel-demeaned ratings of never-treated hotels matched by metropolitan area at the monthly level corresponding to the calendar date for each of the treated group reviews. In essence, this control group captures the expected rating of hotels around the same time and location of each treated hotel review. The time series of both groups are plotted in Figure

1-6. Using our, albeit imperfect, control group, we run a difference-in-differences regression specified in Eq. 1-1 similar to those used in prior literature.

Eq. 1-1
$$r_{ijo} = \beta_0 + \beta_1 \text{Treated}_{\text{ij}} + \beta_2 \text{After}_{\text{ijo}} + \beta_3 \text{After}_{\text{ijo}} \times \text{Treated}_{\text{ij}} + \alpha_j + Y_o + M_o + \varepsilon_{ijo}$$

Treated$_{\text{ij}}$ captures the average difference between the treated and control groups. After$_{\text{ijo}}$ captures any common shocks before and after treatment. The interaction of After$_{\text{ijo}}$ and Treated$_{\text{ij}}$ is the DD variable of interest, our average treatment effect. We also include dummies $\alpha_j, Y_o,$ and M_o to control for firm, year, and month fixed effects respectively. As indicated in Table 1-2, we find a highly significant causal positive impact of manager response on subsequent ratings.

	Estimate	S.E.**	t-stat	p-value
Constant	-0.3221	0.1194	-2.697	0.00699
After	0.0177	0.0006	27.711	0.000
Treated	-0.0083	0.0007	-11.597	0.000
After X Treated	0.0108	0.0008	13.264	0.000

Table 1-2 - Difference in Differences Estimates
We find a statistically significant DD parameter estimate. Controls are omitted for clarity.
** Venue-clustered standard errors

However, even this approach is fundamentally flawed because ε_{ijo} can be correlated with the decision to respond in the next period, $\text{After}_{\text{ijo+1}}$. As a result, managers could be responding to a string of random fluctuations in site-specific shocks. It is intuitive that some managers might be cherry-picking response start times based on observing negative reviews that are the result of random fluctuations in reviewer sentiment. If this is the case, the return to "normal" long run average ratings should not be attributed to the manager's intervention, but rather to mean reversion tendencies in ratings. In fact, Figure 1-6 seems to suggest a nice story of locally underperforming hotels recovering to a normal level of ratings in line with the expected control group performance.

Another shortcoming of the above approach is that we focus on a single manager response to represent a regime change for managers. However, the probability of manager response dips for the reviews following a hotel's initial response. In fact, in the first 30 reviews after the initial manager response, the correlation between manager response and demeaned review rating is - 0.76. If manager response truly improves the subsequent ratings, we should look more closely at the effect of all responses, and in particular the differences between when responses are observable versus when they are not.

Year	Response Delay	Review Delay	% Response Seen
2009	157.57	24.86	24.98%
2010	72.82	18.26	20.88%
2011	44.06	12.72	21.68%
2012	24.45	8.26	20.39%
2013	15.29	6.10	18.34%
2014	11.42	5.22	17.07%
2015	7.53	4.72	16.72%

Table 1-3 - Response Delay
Response delay, review delay, and the percentage of responses observable to next reviewer at the time of writing their review.

In order to identify when a reviewer might observe a manager response, we rely on the timestamps of reviews and manager responses. We summarize the delay in manager response in Table 1-3. Managers have significantly decreased their response delay over time. In 2009, the average response from a manager was 157 days after the review, while the average delay is now just a little over a week. The difference between the response date of the last review and the rating date of the focal review identifies whether or not the focal reviewer is able to observe the response to the previous review just prior to clicking the "write a review" button on TripAdvisor. In the third column of Table 1-3, we see that, despite hotels speeding up their response to reviews, the increased frequency of reviews has actually lowered the percentage of reviews with an observable response. Nonetheless, the sheer volume of our dataset allows us to create a smaller dataset of only reviews immediately following a review with a response. This dataset includes 6,261,840 reviews without an observable response and 1,388,132 reviews that can observe the previous review's response. Using this dataset, we test the effect of manager response on subsequent reviews with observability as the treatment variable. The benefit of using observability lies in three components. First, we can test the effect of *all* manager responses, rather than only using the first instance as a regime change indicator. This way, we can say more about specific differences between the effects of MR-P and MR-N on subsequent opinion. Second, we remove endogenous response policy as a potential explanation for the effects identified by the DD specification in equation 1 by using only post-response data. Third, we can actually make a cleaner link of the mechanism that leads to changes in ratings when using observability as a treatment. We can demonstrate that any effect of responding to a review on subsequent ratings must be the result of actually *knowing* that managers are responding to reviews. Without determining observability, we cannot truly demonstrate the theoretical mechanism that is driving changes in subsequent ratings.

As a preview of our econometric results, Figure 1-7 documents the empirical phenomena that our causal modeling detects. In both panels, we show the time series plots of the hotel-demeaned monthly average ratings corresponding to observed (blue) and unobserved (green) manager responses. The left panel shows MR-N situations while the right panel shows MR-P situations. These two plots summarize the millions of small "experiments" that we use to identify our causal effects. The consistency and simplicity of this model-free preview of our results over a period of nearly 10 years suggests that the findings from our econometric specifications are robust to the keen observer and not merely a spurious statistical artifact.

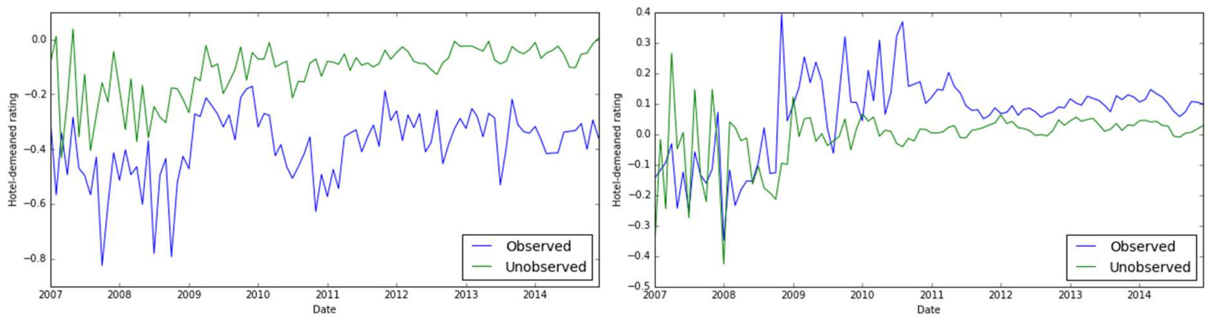


Figure 1-7 - Observable vs. Unobservable Responses
Divergent effect of MR-N (left panel) and MR-P (right panel) on subsequent hotel-demeaned rating (y-axis). Green time series in both represent unobserved response group (control), blue time series in both represent observed response group (treatment)

1.4. Causal Inference

1.4.1. Observed Service Interactions of Peers

In this section, we formalize our empirical test. As described in the previous section, we want to look at the difference between the expected ratings conditioned on the observability of the previous response, or more precisely:

$E[\text{Rating}_{jo} \mid \text{Obs}_{jo\text{-}1} = 1, \text{Resp}_{jo\text{-}1} = 1] - E[\text{Rating}_{jo} \mid \text{Obs}_{jo\text{-}1} = 0, \text{Resp}_{jo\text{-}1} = 1]$. We specify this test econometrically in equation 2. $\text{Observed}_{jo\text{-}1}$ is an indicator for whether the previous review's response is observed, i.e. our treatment variable of interest. $\sum_{k=1}^{10} r_{jo-k} / 10$ is the mean of the last 10 reviews, which controls for any local trends in ratings so that we do not find artificial effects based on the correlation between probability of observing the previous response and average level of review ratings. In other words, we want to rule out the explanation that differences between the treated and untreated groups come from systematic difference in the response timing between high opinion level periods and low opinion level periods. o_{jo} is the continuous review order to control for order trends in reviews, i.e. we control for the phenomenon that the n+100th review might be systematically different than the nth review for a given hotel. We also control for a time trend effect, i.e. reviews may trend higher over calendar time as observed in Figure 1-3. Additionally, we control for firm level heterogeneity with α_j, the firm fixed effect, and seasonality with M_{jo}, the month fixed effect.

Eq. 1-2 $$r_{jo} = \beta_1 \text{Observed}_{\text{jo-1}} + \beta_2 \left(\sum_{k=1}^{10} r_{jo-k} / 10 \right) + \beta_3 o_{jo} + \beta_4 t_{jo} + \alpha_j + M_{jo} + \varepsilon_{jo}$$

The parameter estimates of Eq. 1-2 are summarized in the first column of table 5. We want to point out that the treatment effect of observing a manger's response is quite small. However, this can be due to the effects of MR-P and MR-N offsetting each other. Managers responding to negative reviews have a very different purpose than those responding to positive ones. In the case of negative reviews, managers may be trying to address misinformation and present the hotel as proactively addressing operational issues. In contrast, managers respond to positive reviews to acknowledge reviewers' positive feedback and to humanize the brand as having feelings of gratitude and appreciation for its guests. Accordingly, we also estimate the parameters of Eq. 1-2 separately for reviews subsequent to a MR-P (rating 4 and higher) and a MR-N (rating 3 and lower).

	Pooled	Positive	Negative
Observed	0.009788***	-0.03123***	0.1365***
Average(Rating_10)	1.001***	0.8981***	0.9567***
Review order	0.00001373**	0.000004688	0.00001393**
t	-0.00001744**	-0.00001178	0.000003547
Feb	-0.004644	-0.00719	-0.008345
Mar	-0.003783	-0.003654	-0.02584
Apr	-0.008312	-0.005492	0.008081.
May	-0.005685	-0.0004502	-0.009026
Jun	-0.0306***	-0.02344***	-0.03245*
Jul	-0.02994**	-0.01599***	-0.03986**
Aug	-0.009629	-0.0205***	-0.007494
Sep	-0.001847	-0.008074	0.01153
Oct	-0.0137	-0.009979	-0.01953
Nov	-0.004231	-0.003208.	0.00572
Dec	-0.01047	-0.009703	-0.01414
Within-R2	0.1337	0.1116	0.1186
Full model -R2	0.2859	0.2548	0.3842

‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 1-4 - Equation 2 Estimates

Parameter estimates for equation 2. Standard errors clustered at the hotel level. We see that the effect of observing a manager's response has a negative impact if the review responded to is positive, but a positive effect if the review responded to is negative. Output for hotel fixed effects are omitted.

Comparing our parameter of interest across subsamples, we find that ratings are higher than expected if the reviewer observes the manager responding to a negative review. This effect is also quantitatively large at 0.14 stars. Interestingly, a review following an MR-P is .03 stars lower on average. The lower quantitative effect has intuitive appeal for several reasons. First, managers began responding to negative reviews before they began responding to positive ones. This suggests that managers believe the importance of addressing negative feedback is greater than that of addressing positive feedback. Second, the observed service recovery effort is likely to be viewed more positively than a simple thank you. What seems potentially puzzling is the negative qualitative effect of responding to positive reviews. We suggest that reactance can be the explanation for the negative effect. Recall that reactance should dominate when the utility of a business' personal communication is relatively low (White, Zahay, Thorbjørnsen, & Shavitt, 2008). Response to negative reviews inherently offers greater utility to users of TripAdvisor. In contrast, response to positive reviews offers less utility. It serves no purpose beyond acknowledging a guest's review. As a result, some reviewers may frame the MR-P in the negative light of reactance, consistent with prior research in personalized customer communication.

Having established the divergent effects of MR-P and MR-N on subsequent ratings, we now focus on the relative efficacy of responses across hotel types. First, we want to have a better understanding of whether responding to reviews is better for chains or independent operators. We estimate equation 2 for the 4 subsets of our data (chain/independent × MR-P/MR-N) and present the parameter estimates in table 6. In the last 2 columns, we perform a paired t-test on the parameters of chain versus independent hotels. We find that the magnitude of the effect of a chain hotel's response on subsequent ratings is greater for both positive and negative reviews. While it is unsurprising that chains' response to negative reviews can significantly improve subsequent ratings since chains are likely to develop better response procedures to negative comments, it is somewhat surprising that chains' response to positive reviews lead to even lower ratings in subsequent reviews. However, if we continue the reactance explanation, we can argue that when a large corporation responds to a positive review, it may more likely be framed as part of a broader automated policy employed to influence perception rather than a genuine acknowledgement of a guest's comments. Therefore, chains' MR-P will more likely lead to psychological reactance in the subsequent reviewer, and in turn lower expected rating.

	Positive		Negative		Pr(Chain=Indpt)	
	Chain	Independent	Chain	Chain	MR-P	MR-N
observed	-.04912***	-.01317***	.1799***	.08226***	0.000	0.00
Avg(rating_10)	.8367***	.9594***	.9359***	.9785***	0.000	0.00
Within R^2	0.1005	0.1233	0.1103	0.1286		
Full model R^2	0.2437	0.2659	0.3694	0.3959		

'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1-5 - Chain vs. Independent

Parameter estimates for equation 2 split by chains vs. independents and MR-P vs MR-N. We find that the effect of a chain responding is of a greater magnitude in both the positive and negative conditions. Output for fixed effects are omitted.

A natural question to ask, given the differing impact of manager response between chains and independent hotels, is whether the price range of the hotel makes a difference. In order to more concisely estimate the effect of price range, we turn to a random effect specification Eq. 1-3. The random effect specification allows us to estimate the pooled effect of price range whereas a fixed effect model would wipe out any constant variables within a hotel. Here, α_j is the random effect rather than the fixed effect designated in equation 2. We are interested in the parameters of the interaction between observability and price levels, δ_i for i $\in \{0,...,4\}$.

Eq. 1-3 $$r_{jo} = \beta_0 + \beta_1 \mathrm{Obs}_{\mathrm{jo\text{-}1}} + \sum_{i=1}^{4} \delta_i \mathrm{Obs}_{\mathrm{jo\text{-}1}} \times \mathrm{P}^i_{jo-1} + \mathrm{P}_{\mathrm{jo\text{-}1}} \mathbf{b}_p + X\mathbf{b}_x + \alpha_j + \varepsilon_{jo}$$

We estimate this specification separately for responses to both positive and negative reviews by chains, independents, and all hotels. The parameter estimates are reported in Table 1-6. In the pooled sample, we see that the negative effect of responding to a positive review is no longer significant. However, the interaction with price levels 1 and 2 is negative and significant. It appears as though the negative impact of manager responses is only significant in the lower tiered hotels. This is again consistent with the story of the moderating effect of utility on reactance. One can assume that acknowledging service comments is more important for customers of a higher tiered hotel. Therefore, lower tiered hotels' response should correspond with lower utility of that response, leading to lower subsequent ratings. Similarly, we find a significant additional impact of responding to negative reviews for the 2nd lowest tier hotels.

	Pooled		Chain		Independent	
	Positive	Negative	Positive	Negative	Positive	Negative
(Intercept)	0.3562***	0.2708***	0.6192***	0.343***	0.1246***	0.1536***
observed	-0.007646	0.0643*	0.001567	0.0566	-0.01094	0.06652*
$	0.002877	-0.101***	-0.007973	-0.1092.	0.0008348	-0.06218*
$$	0.01888*	-0.1411***	0.02043	-0.1861***	0.004523	-0.04286.
$$$	0.01892*	-0.03089	0.0122	-0.01834	0.009829	-0.03751
$$$$	0.03432***	0.0000746	0.03279	0.03273	0.01762.	-0.01983
obs x $	-0.03404**	0.06486*	-0.06586*	0.1065.	-0.008637	0.02378
obs x $$	-0.0287*	0.1152***	-0.05549*	0.1815**	-0.002624	0.02821
obs x $$$	-0.01982.	0.03414	-0.04932.	0.03676	-0.007739	0.03618
obs x $$$$	-0.007336	0.02327	-0.02625	0.04102	-0.001075	0.01919
R^2	0.2513	0.3795	0.2407	0.3661	0.2621	0.3896

'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1-6 - Parameter Estimates for Eq. 3

We use a random effects specification at the hotel level in order to estimate pooled effects of interaction between observable managerial response and the price range of the hotel. We estimate the model separately for positive reviews responded to and negative responded to by chain and independent hotel type. Output for control variables suppressed.

1.4.2. Regression Discontinuity Design

The pseudo experiment analyses in the previous section demonstrates that observing managers' responses can change the post-consumption evaluation if response and review timing are uncorrelated with the focal reviewer's rating. One may argue that this assumption is not perfectly plausible since managers may respond more or less quickly depending on the prior rating. This difference in response speed may cause the focal review's rating to be correlated with observability treatment. The more important endogeneity issue is that review rating and the duration between reviews may be correlated. This is the driver of the mean reversion explanation for the prior results. Even though reviews may arrive in a steady manner, there will, nevertheless, be differences in inter-review times. Later reviews may revert to the mean if prior ratings are extreme. The mean-reverting reviews that are posted later are more likely to occur after a manager response has been posted, leading to the divergent effects of MR-P and MR-N.

In order to resolve the mean-reversion confound, we propose a regression-discontinuity test. The logic is simple. Mean reversion should be a smooth process in time; therefore, we should observe a steady change in ratings around the response date. There should not be a significant "jump" for reviews that occur just before and just after the response. To illustrate this point, we present graphical evidence of a jump just before and after the manager response (Figure 1-8). In expectation, the days leading up to an MR-N exhibit lower than average ratings while the days following the MR-N event exhibit higher than average ratings. Conversely, the days leading up to an MR-P exhibit higher than average ratings while the days following the MR-P exhibit lower than average ratings. In both cases, it does not appear that any continuous trend can explain the gap between pre and post response ratings. Given this empirical evidence, it seems plausible that we can confirm a systematic statistical difference between reviews before and after a manager response is posted.

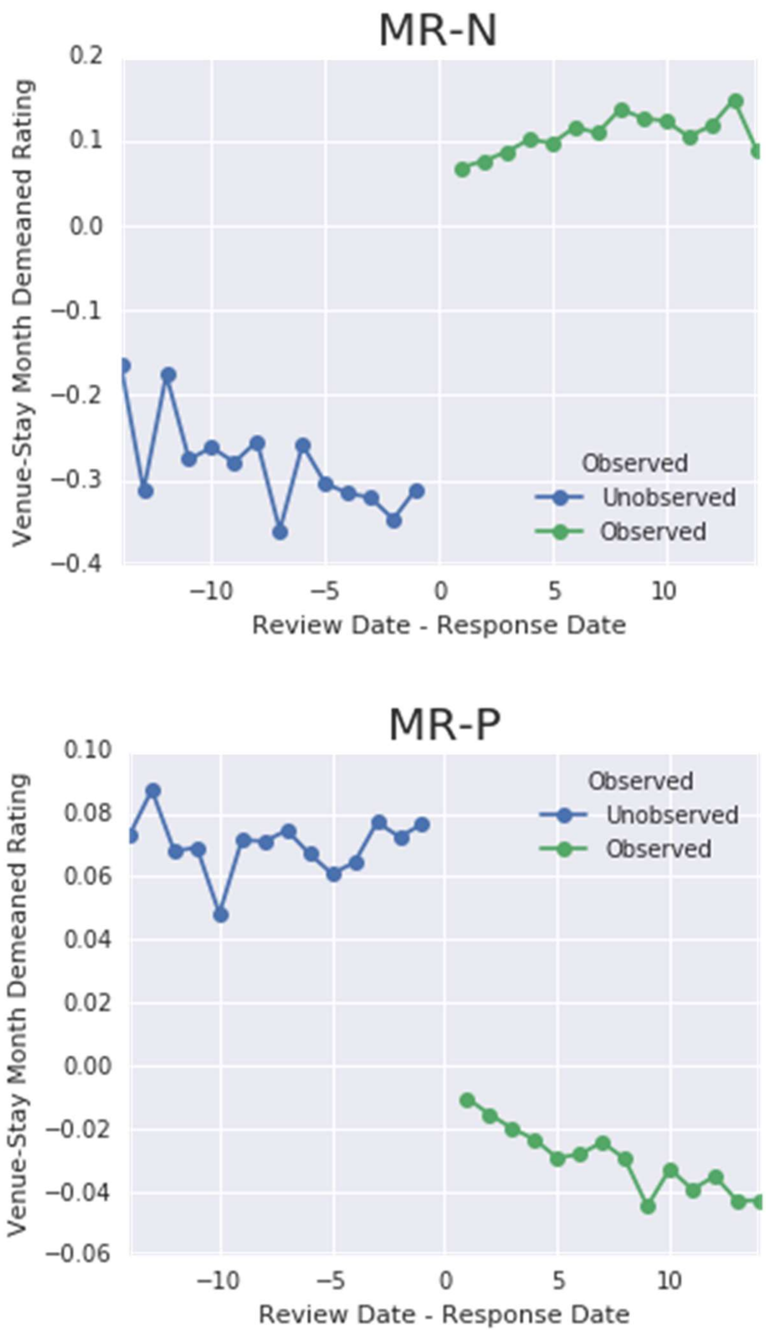


Figure 1-8 - Graphical Evidence of Jump
Venue and stay month demeaned ratings are plotted for the 2 weeks immediately preceding and following the manager response. The top panel shows a jump upwards in demeaned ratings while the bottom panel shows a jump downwards in demeaned ratings.

Guided by the graphical evidence, we specify the following locally linear parametric regression discontinuity design (RDD) test (Eq. 1-4) where d_{jo} is the days from manager response of the focal review, τ_{jo-1} is the delay in the response, and ρ_{jo} is the average rating in the stay month for hotel j. The locally linear specification estimated across many bandwidths has become a standard method of RDD estimation as higher order functional forms induce unnecessary noise that distort the parameter estimates (Gelman & Imbens, 2014). Given that the average response times over the date range of our dataset range from almost a year to a week (Table 1-3), we examine a sequence of bandwidths from 5 days to a month. This range of bandwidths allows us to provide a reasonable sample for most response-delay time frames.

The inclusion of τ_{jo-1} and its interaction with previous rating levels in our fixed effect specification allows us to control for potential correlation between the subsequent review and the non-randomness in the assignment of the "observed" treatment due to managers' urgency in responding. The inclusion of ρ_{jo} controls for the average service quality for the hotel during the month in which the subsequent reviewer stayed at the hotel. Finally, d_{jo} controls for the timing of the next review relative to the response date. If mean reversion is the mechanism that drives the difference between the pre and post response groups estimated in the main results, then we should not expect to see a significant jump in the intercept for the response-treated groups.

Eq. 1-4
$$\begin{aligned} r_{jo} &= \beta_0 + \beta_1 \mathrm{Obs}_{\mathrm{jo\text{-}1}} + \beta_2 \mathrm{Obs}_{\mathrm{jo\text{-}1}} \times \mathrm{d}_{jo} + \beta_3 \mathrm{d}_{jo} + \beta_4 \tau_{jo-1} \\ &+ \beta_5 \left(\sum_{k=1}^{10} r_{jo-k} / 10 \right) + \beta_6 \rho_{jo} + \beta_7 o_{jo} + \beta_8 t_{jo} + \alpha_j + M_{jo} + \varepsilon_{jo} \end{aligned}$$

Furthermore, we also estimate an alternative specification that pools all responses together and allow for rating specific slopes and intercepts for the RDD parameters of interest in Eq. 1-5 (r subscript indicates lagged rating specific coefficient).

Eq. 1-5

$$r_{jo} = \beta_0 + \beta_{r1}\text{Obs}_{\text{jo-1}} + \beta_{r2}\text{Obs}_{\text{jo-1}} \times \text{d}_{jo} + \beta_{r3}\text{d}_{jo} + \beta_4 \tau_{jo-1} + \beta_5\left(\sum_{k=1}^{10} r_{jo-k} / 10\right) + \beta_{r6}\rho_{jo} + \beta_7 o_{jo} + \beta_8 t_{jo} + \alpha_j + M_{jo} + \varepsilon_{jo}$$

The parameters in Table 1-7 replicate the main findings in Table 1-4. Controlling for the speed of the manager's response and the duration between that response and the subsequent review, we find evidence of a significant jump up (down) in ratings following a negative (positive) review. The jump parameters across all bandwidth specifications are in the expected directions and significant to venue-clustered standard errors. Again, we observe an order of magnitude difference between the size of the effect of MR-P and that of MR-N in opposite directions.

	Reviews within bandwidth (days) of MR-P				
	5	7	14	21	30
Obs	-0.0099*	-0.0090*	-0.0129***	-0.0187***	-0.0211***
Delay_rev	-0.0034*	-0.0043***	-0.0032***	-0.0021**	-0.0016**
Delay_res	-0.0001	-0.0003	-0.0007	-0.0006	-0.0006
1st Page R_mean	0.6997***	0.6957***	0.6905***	0.6891***	0.6878***
Stay Mth. R_mean	0.4993***	0.5047***	0.5074***	0.5111***	0.5125***
ObsXDelay_rev	0.0012	0.0025*	0.0018.	0.0016.	0.0012.
Adjusted R^2	.2595	.2589	.2593	.2603	.2607
	Reviews within bandwidth (days) of MR-N				
	5	7	14	21	30
Obs	0.0964***	0.0900***	0.1030***	0.1089***	0.1088***
Delay_rev	-0.0033	-0.0014	-0.0041**	-0.0036***	-0.0030***
Delay_res	-0.0028**	-0.0024**	-0.0013**	-0.0008*	-0.0006
1st Page R_mean	0.7321***	0.7291***	0.7053***	0.7099***	0.7071***
Stay Mth. R_mean	0.5913***	0.5926***	0.5957***	0.5948***	0.5935***
ObsXDelay_rev	0.0079.	0.0066*	0.0076***	0.0050***	0.0039***
Adjusted R^2	.3525	.3560	.3569	.3565	.3554

‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 1-7 - RDD by MR-P and MR-N

Parameter estimates replicate the results from the non-RDD specifications in table 1-4.

As further evidence of the robustness of our findings, we demonstrate that a pooled specification with fixed effects of each lagged rating level and lagged-rating-varying slopes of response along with lagged-rating specific pre and post response trends does not alter the main findings of this study. Interestingly, the various bandwidth specifications do not consistently reveal non-zero pre or post response trends, suggesting that mean reversion is not a crucial concern. Meanwhile, the consistent net negative observed response intercepts for lagged rating levels 4 and 5 combined with the statistically insignificant difference in observed response intercepts for lagged rating levels 1 through 3 lend credence to the choice of splitting MR-P and MR-N between lagged rating levels of 3 and 4. Indeed, it appears that the jump due to the forcing "observed" response variable is consistent within the MR-P and MR-N groups.

	Bandwidths Around Response Date				
	5	7	14	21	30
Obs	0.0460*	0.0423*	0.0604**	0.0663***	0.0763***
Delay (Rev-Res)	0.0036	0.0099	0.0137	0.0143.	0.0119.
R_1 = 2	-0.0024	-0.0177	-0.0146	-0.0163	-0.0120
R_1 = 3	-0.0406	-0.0444	-0.0173	-0.0123	-0.0075
R_1 = 4	0.0527**	0.0486*	0.0829***	0.0844***	0.0904***
R_1 = 5	0.0329	0.0335*	0.0637***	0.0697***	0.0780***
Delay (Res-Rev_1)	0.0003	0.0036	0.0125	0.0134.	0.0126*
First Page R_mean	0.7096***	0.7065***	0.6987***	0.6977***	0.6957***
Stay Month R_mean	0.5432***	0.5488***	0.5533***	0.5580***	0.5602***
Obs X Delay_rev	0.0081	-0.0020	-0.0114	-0.0141	-0.0123
Obs X R_1=2	0.0098	0.0132	0.0154	0.0198	0.0141
Obs X R_1=3	0.0484.	0.0503	0.0198	0.0097	0.0000
Obs X R_1=4	-0.0663**	-0.0603*	-0.0835***	-0.0914***	-0.1014***
Obs X R_1=5	-0.0614**	-0.0616**	-0.0837***	-0.0964***	-0.1082***
Delay_rev X R_2	0.0042	-0.0072	-0.0134	-0.0148	-0.0124
Delay_rev X R_3	-0.0195*	-0.0237*	-0.0189	-0.0150	-0.0119
Delay_rev X R_4	-0.0061	-0.0138	-0.0150	-0.0152.	-0.0130.
Delay_rev X R_5	-0.0072	-0.0130	-0.0161	-0.0157.	-0.0127.
Delay_res X R_2	-0.0041	-0.0066*	-0.0112	-0.0118	-0.0107
Delay_res X R_3	-0.0090	-0.0105*	-0.0136	-0.0119	-0.0104
Delay_res X R_4	-0.0012	-0.0045	-0.0132.	-0.0135.	-0.0129*
Delay_res X R_5	-0.0007	-0.0042	-0.0127	-0.0135*	-0.0128*
ObsXDelay_resXR_2	-0.0136	0.0076	0.0168	0.0177	0.0148
ObsXDelay_resXR_3	0.0108	0.0183	0.0191	0.0156	0.0130
ObsXDelay_resXR_4	-0.0060	0.0053	0.0116	0.0145	0.0131.
ObsXDelay_resXR_5	-0.0080	0.0026	0.0123	0.0149	0.0125
Adjusted R^2	.3525	.3560	.3569	.3565	.3554

'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1-8 - Pooled RDD

Pooled RDD regression parameters with rating specific fixed effects and slopes on pre and post response trends. The same findings in 1-7 are replicated in this pooled specification.

1.4.3. Response Tailoring

So far, we have explored whether *the act* of responding to reviews can have an impact on subsequent opinion. In this section, we dig deeper to analyze whether *the way* in which a manager responds to a review can moderate the impact of responses on subsequent opinion. In particular, we investigate the role of response tailoring. The tailoring effect is important in establishing the mechanisms proposed previously. In the MR-N case, we proposed that managers positively influence subsequent opinion by addressing specific complaints in prior reviews. Therefore, we would expect to find response tailoring positively moderating the impact of manager responses. In the MR-P case, we proposed that managers negatively impact subsequent opinion due to reviewers' psychological reactance to the unnecessary responses. We hypothesize that response tailoring to positive reviews leads to reiterating the same positive experiences detailed in a review. This redundancy of information makes MR-P more susceptible to unfavorable framing by an observer, leading to increased reactance and lower rating. In order to calculate a measure of tailoring, we introduce the textual analysis methods below.

The textual analysis procedure includes three components. First, we preprocess our database of reviews and responses by removing stop words (words that appear either rarely or often) and word stemming (singularizing nouns and extracting infinitive forms of verbs). We considered any word that appears only once as rare and also eliminate the most common .1% of words in our data. We choose these less restrictive cutoffs to allow for maximum flexibility in our subsequent topic modeling. The resulting corpus of 8 million reviews is transformed into "bags of words" that are represented in a sparse vector space of the final 934,202 words that compose our dictionary. Given the vector-space representation of our reviews and responses, we are able to apply unsupervised machine learning methods to identify latent topics spanned by reviews. Specifically, we apply latent Dirichlet allocation (LDA) (Blei, Ng, & Jordan, 2003) to our corpus of reviews to obtain a mixture of topic distributions, with each topic represented as a weighting scheme of relative importance of all 934 thousand words in our dictionary.

Borrowing Blei et al.'s notation (2003), we specify the following preliminaries of the LDA model. Each review document, $d \in \{1,2,..,M\}$, is composed of N words, w_{dn} where $n \in \{1,2,..,N_d\}$. Each word comes from our "bag of words" dictionary of V entries where $V = 934$ thousand. We specify the number of topics that a review can represent as K=10. We choose 10 topics after experimenting with as few as 5 and as many as 100 topics. The choice of 10 provided the best combination of face validity independence among topics and coverage of potential review topics. Results do not qualitatively differ with more topics. Each of the kth topic represents a point in the V-1 simplex. In other words, each topic is represented by a linear combination of the words in our dictionary where the weights sum up to one. We define the vector of these weights as $\boldsymbol{\beta}_\mathbf{k}$ where each element of the vector, β_{kw}, is a weight for word $w \in \{1,2,...,V\}$. Each document d, in turn, is characterized by a distribution vector $\boldsymbol{\theta}_\mathbf{d}$ over the K topics. Thus, $\boldsymbol{\theta}_\mathbf{d}$ is a point in the K-1 simplex where each element θ_{dk} represents the probability that the document is generated by topic k. Each word w_{dn} in each document d is assumed to be drawn from a single topic z_{dn}. Given the preliminaries above, the joint probability of observing our sample of reviews is given in Eq. 1-6. Following Blei et al. (2003), $\theta \sim Dir(\alpha)$ where α

is a prior hyper-parameter assumed equal to 1/K for all topics, topic

$z_n \sim Multinomial\ (\theta)$ for each word w_{dn} , and each word $w_n \sim p(w_n|z_n, \boldsymbol{\beta})$.

Eq. 1-6 $$p(D|\alpha, \boldsymbol{\beta}) = \prod_{d=1}^{M} \int p(\theta_d|\alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn}|\theta_d) p(w_{dn}|z_{dn}, \boldsymbol{\beta}) \right) d\theta_d$$

Following Blei (2003), we make use of variational Bayes methods to derive a lower bound on the distribution of latent variables that are conditional on model parameters indicated on the LHS of Eq. 1-7. The lower bound that is unconditional on model parameters is written on the RHS of equation 5. The optimal variational parameters, γ and ϕ, can be computed by minimizing the Kullback-Leibler divergence between the variational (RHS) and true posterior (LHS) distributions of latent variables. Blei et al. (2003) derives 2 parameter update equations conditional on best estimates of model parameters α and $\boldsymbol{\beta}$ reproduced here in equations Eq. 1-8 and Eq. 1-9 where i indexes the iteration of estimation.

$$\left[p(\theta, \mathbf{z}|\mathbf{w}, \alpha, \boldsymbol{\beta}) = \frac{p(\theta, \mathbf{z}, \mathbf{w}|\alpha, \boldsymbol{\beta})}{p(\mathbf{w}|\alpha, \boldsymbol{\beta})} \right]$$

Eq. 1-7 $$> \left[q(\theta, \mathbf{z}|\gamma, \phi) = q(\theta|\gamma) \prod_{n=1}^{N} q(z_n|\phi_n) \right]$$

Eq. 1-8 $$\phi_{ni} \propto \beta_{iw_n} \exp\{\mathrm{E}_q[\log(\theta_i)\,|\gamma]\}$$

Eq. 1-9 $$\gamma_i \propto \alpha_i + \sum_{n=1}^{N} \phi_{ni}$$

Using equations Eq. 1-8 and Eq. 1-9, we can compute the lower bound of the model parameter marginal log likelihood function (Eq. 1-10). For a more detailed explanation of the estimation procedure and derivations, please reference Appendix A3 in Blei et al. (2003).

Eq. 1-10
$$LL(\alpha,\beta)=\sum_{d=1}^{M}\log p\left(\mathbf{w}_d \mid \alpha,\boldsymbol{\beta}\right)$$

We maximize this log likelihood and update equations Eq. 1-8 and Eq. 1-9 with the newest estimates of model parameters for each document in our corpus. This expectation-maximization problem is iterated until convergence to solve for α and β. Given the estimated parameters over our entire dictionary of words, we can assign topic probabilities to each of our reviews.

Figure 1-9 - Wordcloud representation of LDA topics

Figure 1-9 summarizes our ten topics using word cloud representations, a graphical tool used to show relative frequencies of words within each topic. While the topics overlap on many key words, as is allowed by the LDA model, there are distinctive differences across topics. For example, topic 1 is highly suggestive of a family oriented review with distinctive keywords such as family, child, kid, and holiday. Topic 7, on the other hand, clearly focuses on dining with keywords like breakfast, bar, restaurant, food, and drink. These topics reflect not only the attributes of a hotel, but also the travel purpose and customer demographic of the reviewer. For example, topic 3 assigns high weights to "beach" and "resort" suggesting a reviewer spending time on a coastal getaway. Meanwhile, topic 4 assigns high weights to "spa, suite, experience, and wonderful" suggesting a reviewer who has enjoyed a relaxing retreat at a high-end resort. The grouping of these distinctive words lend face-validity to the unsupervised identification of latent topics using LDA.

Having identified latent topics, we assign topic probabilities to each review and response. We can use these probabilities to calculate a cosine similarity score between each pair of review and response as specified in equation 9 where *rev* and *res* are the 10-topic dimensional vector representations of the review and response respectively.

$$similarity = \cos(rev, res) = \frac{rev \cdot res}{\|rev\|\|res\|}$$

Eq. 1-11

$$= \frac{\sum_{i=1}^{n} rev_i * res_i}{\sqrt{\sum_{i=1}^{n} (rev_i)^2} * \sqrt{\sum_{i=1}^{n} (res_i)^2}}$$

Figure 1-10 presents the distribution of similarity scores over review-response pairs. It is clear that the distribution is right skewed, meaning that fewer responses are highly tailored. Moreover, the large point mass on dissimilar review-response topics suggests that a large proportion of responses are boilerplate. Figure 1-11 shows two extreme examples of boilerplate and tailored responses. These two examples highlight the face validity of our similarity measure. While the first reviewer mentions housekeeping and cleanliness of the room, the manager does not reiterate any points related to these topics. Alternatively, the second review mentions a problem with the air conditioning, which the manager specifically addresses, elaborating that the problem has been resolved for future guests.

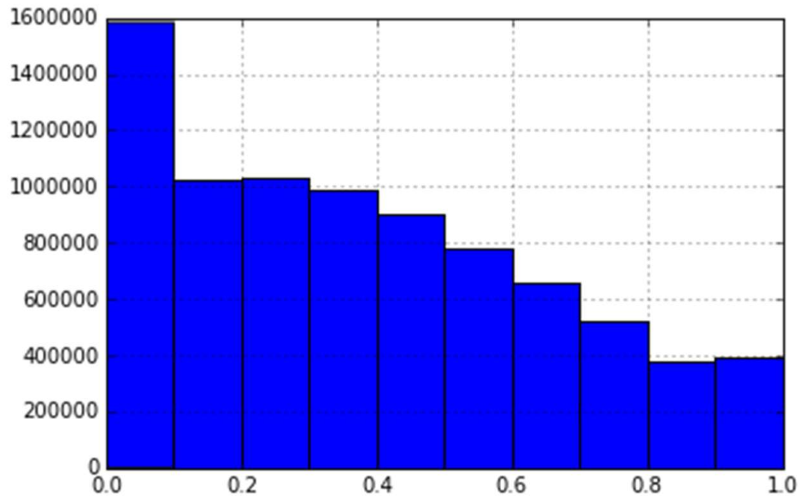


Figure 1-10 - Response Tailoring Distribution
Histogram of review-response pair cosine similarity scores. The distribution is skewed to the right and exhibits a large point mass on low similarity responses (boilerplate responses).

'A new hotel, well organized, very clean. Staff very helpful. At the front desk when we checked in was the GM, Jennifer Hartman. greeted us with a genuine smile and great attitude. The housekeeping staff were very considerate..not wanting to get in there and clean the room BEFORE we were ready to check-out.......past experience...(NOT at this hotel)...plan on returning in June to the same hotel just because....' - Review *'Thank you so much for choosing our hotel and for the great comments. It was my pleasure! Hope to see you again in the future.'* – Response
'After we went to sleep, the front panel fell off the heater and woke us up. Dust and trash blew around the room. We could not run the heater because of the dust. We told the front desk the heater was broken. The gentleman at the front desk came to look at the heater and taped the front panel with tape that did not hold. We had to re-tape the panel several times. We did not have time to move to a different room because we spent most of our time at the hospital. We stay at this hotel every time we visit, but mot any longer.' – Review *'We are so sorry to hear about the faulty heater. I hope your stay other then the faulty heater was good. We are really sorry for the inconvenience caused and we appreciate your honest comments. And we already have fixed the AC . We hope to see you next time.'* – Response
Figure 1-11 - Examples of Similar vs. Dissimilar Responses Examples of dissimilar (top panel) and similar (bottom panel) responses. The top panel response is generic and does not address the specifics mentioned in the review. The bottom panel addresses the guest's complaint of the broken heater.

Using our measure of similarity, we can investigate the effect of response tailoring on subsequent reviewer sentiment. Again, we rely on the same identification strategy as in our main results. We compare the net difference in expected ratings between observed and unobserved responses. The key difference is that we also examine the effect of the interaction between observing a response and the similarity score of that response. Our empirical specification is formally stated in Eq. 1-12 where we modify Eq. 1-2 to include the full factorial interactions between observed response, corresponding rating, and similarity score. Note that we include prior review rating in this specification as a continuous variable whereas our main results split samples between positive and negative reviews to emphasize the divergent effect directions between the two types. In equation 10, the continuous rating control allows us to investigate more efficiently the divergent moderating role of response tailoring.

Eq. 1-12
$$r_{jo} = \beta_1 \mathrm{Ob}_{\text{jo-1}} \times \mathrm{Sim}_{\text{jo-1}} \times r_{jo-1} + \beta_2 \mathrm{Ob}_{\text{jo-1}} + \beta_3 \mathrm{r}_{\text{jo-1}} + \beta_4 \mathrm{Sim}_{\text{jo-1}}$$
$$+ \beta_5 \mathrm{Ob}_{\text{jo-1}} \times \mathrm{Sim}_{\text{jo-1}} + \beta_6 \mathrm{Ob}_{\text{jo-1}} \times \mathrm{r}_{\text{jo-1}} + \beta_7 \mathrm{Sim}_{\text{jo-1}} \times \mathrm{r}_{\text{jo-1}} + X\mathbf{b} + \varepsilon_{jo}$$

	Coefficient
Observed	0.02570***
Lag(Rating)	-0.08882***
Similarity	-0.03797*
Observed X Lag(Rating)	-0.00410***
Observed X Similarity	0.07758*
Lag(Rating) X Similarity	0.01421*
Obs X Lag(Rating) X Similarity	-0.02250**
Avg(Rating_10)	1.07500***
Within-R2	0.1391
Full model -R2	0.2861

'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1-9 - Response Tailoring Estimates
Parameter estimates for equation 11. We test the hypothesis that response tailoring moderates the effect of observing manager response on subsequent opinion. Tailored messages increase the positive impact of MR-N and increase the negative impact of MR-P.

Table 1-9 summarizes the point estimates of our coefficients of interest. While interpreting triple interactions can be misleading on their own, we point out that the highly significant triple interaction suggests that there is a diminishing return to observed response tailoring when the response is to a highly positive review. Moreover, our main effect is captured in the coefficient for observed previous response (0.025 $p < 0.000$) and interaction of observed response and previous review rating (-0.0041, $p<0.0018$). In other words, responding to a review increases expected subsequent opinion but this effect diminishes as the rating of the review receiving a response increases. However, to truly gauge the overall impact of all the interaction effects put together, we turn to the contour plot of net effect size in Figure 1-12. This figure plots the difference in expected subsequent rating between observed and unobserved response cases conditioned on response similarity score (x-axis) and previous review rating (y-axis). The insight here is that tailored MR-P leads to larger negative effects on subsequent opinion (red region) while tailored MR-N leads to larger positive effects on subsequent opinion (green region). However, tailoring of responses to neutral reviews does not significantly affect the expected difference in subsequent ratings.

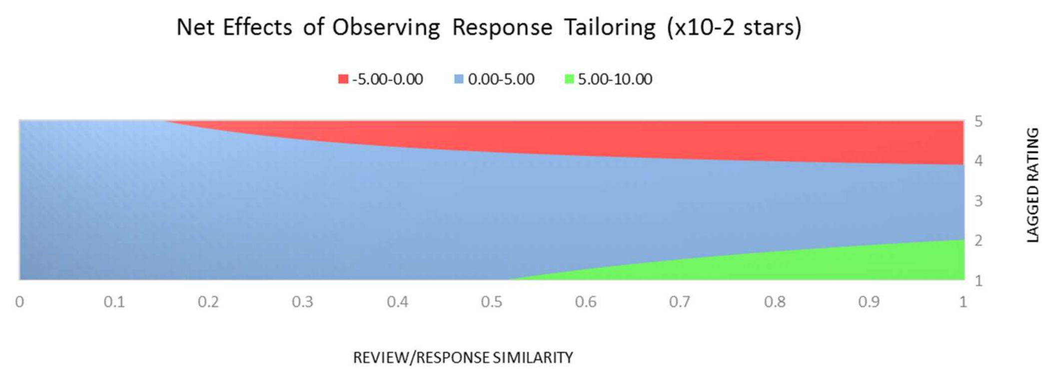


Figure 1-12 - Net Tailoring Effects
Contour plot of net effect of observing response tailoring. While tailored responses positively moderate the positive effect of MR-N (green region), they negatively moderate the effect of MR-P on subsequent opinion (red region).

Our textual analysis results further support the proposed mechanisms of the divergent impact of MR-P and MR-N on subsequent opinion. When managers offer highly tailored responses to positive reviews, the response is no longer framed as benefiting the original reviewer – as the reviewer is well aware of the positive topics mentioned in his or her own review. Consequently, the subsequent reviewer frames the tailored MR-P as even more deliberately manipulative than had the MR-P been merely a boilerplate response. Therefore, greater reactance is expected, leading to a lower subsequent opinion. On the other hand, response tailoring in MR-N situations validates its assumed purpose. Managers respond to negative reviews to address concerns and publicize their initiative to fix problems. The manager can only achieve this by addressing specific issues in previous reviews. Therefore, a subsequent reviewer observing a highly tailored response will interpret the MR-N as a more useful service recovery effort. In both cases, we demonstrate that not only can post-consumption observation of peers' service interactions influence a focal consumer's stated satisfaction, but also the very specific way in which the interaction unfolds has a measurable impact on this publicly stated satisfaction.

1.5. Discussion

The current study adds to the expectation-disconfirmation paradigm of satisfaction research in the digital realm by studying one common instance of post-consumption social influence on satisfaction – the effect of manager response to online reviews on subsequent reviewer opinion. While the prior literature studies social influence in the expectation formation stage, we expand the sphere of social influence, in particular manager influence, to the satisfaction evaluation stage. The results of our study are well highlighted by our opening restaurant analogy. We posited that observing a genuine positive service recovery interaction between a waiter and fellow customers can improve one's overall evaluation of service quality by augmenting one's private experiences. However, we posited that observing others' service interactions can be susceptible to an observer's framing of that interaction. In particular, publicly stated "thank you's" may be framed as disingenuous, leading to psychological reactance. Such is the case in our hypothetical example of interpreting a waiter thanking another customer for their generous tip as that waiter's tactic to increase the tips of surrounding customers. Our results in this study suggest the same two diverging forces are at work when it comes to managers' responses to reviews influencing the opinions of subsequent reviewers. First, managers' response to negative reviews are viewed positively as a service recovery effort by a subsequent reviewer, leading to that subsequent reviewer's improved post-consumption satisfaction. Second, managers' response to positive reviews may appear disingenuous and of low utility to subsequent reviewers, leading to psychological reactance and decreasing subsequent reviewers' satisfaction.

In addition to introducing this new sphere of social influence to the eWOM literature, we also contribute to the causal-inference literature with our novel identification strategy based on the observability of manager responses. This strategy allows us to preclude alternative causal mechanisms to pinpoint managers' response as having a direct impact on subsequent reviews. This natural experiment strategy departs from prior literature's use of DD strategies that cannot differentiate between the effect of managers' response from a synthetic effect due to managers adopting response policies as a reaction to random fluctuations in TripAdvisor ratings and their inevitable reversion to long-run means.

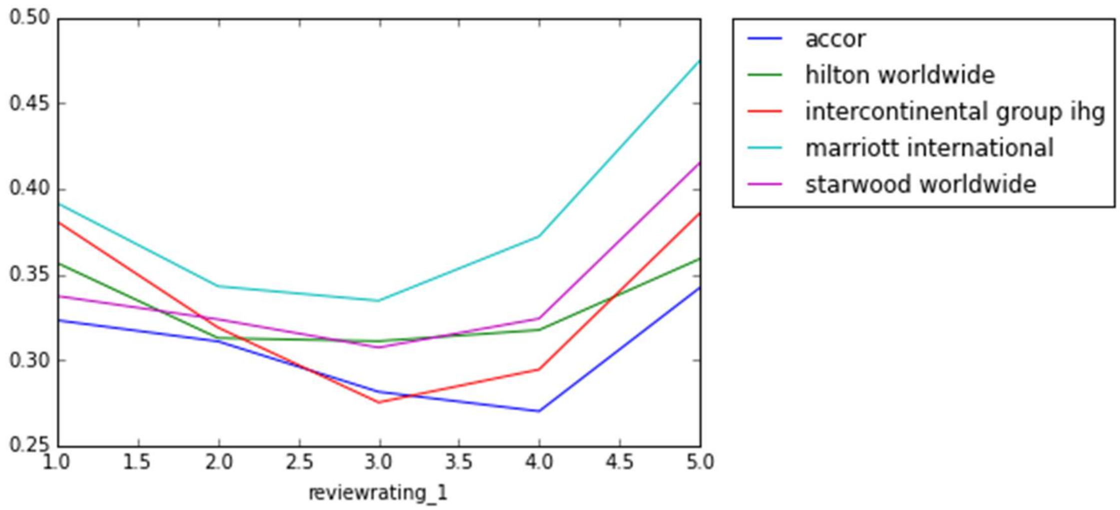


Figure 1-13 - Top Brand Response Tailoring
The figure shows the average similarity score in responses by the top 5 brands by review-response pair volume in our dataset.

We also provide further insight into whether and which managers should respond to all reviews. It is clear that managers of chains have more influence on subsequent reviewers, but not always in the desired direction. Chains are more susceptible to the negative effect of responding to positive reviews. At the same time, chain hotels are better at positively influencing subsequent reviews by responding to negative reviews. Perhaps most interestingly, we find that response tailoring plays a significant role in the impact of manager response on subsequent opinion. Drawing from the results on response tailoring, we conclude that managers should pay close attention to addressing consumers' complaints, but should apply boilerplate responses to consumer praises (if they choose to respond at all). Both of these strikingly opposite effects support our main results based on reactance theory. Looking at our identified chains (Figure 1-13), we see that managers of the top five chains in our dataset tend to write personalized responses to both 1-star and 5-star reviews, but offer relatively less tailoring in their responses to 3-star reviews. While these managers' tailoring efforts are consistent with the managerial implications of our empirical results for the negative and neutral reviews, it may surprise managers to learn that their efforts in responding to positive reviews may be counterproductive. Sometimes, the simplest action, or no action at all, is the best policy. Letting your customers speak for you, i.e. WOM, can be more impactful than trying to manipulate sentiment with highly tailored MR-P.

Given our findings, based on the objective of maximizing a hotel's online reputation, managers, especially of chains, should respond to negative reviews but not to positive ones. However, one of the limitations of the current study is that we cannot tie manager response to other, perhaps more important, outcomes like bookings, revenue, or prices. At a very minimum, given the extensive literature documenting the positive effect of online reviews on sales, we would expect MR-P to have an indirect negative effect on those performance outcomes. We leave it to future research to address the direct effects of manager response on hotel performance outcomes.

Chapter 2

Hotel dynamic pricing

The current study contributes to the largely theoretical field of revenue management with an empirical investigation into the sub-optimality of managerial dynamic pricing policies as evidenced in the Las Vegas hotel market. We demonstrate in this advance selling setting that managers consistently choose prices that yield revenues approximately 25% below optimal levels. Specifically, we show that managers appear to choose prices in a manner consistent with maximizing a mix of occupancy and revenue. We find support for the hypothesis that the unobservability of counterfactual revenues may drive managers' suboptimal pricing policies when the hotel is expected to fill capacity. Additionally, we explore a novel managerial use of online reviews in pricing decisions and the effect of competitors' pricing strategies on a focal hotel's optimal prices. We discover that predicting mean reverting tendencies of online reviews can marginally improve the focal hotel's bottom line during slow seasons. Similarly, we show that there is an economically significant impact of predicting competitors' prices on the focal hotel's pricing policies.

2.1. Introduction

Dynamic pricing (DyP), the practice of charging different prices for the same good or service over time, has become the norm in many industries such as fashion, travel, services, and entertainment due to the amount of data managers have access to and the relative ease with which prices can be changed (Elmaghraby & Keskinocak, 2003). With the increasing prevalence of DyP in the economy, it is vital for researchers to understand the effectiveness of managers' DyP policies. While many theoretical investigations have been made into how managers ought to practice DyP in the normative sense, it is unclear whether managers are able to implement DyP strategies successfully. Moreover, while researchers readily acknowledge suboptimal and irrational behavior on the part of consumers, few existing investigations have examined whether managers are equally unsuccessful at decision-making in the context of DyP[1]. The main interest of the current study is to address these gaps in the literature with an empirical investigation of managers' pricing practices in the Las Vegas hotel market. We choose this market due to the availability of data and the high managerial involvement in day-to-day pricing decisions. While many DyP software purveyors exist for this market, all managers we contacted still exert complete control over pricing decisions. We obtained daily booking data from one major competitor in this market that has subscribed to a DyP software service but routinely disregards the software recommended prices due to managers' belief

[1] One notable exception is the set of experimental studies conducted by Bearden et al. (2008)

that the suggested prices do not conform to their expectations. Instead managers commonly rely on heuristics developed from experience to determine appropriate prices.

Specifically, we examine how good are managers' intuitive and experience based pricing rules compared to a normative DyP model. In doing so, we also posit that the pattern of suboptimal prices can be explained by managers' incentive to maximize occupancy in addition to managers' bounded rationality. Furthermore, we investigate how much can be gained by anticipating competitive pricing strategies. Finally, we explore potential informational advantages that can be gained through the novel use of online reviews in the DyP decision.

We find, as expected, that managers are not pricing optimally to the tune of 12-38% (25% average) loss in revenue depending on the market conditions for a particular day of stay. In addition, we observe evidence that managers are consistently underpricing the hotel, especially on busy days. Interestingly, the underpricing is less pronounced, or altogether nonexistent, on slow days. This finding suggests that managers are more concerned with the directly observable outcome of occupancy than with their tasked objective of maximizing revenue. Contributing to the emphasis on occupancy is the managers' intuition that empty rooms at the end of a sales window are always bad since they could have been rented for some price. Note that this intuition does not apply when managers are faced with a discrete time problem where prices cannot be changed for every room booked.

The chapter is organized as follows. In section 2, we review the relevant literature in DyP, managerial decision-making, and online reviews. In section 3, we present our econometric specification and normative DyP model. In section 4, we describe our empirical setting, data, and institutional details. In section 5, we present our estimation results and discuss the important qualitative implications of the parameters. In section 6, we discuss our main findings with respect to the efficacy of manager's pricing policies, gains in revenues due to anticipating competitive prices, and informational advantage of predicting hotel ratings in the optimal DyP problem. Finally, in section 7, we discuss managerial implications of the current study, limitations of our current research, and directions for future research.

2.2. Literature

While the objective of the current study to examine the empirical efficacy of managerial pricing decisions in an oligopolistic DyP setting with perceived quality differentiation is novel, the space in which this study is positioned spans a rich literature in DyP, managerial decision making, and online reviews.

2.2.1. Dynamic Pricing with Inventory Constraints

DyP with inventory constraints has a rich history of academic inquiry in operations management, marketing, and economics. However, the bulk of this literature is in the theoretical realm (Elmaghraby & Keskinocak, 2003)[2]. The theoretical literature on DyP has framed the problem as an applied dynamic optimization problem. Particularly, due to mathematical tractability, DyP models have been formulated as continuous time, finite horizon dynamic programs in which demand follows some form

[2] Elmaghraby & Keskinocak (2003) also presents a good overview of the theoretical literature.

of a Poisson arrival process in the tradition of Gallego & van Ryzin (1994). Two types of extensions to this model provide relevant insights to our empirical setting. First is the extension to time-varying demand. Second is the extension to incorporate competitive markets.

Poisson models of DyP have traditionally assumed a constant, or homogeneous, arrival rate to represent the intensity of demand. However, this is not the case for most markets. For example, demand is more intense at the beginning of a sales season and begins to decline towards the end in fashion markets. Alternatively, in leisure hotel markets, it is not uncommon to observe increasing booking interest as the sales window approaches arrival date. Feng & Gallego (2000) model this type of DyP problem as a time heterogeneous Poisson demand process, i.e. an arrival process with a time varying arrival intensity. The authors characterize optimal price switching times for a given finite set of predetermined, and possibly state and time contingent, prices. Feng and Xiao (2000) extend this heterogeneous Poisson demand model to analyze cases that allow for reversals in prices within a predetermined finite set of price changes. Extending this line of inquiry to the fashion scenario in which both reservation valuations and arrival rates are time dependent, Zhao & Zheng demonstrate potential revenue gains over a fixed price policy as high as 100% in numerical examples (2000). Given that managers believe hotel bookings generally increase towards the end the booking window, the conclusions of this stream of theoretical literature suggest that any empirical and normative investigation must take time effects of demand into account.

A more recent development in the theoretical DyP literature is that of incorporating competition into pricing models. This is a critical development given that the majority of markets are not monopolistic. To date, this literature has largely characterized competitive DyP as differential games with an open loop equilibria (Kwon, Friesz, Mookherjee, Yao, & Feng, 2009; Levin, McGill, & Nediak, 2009; Gallego & Hu, 2014). In particular, Gallego and Hu (2014) construct a differential game model of competitive DyP where demand is pseudoconvex, as is the case with linear and multinomial logit demand. The authors show that such games have relatively simple open loop equilibria. The current study does not formulate a complete game given that managers are fairly myopic in regards to thinking about competitors' strategies at the operational level. In fact, one of the major concerns of managers is that they do not have a straightforward way of incorporating competitors' prices in their own pricing problem. Furthermore, the current open-loop approach to competition does not correctly characterize the closed-loop nature of competitive dynamic pricing. In other words, not allowing for state contingent pricing policies and opting for only time dependent pricing policies does not describe the true competitive problem. Solving for the closed loop equilibrium of such DyP games is a non-trivial theoretical problem outside the scope of our current empirical investigation. Nonetheless, we do consider the case in which managers can forecast not only demand but also competitors' pricing as a function of observable state variables. Though this formulation does not contribute to the theoretical understanding of DyP, it does provide us with insight into the importance of being able to predict market conditions outside of focal demand. In particular, this partial equilibrium approach, where competitors' policies are held constant, provides an upper bound on gains to incorporating competitive strategy in DyP settings. As we will demonstrate, the empirical evidence suggests that the gains are not particularly high.

In addition to the rich theoretical literature on DyP, there is a budding empirical literature that is primarily focused on documenting stylized facts about either consumer demand or managerial DyP policies in several industries including airlines, cruises, and hotels. For example, Li, Granados, and Netessine (2014) exploit the insight that both perfectly forward looking and myopic consumers will behave in the same way when prices increase monotonically to separately identify price elasticity from the segment size of strategic consumers. The authors find that in the airline market, there are as few as 5% strategic consumers. Given that even in the most likely market for strategic purchase timing there are only few consumers who can be categorized as such, it is justifiable to ignore this unnecessary complication in the current study. Additionally, the focal hotel in this current study exhibits a 3% cancellation and rebooking rate for customers who booked earlier at a higher price, further suggesting the relative myopic nature of consumers in our setting.

On the other end of the spectrum, researchers have used data to test theoretical predictions of DyP models. McAfee and Te Velde (2006) review the implications of current theoretical work in DyP to show that the data generally do not reflect predictions of those models, especially in regards to general price trends during the course of the booking window. Koenigsberg, Muller, and Vilcassim (2008) estimate the effect of consumer factors on depth and length of discounted prices to show potential gains of last minute deals in the airline setting. Perhaps most closely addressing the problem we are investigating is Vulcano, van Ryzin, and Chaar's study on optimal pricing with choice based demand (2010). The authors present a method of estimating demand with a multinomial logit formulation and show that this type of demand formulation improves optimal pricing by 5% in counterfactual simulations. While choice based models are often considered ideal when measuring consumer price sensitivities, many situations, such as the one we study, do not allow for such individual level analysis. Moreover, aggregate level demand is generally more susceptible to endogeneity concerns that these authors ignore at the individual level. We build on this literature to quantify the bottom line impact of managers' deviation from optimal pricing policies by resolving endogeneity concerns and showing counterfactual gains above descriptive models of empirically observed managerial pricing rules.

2.2.2. Managerial Decision Making

Another academic tradition that the current study builds upon is the analysis of managerial decision-making. We are particularly interested in suboptimal decision making from the firm's perspective, stemming from two types of explanations. First, managers can have difficulty making correct decisions in complex situations such as DyP. Second, managers can have skewed incentives due to an agency problem. There is a significant literature in decision biases, but we focus on decision biases by operations managers in a dynamic setting. Sterman (1989) first examined such problems in an experimental setting by asking subjects to play the now famous "beer distribution game" in which players must manage an inventory system with a complicated feedback dynamic. Sterman finds that in this game, a simplified version of real world inventory management, subjects perform dismally, exhibiting anchoring biases, inability to learn, and poor ability to forecast demand. Sterman concludes that managers, or at least lab subjects put in a managerial role, are prone to make persistently suboptimal decisions.

This finding gives credence to our goal of documenting persistent managerial biases in DyP settings.

In the DyP domain, Bearden et al. (2008) show that experimental subjects exhibit persistent biases in a price-bidding setting. The subjects' are asked to accept or reject simulated bids in a behavioral economics paradigm with performance compatible incentives. The authors demonstrate that the managers are unable to learn in a repeated setting unless a simple policy heuristic is forced upon them. Furthermore, subjects demanded too high a price when inventory levels are high and too low a price when inventory levels are low. The authors state that the mispricing behavior is suggestive of subjects' use of a heuristic that set reservation price to be a convex combination of the optimal price and a reference price approximately equal to the optimal price associated with the state of the world with half the inventory remaining. This behavior is termed "regressive," as the prices tend to be closer to optimal prices of a less extreme state of the world.

In an empirical investigation of a fashion retailer, Heching et al (2002) demonstrate a similar suboptimality in markdown pricing behavior. The authors of this study estimate a linear demand function using weekly sales data and compare various full information and adaptive pricing policies with practical constraints to the actual pricing used by the firm. Specifically, the authors find that the apparel retailer was using lower than optimal markdowns and doing so too late in the sales season. In other words, managers are found to do too little, too late. The current study adds to this literature by studying a more complex data and pricing environment where price changes may not be monotonic, competitors' prices can affect each other's demand and thus pricing, and consumer reviews may induce demand shocks to the market. We expect, with the increased complexity of the market and greater volume of price changes, that managers may be falling even shorter of optimal revenues.

While bounded rationality implied by heuristics may lead to suboptimal behavior, fully rational managers can also make suboptimal decisions for the firm when their respective incentives are misaligned. The agency problem has been one of the better-studied problems in economics. The main finding of this literature is that agents will tend to shirk when monitoring on the principal's desired outcome is imperfect (Holmstrom, 1979). In an environment such as the Las Vegas resort market, it is unclear how revenue managers' performance is best measured since counterfactual demand is never directly observed. However, the economic intuition that empty rooms represent deadweight loss is a highly prevalent belief held by managers. As such, one would expect that managerial performance might be monitored by occupancy rates in addition to revenues. Therefore, one implication of such an inclination is that managers may consistently underprice compared to optimal levels, especially when capacity is expected to be reached. Our empirical analysis will show evidence of this behavior and demonstrate some partial evidence that managerial suboptimal decision making may be at least in part due to revenue maximization-incompatible incentives.

2.2.3. Online Reviews

Given the availability of data for online reviews and its potential to serve as a source of demand shocks in our econometric analysis, we also have the opportunity to study a potentially novel managerial use of online reviews as an informative variable in DyP. The present literature of online reviews has largely been consumer centric, investigating the impact of online reviews on customer purchase behavior in a variety of product categories such as video games (Zhu & Zhang, 2010), books (Chevalier & Mayzlin, 2006), restaurants (Luca, 2011), and movies (Liu, 2006). Naturally, the effect of online reviews on hotel bookings has also been investigated. Vermeulen and Seegers (2009) show in an experimental setting with implicit attitude measures that exposure to online reviews of hotels increases the likelihood of that hotel entering the consideration set and that the valence of those reviews affect the attitude of consumers towards the hotel. Ye et al (2009) use data from an online travel site to demonstrate the potential empirical impact of online ratings on hotel bookings using the number of reviews as a proxy for demand. In the current study, we further document the importance of hotel online reviews on demand not only for the corresponding hotel, but for competing hotels as well. Given the empirical evidence in hotel and other markets, it is clear that online word of mouth impacts demand. What is unclear is how managers can use this knowledge.

The extant literature on online reviews from a managerial perspective has largely focused on the strategic faking of reviews, both positive self-promoting and negative competitive denigration. Mayzlin et al (Forthcoming) cleverly exploit institutional differences between TripAdvisor and Expedia, the former having no qualification restrictions on reviewers and the latter allowing only paid customers to review, to demonstrate evidence of negative review manipulation. Specifically, the authors show that ratings for hotels neighboring other hotels with low ratings on Expedia are rated significantly lower on TripAdvisor than on Expedia. While we do not deny the strategic importance of perception manipulation through fake reviews, we propose that there may be more ethical and perhaps less illegal ways to take advantage of our understanding of the effect of online reviews. One such way is to systematically incorporate online reviews into DyP decisions. Specifically, the ability to predict changes in online ratings can give hotels an informational advantage in the DyP problem.

2.3. Model and Estimation

In this section, we introduce our demand and empirical pricing models. We outline our econometric strategy and model specification. In addition, we describe the general form of the normative optimization model from which we perform our benchmark tests.

2.3.1. Econometric Demand and Pricing Estimation

One of the major roadblocks to an empirical examination of managerial performance in DyP is the ability to quantify demand. Choice models are often impractical to implement since many, if not a majority, of customers do not make a repeat purchase. Moreover, given that managers practice DyP to influence the number of rooms booked, issues of endogeneity will complicate any demand estimation. While our research objective is not to contribute methodologically to demand modeling, we are mindful of these issues in our model specification and econometric strategy. Following the precedence of linear demand models in the limited empirical DyP and hotel bookings literature (Heching, Gallego, & van Ryzin, 2002; Li, Granados, & Netessine, 2014), we introduce a linear demand model that attempts to capture some of the features found important in the literature and deemed important in the specific market of the current study.

Based on the data that the managers observe, we formulate a model of demand that is indexed on two time dimensions. First there is the stay date timeline, $t \in \{0,...,T\}$. This indexes the room-nights that the manager attempts to sell. Second, there is the booking window timeline, $l \in \{0,...,\mathrm{L}\}$. We normalize this such that 0 is the first day of the booking window and L is the last. Given insights from the literature and commonly documented lead-time dependent and seasonal booking volumes, we want the linear demand model to capture these effects. Additionally, firms do not operate as monopolies in this and most markets, so we allow for firm index $j \in \{0,...,\mathrm{J}\}$. As a result, our demand specification is a function of the set of information available to each firm not only about its own operations, but also the set of publicly observable data of its J competitors. Therefore, we specify our demand function as follows.

Eq. 2-1
$$d_{tl} = \beta_1 p_{tl} + \beta_2 r_{tl} + P_{tl}^{-0} B_3 + R_{tl}^{-0} B_4 + \beta_5 d_{tl-1} + w_{tl} B_6 + \tau_t + \varepsilon_{tl}$$

Where demand, d_{tl}, for stay date t at a lead time l is a function of own concurrent price, p_{tl}, prices of competitors, P_{tl}^{-0}, own ratings, r_{tl}, competitors' ratings, R_{tl}^{-0}, previous day bookings, d_{tl-1}, day of week of the booking, w_{tl}, and a fixed effect for the day of arrival, τ_t, with some error, $\varepsilon_{tl} \sim N\left(0,\sigma^2\right)$. We allow for serial dependence of bookings because one would expect that increased bookings on one day will decrease bookings on the following day, i.e. there exists some degree of intertemporal cannibalization. Furthermore, we transform prices into log prices, to reflect the expectation of decreasing marginal effect of price on bookings. This concavity in price sensitivity is consistent with microeconomic intuition that consumers who are willing to pay a high price are less sensitive to changes in that price.

In addition to the demand specification, we also want to characterize the manager's simultaneous pricing policy. In the spirit of hedonic pricing models, we characterize the manager's pricing policy as a linear function of the set of characteristics observable to a decision-making manager. In essence, we reconstruct the set of information available to the manager at the time of making each pricing decision. Each firm j at calendar time t observes the following data structure for all stay dates $t+l$ $\forall l \in \{0,...,\mathrm{L}\}$ that are within the L day booking window: changes to rooms availability due to reallocation of rooms to separately managed segments $a^{j}_{L-l,t+l}$, previous day's bookings for the focal hotel, $d^{j}_{L-l-1,t+l}$, the previous booking day's prices for competitors, $P^{-j}_{t+l,L-l-1}$, own price from the previous booking day, $p^{j}_{t+l,L-l-1}$, and expected demand as described in Eq. 2-1. Given this information set, we form the following pricing specification (Eq. 2-2) for the generic hotel, j. Given the data we do observe, our focal hotel can be specified exactly by this equation (Eq. 2-3).

Eq. 2-2 $$p^{j}_{tl} = \lambda_t + \lambda^{j}_{1} a^{j}_{tl-1} + \lambda^{j}_{2} p^{j}_{tl-1} + \lambda^{j}_{3} d_{tl} + P^{j}_{tl-1} L^{j}_{4} + \lambda^{j}_{5} l + \lambda^{j}_{6} l^{2} + \gamma^{j}_{tl}$$

Eq. 2-3 $$p_{tl} = \lambda_t + \lambda_1 a_{tl-1} + \lambda_2 p_{tl-1} + \lambda_3 d_{tl} + P^{-0}_{tl-1} L_4 + \lambda_5 l + \lambda_6 l^{2} + \gamma_{tl}$$

However, we do not observe the private booking data for all other hotels. Therefore, we select some proxies for the competitors that the focal hotel and the econometrician can observe so as to provide a model for the manager to predict competitive pricing. To proxy for availability and past and expected bookings, we use our focal hotel's availability and the set of hotel ratings to capture some idiosyncratic demand shocks and market level demand. In accordance with these substitutions, we specify the competitors' prices in Eq. 2-4.

Eq. 2-4 $$p_{tl}^{j} = \lambda_{0t}^{j} + \lambda_{1}^{j} a_{tl-1} + \lambda_{2}^{j} p_{tl-1}^{j} + \lambda_{3}^{j} d_{tl} + P_{tl-1}^{-j} L_{5}^{j} + \lambda_{6}^{j} l + \lambda_{7}^{j} l^{2} +$$

Given our specification of the focal hotel's demand and pricing functions, the most natural estimator is the three stage least squares (3SLS) estimator (Duan, Gu, & Whinston, 2008; Parke, 1982; Zellner & Theil, 1962). Note that both the pricing and the demand equations are simultaneously identified as there are exclusionary variables in both equations. While the demand equation includes contemporaneous hotel ratings and day of week effects, the pricing equation does not. Intuitively, these exogenous shocks to demand shift the demand curve to identify the supply curve inverted as a pricing equation. To our knowledge, this is the first documented use of online reviews as an instrumental variable for demand in a supply equation. We point this out due to the broad applicability of this strategy in resolving endogeneity of demand with supply in an operational setting. Note that this strategy may not be effective in a setting where price and quality are both endogenously determined.

Turning our attention to the pricing equation, consumers do not observe changes to availability due to casino and group segments' reallocation of capacity in to and out of the individual traveler's block; therefore, this private information of the hotel manager acts as an exclusionary variable from the demand equation. However, since the focal hotel's contemporaneous bookings do not enter the competitors' pricing equation, we estimate equation 4 separately for each of the focal hotel's competitors. We are not too concerned with the existence of competitive price endogeneity because, according to managers, competitors' prices are generally set in response to market prices in the previous period, not in anticipation of new prices in the current period as the majority of the informative data comes from hotel specific unobserved data.

2.3.2. Optimization Model

Following Dolgui and Proth (2010), we define our optimization model as a stochastic version of the discrete time finite horizon dynamic program. The basic problem can be expressed as Eq. 2-5, where demand follows Eq. 2-1. Note that we drop the t subscripts and model each day of stay independently.

Eq. 2-5
$$Max\sum_{l=0}^{L} p_l d_l,\ s.t.\ \sum_{l=0}^{g} d_l \le K_t \text{ where } 0 \le \text{g} \le \text{L}$$

We can rewrite Eq. 2-5 as a Bellman equation for finite horizon problem, which can be solved through backward iteration. First, the continuation payoff at any time, g, in the booking window can be written as equation 6 where $\boldsymbol{a_g = a_{g\text{-}1} - d_{g\text{-}1}}$ is the amount of capacity available and other state variables evolve according to equations 1, 3, and 4. For now, we leave ratings as purely a random walk, so that the rating at time g+1 is in expectation equal to the rating at time g. We will discuss this further in section 6 to account for mean reversion properties of ratings. Eq. 2-6 characterizes the problem that the optimizing manager should solve at every point in time, g, in the booking window.

Eq. 2-6
$$V_g^+\left(P_{g-1}, R_{g-1}, a_g, d_{g-1}, w_g\right) = \underset{\{p_g, p_{g+1}, \dots, p_L\}}{Max} \sum_{l=g}^{L} p_l d_l,\ \text{s.t. } a_g - \sum_{l=g}^{G} d_l \ge 0 \text{ where } g \le G \le L$$

We can write the dynamic program as a standard value function as in equation 7, where its backward-iteration from l =L to 0 will numerically solve for the optimal pricing path for any given state and lead-time. Note that since rooms have no value at l = L, we set $V_{L+1} = 0$. Additionally, we do not include a discount factor, i.e. discount factor = 1. This is because, in theory, managers should only care about total revenues at the end of the booking window when all transactions are deemed completed.

Eq. 2-7 $$V_g\left(P_{g-1}, R_{g-1}, a_g, d_{g-1}, w_g\right) = \underset{p_g}{Max}\left[E\left(p_g d_g(p_g) + V_{g+1}^{+}\right)\right]$$

To set the stage for our various counterfactual comparisons, we define several sets of expectations that an optimizing manager may have. For a manager who is naïve about competitors' prices may believe that competitors' prices are fixed and that changes in those prices are unpredictable. In this scenario, the naïve optimization problem that the manager solves is the same as in Eq. 2-7, but the state transition for competitor prices is simply $P_{g+1}^{-0} = P_g^{-0}$ with some white noise component with variance equal to the observed variance in prices. We call this the base case. However, a more sophisticated manager may take expectations over the competitors' prices according to Eq. 2-4, such a manager would weigh the future continuation payoffs based on the probabilities that competitors' prices are expected to be in each possible state as defined by the parameters and estimated noise in eq. 4. Note that in this scenario, the set of optimal prices accounts for the focal hotel's prices' effect on the competitive pricing environment in every subsequent period. Therefore, the focal managers' actions do not only impact sales directly through the demand function, but also indirectly by entering the competitors' pricing policies as can be best inferred from the focal firm's limited information set. We call this the competitive case. Finally, if managers can predict mean reversion tendencies of hotel ratings, they can take those expectations into account. We call this set of expectations the full case. Equation 8-10 summarizes the 3 types of expectations that we allow the manager to form (base, competitive, full respectively).

Eq. 2-8 $$E\left(p_g d_g(p_g)+V_{g+1}^{+}\right)=p_g E\left[d_g(p_g)\right]+E\left(V_{g+1}^{+}\right)$$

Eq. 2-9 $$E\left(p_g d_g(p_g)+V_{g+1}^{+}\right)=p_g E\left[d_g(p_g)\right]+E\left[V_{g+1}^{+}\left(p_g,P_{g+1}^{-0}\left(p_g\right)\right)\right]$$

Eq. 2-10 $$E\left(p_g d_g(p_g)+V_{g+1}^{+}\right)=p_g E\left[d_g(p_g)\right]+E\left[V_{g+1}^{+}\left(p_g,P_{g+1}^{-0}\left(p_g\right),R_{g+1}\right)\right]$$

2.4. Market Description and Data

In this section, we describe the empirical setting for the remainder of our analysis. We begin with a description of the market with institutional insights, followed by a description and summary statistics of the data.

2.4.1. Market Description

The market that we are studying is the Las Vegas resort market between September 2010 and August 2011. Specifically, we are studying the demand and competition for what the industry refers to as free and independent travelers (FIT) whose primary purpose is for vacation and pleasure. Approximately 50% of all travelers can fall under this category. The average number of trips that each visitor makes in a year is 1.24. This means that it is difficult for hotels to observe repeat purchases for this segment within the same year, rendering individual level marketing of the FIT segment difficult. We focus on the 30 days prior to arrival since this was the consensus period that revenue managers acknowledged as the most carefully managed. Approximately 79% of all FIT reservations are made within this 30-day window. The choice of 30-day window also helps simplify the problem given that the vast majority of group and convention room blocks are contracted to release free rooms by 30 days prior to arrival. Therefore, we do not have to worry about group bookings, which is a displacement (reject or accept) problem rather than a typical daily level DyP problem. (GLS Research, 2011)

Another important feature of the market is travelers' access to many different rate types through a variety of channels. In addition to walk-ins, call center, and travel agents, 40% of all bookings were made online. Many websites compete in the online channels including the hotels' brand site (32%), Expedia (16%), Hotels.com (13%), airline website (7%), LasVegas.com (6%), Travelocity (6%), Priceline (6%), Orbitz (4%), and Vegas.com (3%). While the variety of channels offer hotels a potential outlet to price discriminate, it has become standard for third party sites to demand price parity contracts with partner hotels. This means that price changes on the prevailing rates available through the hotel must be the same as that offered on a third party booking site like Expedia.com. This allows us to collect pricing data through a single third party site, knowing that it reflects the standard rates available across channels.

One important aspect of any market is the degree of vertical differentiation. Vertical differentiation is easily distinguished in the hotel industry through the Forbes (formerly Mobil) star and AAA diamond rating systems. We focus on the higher spectrum of the market in this analysis using data from three properties with at least a 4-star and 4-diamond rating during the timeframe covered by the data. Our assumption is that the latent quality of the hotel is fixed, i.e. the quality of the rooms, public areas, and service is roughly identical for each hotel throughout the time period. To bolster the credibility of these assumptions, we choose three properties that did not make major renovations during the timeframe of this study.

While we assume that the quality of the hotel does not change, what does change is the consumers' perceptions of quality. The perception of quality can be influenced by online reviews. According to the annual visitor profile study commissioned by the Las Vegas Visitor and Convention Authority (GLS Research, 2011), over 52% of all travelers, including repeat visitors of Las Vegas, look for non-price information about accommodations on travel websites. While there may be a variety of information about hotels, we focus on the ratings in the first page of reviews, as it has been well documented that the most visible reviews in terms of page rank will have the biggest impact on consumer perceptions and demand (Pavlou & Dimoka, 2006). Note that this happens in calendar time at the time of bookings, so changes in online reviews will have a shock to demand across multiple dates of stay booked on the same day. We construct this dataset retroactively by building a rolling window of the most recent 25 reviews, the default number of reviews per page during the time period concerning our data. While ideally, one would like to see the impact of site specific ratings on corresponding site bookings since it is very likely that travelers who book on one site reads the reviews from the same site, due to the lack of segmented bookings data, we cannot investigate site specific effects. Instead, we assume that Hotels.com reviews can influence aggregate demand beyond just the 13% of online bookings that are sourced from the site. The strong effect of review ratings in the estimation results in section 5 provides some compelling evidence that this may be the case. We interpret this as Hotels.com being a particularly influential source of information among travelers looking for accommodations-specific information.

2.4.2. Data Description

We obtained daily level booking data from a large upscale resort located on the Las Vegas strip for the period of September 2010 through August 2011. The data is indexed by stay date and booking date. In addition to daily level bookings, other variables recorded include the allotted availability, which accounts for overbooking and unfilled group and blocks. To augment this dataset, we collected room rates of competitors from Orbitz and Hotels.com. While we collected rates for every property located on the strip, we use only two of the competitors' data due to the state space limitations of our dynamic optimization model. We chose the two closest competitors based on our conversations with the focal firm's managers. The collection of the data occurred during the same time period as the booking data since historical prices cannot be recovered post hoc. In addition to pricing data, we collected hotel ratings from Hotels.com. The choice for this source of ratings is due to the relative specialization of the website and the greater proportion of travelers who book through Hotels.com. Intuitively, it is more likely that travelers who did not book through Hotels.com are more likely to read reviews from a site that specializes in lodging than through other all-purpose travel sites.

	Obs	Mean	Std. Dev.	Min	Max
P0	10782	224.94	82.90	127	699
P1	10470	267.69	121.47	135	749
P2	10707	215.73	82.24	119	699
D0	10788	27.23	29.07	-9	195
R0	10788	4.45	0.20	3.84	4.84
R1	10788	4.63	0.21	4.24	4.92
R2	10788	4.42	0.17	4.04	4.8

Table 2-1 - Summary Statistics
We have complete booking and ratings observations for 348 days and missing certain dates for prices.

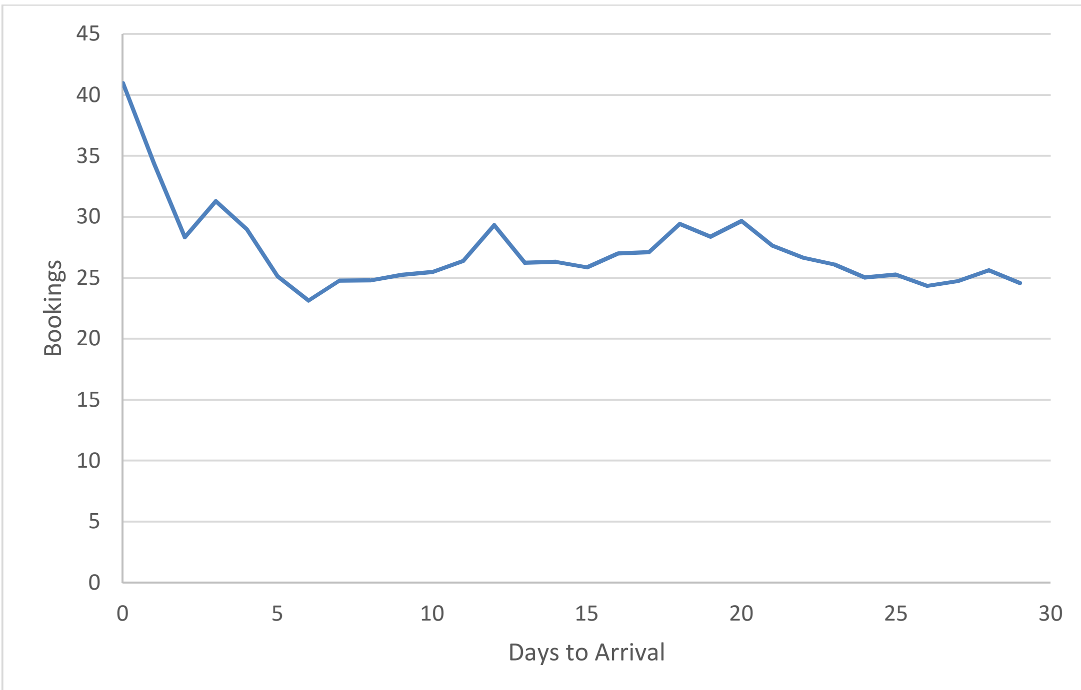


Figure 2-1 - Bookings by Lead Time
This plot shows that there is on average an increasing trend in bookings over the course of the booking window (as booking date nears stay date).

Our datasets includes three types of raw variables: prices of focal hotels and its competitors, average ratings of 25 most recent reviews on Hotels.com for all 3 hotels, and daily booking data for the focal hotel. Table 2-1 summarizes the main variables that we observe. Note that our focal hotel’s average price is between that of its two main competitors as is its average rating. There is also a large range in the total bookings. Seasonal effects largely drive this variation, with the greatest number of bookings occurring during peak seasons. Figure 2-1 plots average bookings by lead-time. It is apparent that the general trend is a gradual increase in bookings each day until arrival. This is consistent with the managers' stated intuition that demand picks up through the course of the booking window. Taking a look at the overall bookings for the FIT allotment, we see that there is on average on 811 rooms left to sell at the 30 days to arrival mark, including overbooking capacity, and on average 223 rooms remaining at the time of arrival.

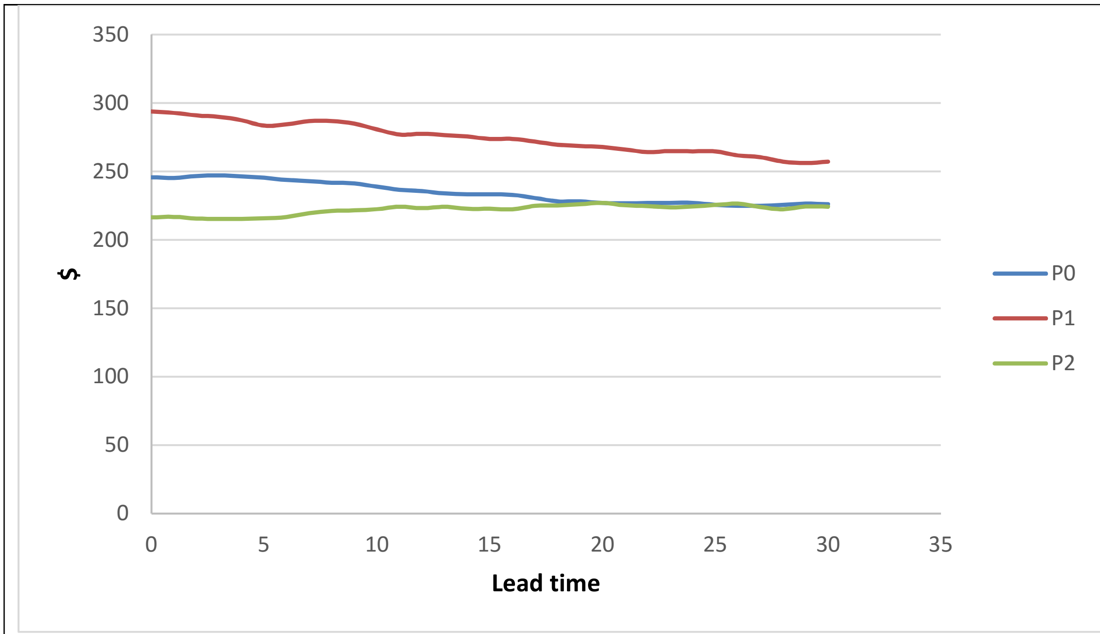


Figure 2-2 - Prices by Competitor
Prices by lead time for focal hotel and its two competitors show some variation within the 30 day window.

Figure 2-2 plots the average prices of all three hotels by lead-time. Notice that the average prices over the booking window are relatively constant for all three hotels and the focal hotel's prices increase slightly towards the end of the booking window.

Breaking down the prices of the focal hotel by day of week of stay, we see that the slight increase in prices is a common trend across all days of stay and their corresponding average price levels (Figure 2-3). Moreover, it is clear that Fridays and Saturdays have the highest prices with Thursdays trailing on average by more than $50 and the rest of the week days clustered around the $200 mark.

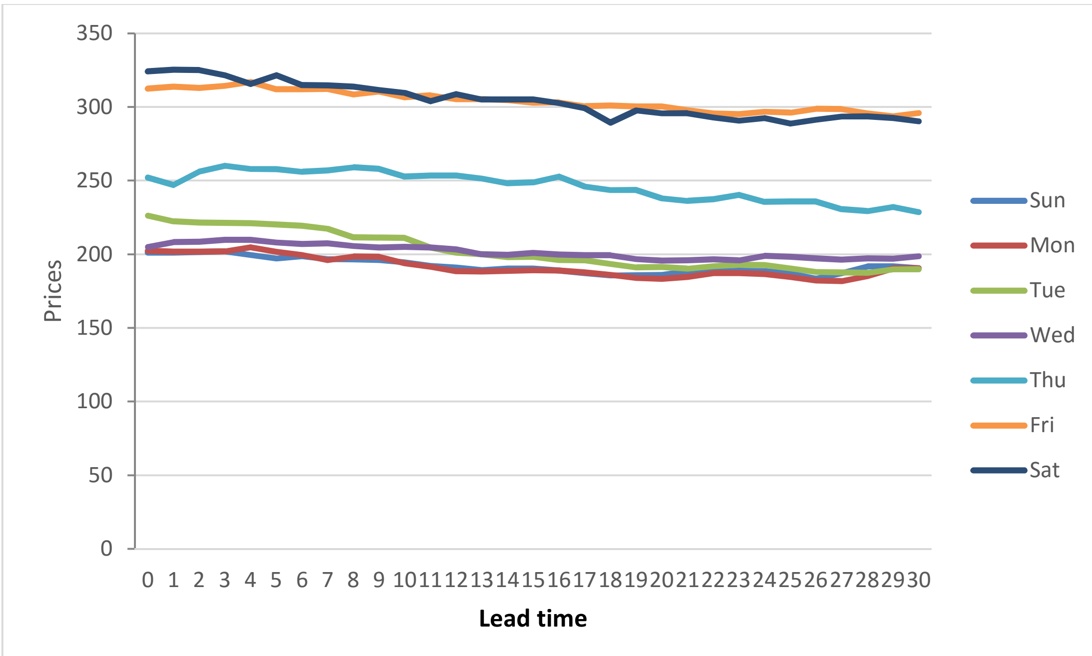


Figure 2-3 - Prices by Day of Week
Focal hotel prices split by day of week and averaged across lead time indicates a similar pattern in prices across all days of week with substantial increases for weekend prices.

In addition to bookings and prices, we also have data about online reviews. While the long run average of the online ratings do not vary dramatically over the timeframe of the data, the average of the ratings of the first 25 reviews that appear on the first page does exhibit significant variation (Figure 2-4). The first page average ratings appear to exhibit cyclicality, reverting back to long run averages as they deviate farther from that average. In our simulation studies to follow, we will attempt to take advantage of this mean reverting trend to gain an informational advantage in the DyP problem.

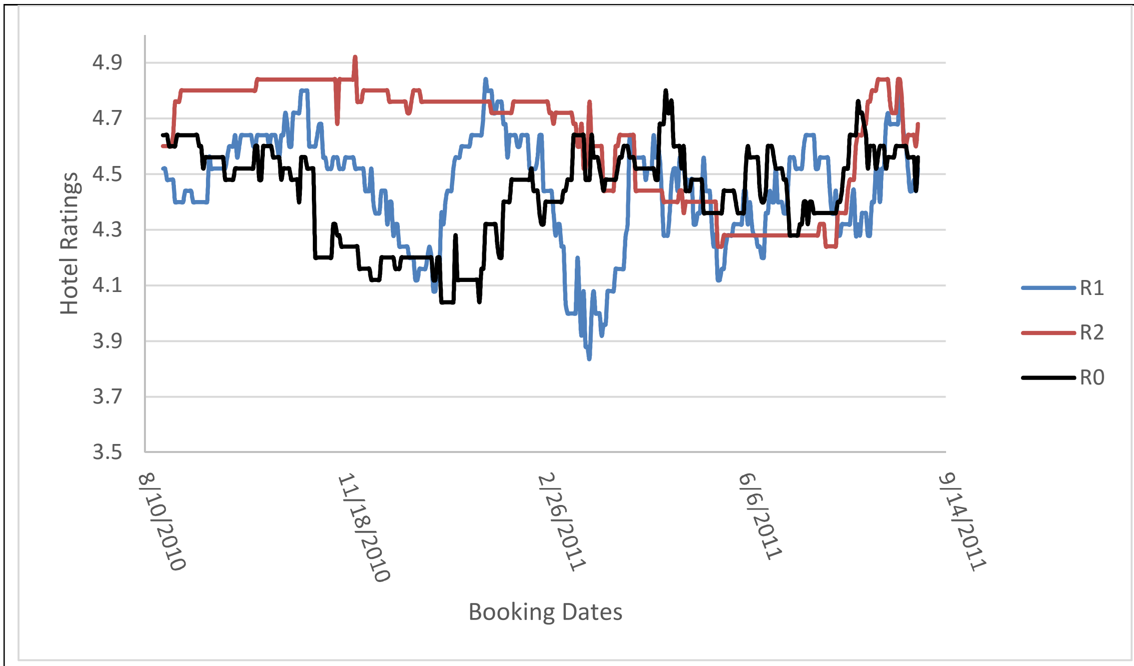


Figure 2-4 - Review Ratings of Competitors
Average first page ratings from Hotels.com shows considerable variation through the date range of the data.

2.5. Estimation Results

Parameter estimates of equations 2-4 provide some intuition about the optimization results in the next section. Table 2 presents the estimates for equations 2 and 3, the jointly estimated pricing and demand equations for the focal firm. The top panel consists of the estimates for the proposed alternative specifications of the demand equation while the bottom panel consists of the various pricing equation parameters. Fixed effects for stay dates are omitted from all specifications and are summarized separately. We present the results for several specifications, including the first column, which represents the parameters from the separately estimated pricing and demand equations, and the last four columns that represent 3SLS estimates using exclusionary variables as instruments. Notice that comparing column 1 with 5, that the magnitude of the focal price coefficient is underestimated without addressing the simultaneity of the two equations ($z=3.08$, $p<.01$). However, unlike the common endogenous pricing problems in econometrics, we do observe theoretically correct signs for coefficients on prices. We suggest that this is the case because controlling for stay date fixed effects mitigates a significant portion of the endogenous pricing problem that is due to seasonal demand variations. Specifically, estimated effects of price changes are representative of correlation with general levels of demand, which varies mostly across stay dates rather than booking dates. Indeed, there is a high negative correlation ($\rho = -.53$) between final availability and prices.

	m1	m2	m3	m4	m5
Lag(Bkg)	-0.6310	-0.6281***	-0.6351***	-0.6344***	-0.6331***
P0	-78.3342***	-64.0256***	-97.1912***	-95.3025***	-128.7538***
R0	24.7991***	15.9836	22.0422*	22.8407*	23.3962**
Lead	0.9832	0.8851	1.0380*	1.0489*	1.1048**
Lead2	-0.0202	-0.0138	-0.0209	-0.0212	-0.0212
P1	38.0945***		42.6802***	41.1351***	47.8742***
P2	20.9273***		26.1706***	27.1407***	30.1035***
R1	-26.2208***			-27.2464*	-27.1276*
R2	-17.9108***			-13.7655*	-15.1894*
Mon	9.7273***				9.4308**
Tue	-1.6833***				-1.9453
Wed	23.9109***				23.6560***
Thur	20.0750***				19.8371***
Fri	11.7938***				11.5205***
Sat	28.7180***				28.6505***
Constant	197.1803***	308.2186***	72.9253	253.4241**	376.7605***
Adj R2	0.38	0.38	0.39	0.39	0.40
Booking	5.72E-6***	3.15E-5***	3.87E-5***	3.87E-5***	4.02E-5***
L(P0)	8.49E-1***	8.48E-1***	8.43E-1***	8.43E-1***	8.42E-1***
Lead	6.78E-4***	1.05E-3***	1.03E-3***	1.02E-3***	1.56E-3***
Lead2	-3.23E-5***	-3.77E-5***	-3.58E-5***	-3.58E-5***	-3.56E-5***
Avail	-3.72E-5***	-3.32E-5***	-2.81E-5***	-2.84E-5***	-2.84E-5***
L(P1)	1.85E-2***		1.57E-2***	1.57E-2***	1.51E-2***
L(P2)	8.37E-3***		4.86E-3	4.87E-3	4.68E-3
Constant	6.85E-1***	8.74E-1***	7.78E-1***	7.79E-1***	7.69E-1***
Adj R2	0.97	0.95	0.97	0.97	0.97

Table 2-2 - Demand and Pricing Parameters

Focal demand and pricing estimates. Top panel represent 5 specifications of demand, the first column is OLS estimates, m2-5 are 3SLS estimates. Bottom panel represents pricing estimates.

Comparing model 2 to model 3, we see that ignoring competitors' prices also leads to an underestimation of the effect of the focal price (z=2.34, p<.05). This is reasonable as the positive correlation between focal and competitor prices leads to the focal price only model capturing a large portion of the positive effect of competitive prices in one parameter. More importantly, this difference suggests that managers should consider competitors' prices when making pricing decisions. Otherwise, managers may be underestimating the effect of their own actions. Interestingly, we see a consistent negative effect of lagged bookings that suggests there is a between booking day cannibalization effect, i.e. bookings today partially come at the expense of tomorrow's consumers. The large effect of price on bookings combined with this inter-day tradeoff of demand leads one to project that there should be some significant price variation from day to day in anticipation of demand changes. To bolster the claim that there should be more daily variation in prices based on our aggregate demand parameters, we also observe that bookings by day of week on which reservations are made vary dramatically. Nonetheless, we do not observe this type of daily price changes in the data as there are on average 2.8 price changes in a 30-day booking window.

Next, we turn our attention to the effect of online ratings. We find support that the average ratings of the most recent 25 reviews that comprise the first page of Hotels.com reviews for the focal hotel has a significant positive effect on demand. Moreover, the ratings for the two competitors negatively impact focal demand. This is consistent with our hypothesis that online ratings can be used as demand shifters given the institutional insight that this information is not currently being collected or used by the managers in their pricing decision. More importantly, we see a quantitatively large effect of star ratings on average bookings. A one-star improvement in ratings can increase this number by more than 30 rooms per booking day, a large effect when compared to the average daily bookings of approximately 28 rooms. Over the course of a booking window, this amounts to more than $150,000 for one night of stay at the historical average daily rate

(ADR). A similar increase in the star rating of either competitor can decrease bookings by 27 and 15 rooms per booking day respectively. Of course, it is impossible to achieve this one-star increase given that the average rating for all three hotels is around 4.5 out of 5 stars. Nonetheless, we take this as compelling evidence that the customer perceived quality plays a large and overlooked role in the booking process and should have a significant impact on the pricing decision.

Turning our attention to the focal hotel pricing parameters in the bottom panel of Table 2-2, we observe that there is no quantitatively significant effect (though statistically bigger than 0) of daily bookings on the focal firm's price in the 3SLS-m5 pricing equation. This suggests that managers are not anticipating day-to-day idiosyncratic shocks to demand in any meaningful way. We also observe that there are small, though statistically significant, effects of competitors' prices and remaining availability. Consistent with visual evidence in Figure 2-4, we do not see much evidence that managers are responsive to daily variations in their own or market data. One plausible explanation is that changing prices is costly; as price parity contracts combined with different pricing interfaces across channels make price changes time and labor intensive to implement. Additionally, the large unpredictable variability in bookings, evidenced by the 0.4 R^2 in the demand equation, means that there is a high noise to signal ratio for predictive covariates. As a result, variations in these variables do not give managers a precise indication that any price changes need to be made. Whatever the reason for the lack of changes, it is clear that in a frictionless price changing environment, it should be optimal to observe more rate changes from day to day given the predictable, albeit noisily predictable, changes in demand.

Similarly, for the competitor prices, we observe relatively stable prices that respond in statistically significant, though in quantitatively small degrees, to changes in the other two hotels' prices (Table 2-3). Our proxies using focal hotels' availability and competitors' ratings seem to have mixed results. For competitor one, the proxy has a significant negative effect, while the opposite is true for hotel 2. Obviously, we would expect both of these to be positive, so it seems that the expected positive correlation with competitor ratings and bookings is not sufficient to induce a positive coefficient in the pricing equation that one would expect. Nonetheless, the overall fit is strong, and it is clear that focal hotel's prices have a significant impact on competitors' subsequent prices.

	P1	P2
Lag(Rate1)	8.162E-001***	-2.817E-002***
Lag(Rate0)	5.388E-002***	4.273E-002***
Lag(Rate2)	-4.138E-002***	8.049E-001***
Lag(Avail0)	3.090E-005***	4.680E-006
Lead time	1.588E-003***	2.510E-005
Lead time^2	-4.570E-006	-8.070E-006
Rating (own)	-1.406E-003*	6.810E-003*
Constant	9.151E-001***	9.340E-001***
R2	0.702	0.642

Table 2-3 - Competitors Pricing Parameters

Turning our attention to the fixed effects of booking as estimated in model 5, we see in Table 2-4 the break down the marginal contributions of day of week, month of year, time trend, and holidays to the bookings fixed effect. As expected, FIT demand is highest on the weekends, during the summer months, and during holidays. The top 5 holiday weekends include New Year's, Chinese New Year, Veteran's Day, Independence Day, and Memorial Day (Fig 6). The worst days of the year include the end of May and the mid-September. One plausible interpretation of these low periods is that they correspond to back to school and college finals. We interpret the fixed effects as the innate demand for a particular date of stay. The higher this fixed effect, the more demand there is for the focal hotel. As evident in Figure 2-5, there is a tremendous degree of heterogeneity in fixed day of stay effects on bookings. We will use this heterogeneity as the basis for our simulation conditions to present a representative sample of optimal versus managerial policies and counterfactuals in the following section.

	Coef.	SE	t
t	**-0.29**	**0.13**	**-2.29**
Tue	-0.95	4.09	-0.23
Wed	-3.09	4.09	-0.76
Thur	**10.03**	**4.15**	**2.41**
Fri	**21.42**	**4.17**	**5.13**
Sat	**27.07**	**4.17**	**6.49**
Sun	2.57	4.09	0.63
Feb	**25.16**	**6.61**	**3.80**
Mar	**30.84**	**9.21**	**3.35**
Apr	**28.48**	**12.56**	**2.27**
May	**28.00**	**16.08**	**1.74**
Jun	**45.09**	**19.77**	**2.28**
Jul	**69.63**	**23.55**	**2.96**
Aug	**79.91**	**27.42**	**2.91**
Sep	**-37.42**	**16.27**	**-2.30**
Oct	-21.46	13.03	-1.65
Nov	**-19.30**	**9.63**	**-2.00**
Dec	-2.42	6.75	-0.36
Holiday	**13.68**	**3.80**	**3.60**
Constant	4.23	16.16	0.26

Table 2-4 - Marginal contribution to fixed effects

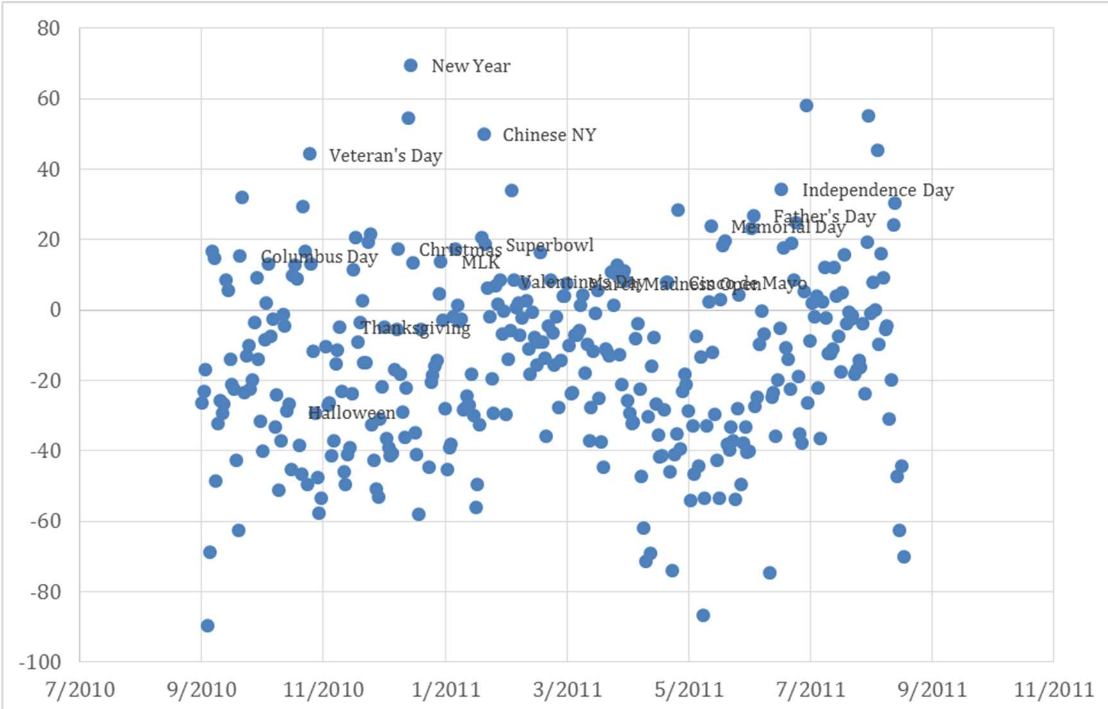


Figure 2-5 - Fixed Effects by Calendar Time
Demand equation fixed effects by calendar time reflects expected peak times that are consistent with managerial intuition.

2.6. Simulation Analysis

To analyze the effectiveness of managers' DyP strategies, we compare the revenues achieved using the managers' estimated pricing rules with those achieved following the policy function derived from numerical solutions of the dynamic program. In addition to evaluating potential revenue gains from solving the DyP problem systematically without predictions of competitive prices and ratings changes (base case), we also examine the informational advantages gained through incorporating competitive price forecasting (competitive case) and ratings forecasting (full case) into the optimal DyP problem.

2.6.1. Base Case

The baseline optimization model uses daily booking demand model estimated from Eq. 2-3. Competitors' pricing equations are not taken into account. That is, the focal hotel solves the DyP problem assuming competitors' prices will stay constant for the remainder of the sales window. However, the actual competitors' prices evolve according to the estimated equations. First, we solve numerically for optimal pricing policies for a representative sample of stay dates. This representative sample covers each day of week of stay, and the 25th, 50th, and 75th percentiles of bookings fixed effects conditional on each day of week where initial prices, availability, and booking rates are the conditional averages for each of these 21 (7 days of week x 3 levels of fixed effects) combinations. Table 2-5 summarizes the initial conditions for each of these 21 cells. Given that we interpret the fixed effect for bookings as the innate demand for each day of stay, one would expect that prices are higher for cells with higher fixed effects, i.e. stay date fixed booking effects are correlated with prices. In Table 2-5, we see that this is the case with a few exceptions. For example, the focal price for the Thursday 50th percentile cell price is lower than that of the 25th percentile cell. Notice also that Friday and Saturday availability is limited in comparison to the other days of week. This can be due to early sales, large group blocks, or greater casino allocation.

		Mon	Tue	Wed	Thu	Fri	Sat	Sun
	P0	175	188	159	189	242	270	170
	P1	192	210	210	210	309	355	253
	P2	193	288	199	180	205	259	167
	Avail	835	884	1028	1013	788	691	1072
25%	FE	-36.33	-42.00	-43.06	-30.83	-9.02	-7.79	-36.14
	P0_FE	-0.076	-0.061	-0.083	-0.072	-0.027	-0.005	-0.086
	P1_FE	-0.020	0.007	-0.025	-0.046	0.045	0.088	-0.006
	P2_FE	-0.009	0.046	-0.010	-0.024	0.010	0.061	-0.030
	Bk	16.0	13.0	14.5	15.5	19.0	16.0	18.0
	P0	191	176	180	179	275	302	180
	P1	223	213	229	186	315	324	218
	P2	193	201	184	184	255	280	157
	Avail	644	724	784	900	739	733	818
50%	FE	-25.85	-29.47	-27.49	-15.84	0.46	7.11	-21.61
	P0_FE	-0.056	-0.060	-0.064	-0.065	-0.010	0.004	-0.069
	P1_FE	-0.027	-0.028	-0.033	-0.045	0.049	0.066	-0.044
	P2_FE	-0.030	-0.020	-0.033	-0.041	0.037	0.051	-0.051
	Bk	14.0	14.0	14.0	17.0	19.0	20.0	17.0
	P0	187	199	219	272	316	311	198
	P1	217	215	233	280	365	344	234
	P2	179	178	213	231	255	240	179
	Avail	949	950	1016	653	550	687	898
75%	FE	-10.55	-7.72	-11.15	-0.17	10.03	18.17	-6.33
	P0_FE	-0.07	-0.05	-0.06	-0.02	0.02	0.00	-0.06
	P1_FE	-0.04	-0.04	-0.02	-0.02	0.08	0.04	-0.03
	P2_FE	-0.03	-0.02	-0.01	0.00	0.05	0.03	-0.04
	Bk	19.0	20.0	18.0	14.0	12.0	16.0	19.0

Table 2-5 - Simulation Initial Conditions
Initial conditions for simulation for each cell. FE are calculated at each respective percentile conditional by day of week of stay. Prices and available rooms are calculated as the mean of prices at the beginning of each booking window for the days whose fixed effects are within a 20 percentile range of the fixed effect represented by each cell.

For each cell, we simulate 1000 sequences of bookings and prices for both the estimated managerial pricing policies and the optimized pricing policies. We summarize the total revenues achieved under both pricing policies in these simulations in Table 2-5.

In expectation, the gains in revenue are between 12 and 38%. In dollar amounts, this translates to $18,608 and $75,310 per night of stay or over $15 million over the course of the year. This annual gain represents roughly 25% of the total FIT segment revenues. Examining the standard deviations of the final revenue, it is apparent that the optimal pricing policy is more risky than the one followed by managers except for the 75th percentile Friday and Saturday cells and the 50th percentile Saturday cell. The smaller relative variation in base case optimal revenues coincides with the higher innate demand as represented by the positive fixed effects for these cells. As a result, the revenue improvements achieved are generally not statistically significant (**Error! Reference source not found.**).

	25%		50%		75%	
	Mgr	Opt	Mgr	Opt	Mgr	Opt
Mon	$ 147,681	$ 178,436	$ 127,094	$ 170,455	$ 170,663	$ 230,765
Tue	$ 158,799	$ 192,544	$ 131,408	$ 176,444	$ 189,752	$ 234,250
Wed	$ 161,016	$ 179,623	$ 141,471	$ 184,336	$ 210,374	$ 251,596
Thurs	$ 173,929	$ 195,679	$ 161,550	$ 205,332	$ 174,274	$ 230,589
Fri	$ 190,640	$ 254,948	$ 199,099	$ 274,409	$ 183,474	$ 221,627
Sat	$ 192,229	$ 263,632	$ 220,491	$ 285,015	$ 204,549	$ 267,774
Sun	$ 173,242	$ 202,630	$ 147,785	$ 190,589	$ 178,473	$ 237,257

Table 2-6 - Base Case Simulation
Mean simulated total revenues (base case).

	25%	50%	75%
Mon	30754.94	43361.38	60102.6
Tue	33744.92	45035.62	44498.47
Wed	18607.19	42864.96	41222.43
Thur	21749.56	43782.22	56315.15
Fri	64308.13	75309.73*	38153.09*
Sat	71403.31*	64523.86*	63224.85*
Sun	29387.93	42803.84	58783.67

Figure 2-6 - Revenue Gains Base vs. Heuristic
Difference in revenues base optimal vs. managerial pricing.
* signifies significant at the 10% level

Turning our attention to prices, Table 2-7 summarizes managerial and optimal average prices across all cells. We observe that optimal rates are consistently higher than managerial rates, especially during expected peak periods. Tracking this pattern, as evidenced by Table 2-8, optimal occupancy is generally lower than expected occupancy under managerial pricing policies. Recall that the high occupancy rates reflect not the occupancy of the hotel, but rather the occupancy of the FIT allocation of rooms remaining at the 30-day lead time mark. The consistent theme across all cells remains that managers charge lower prices and sell more rooms earlier while optimal policies suggest that prices should be higher to take advantage of demand in the full booking window.

	25%		50%		75%	
	Mgr	Opt	Mgr	Opt	Mgr	Opt
Mon	$181.78	$181.54	$183.62	$224.07	$182.08	$229.25
Tue	$182.50	$201.03	$184.31	$219.01	$184.32	$231.12
Wed	$150.74	$174.17	$182.88	$211.02	$221.92	$231.85
Thurs	$181.84	$190.74	$183.49	$208.95	$272.38	$305.32
Fri	$223.06	$297.05	$271.88	$336.39	$330.12	$375.15
Sat	$272.89	$326.40	$329.07	$352.73	$328.59	$372.58
Sun	$181.52	$194.33	$181.88	$210.37	$181.89	$239.28

Table 2-7 - Optimized vs. Heuristic Prices
Mean simulated average daily rates (ADR).

	25%		50%		75%	
	Mgr	Opt	Mgr	Opt	Mgr	Opt
Mon	95%	95%	97%	94%	99%	90%
Tue	98%	91%	99%	93%	100%	91%
Wed	95%	86%	99%	92%	98%	88%
Thurs	95%	88%	99%	90%	100%	96%
Fri	100%	94%	100%	96%	100%	100%
Sat	100%	97%	100%	98%	100%	99%
Sun	97%	96%	99%	91%	99%	90%

Table 2-8 - Simulated Occupancy

While we establish that managers consistently underprice the hotel, especially when expected to sell out, we also point out that on slow days, in particular the slowest Mondays, managers are actually spot on in their average prices. This provides us some evidence that managers may be sensitive to the risk of not selling out when occupancy is expected to be high. However, when occupancy is expected to be low, managers are more aggressive with their prices. This evidence supports our initial hypothesis that an agency issue, specifically the unobservability of counterfactual revenues and the direct observability of occupancy, could be driving the suboptimal pricing policies. Taking a closer look at the Monday 25th percentile pricing path, we see that even though managers' average prices are spot on, the price path is quite different (Figure 2-7). This suggests that though the managers may be accurate in judging general price levels (optimal seasonal prices) when incentives are not skewed, they are not particularly accurate in setting prices across booking days, supporting the existing literature that documents managers' cognitive limitations and bounded rationality in managing complex systems. In particular, the strong autocorrelation in managers' pricing schemes suggest that anchoring biases significantly limits managers' ability to price optimally.

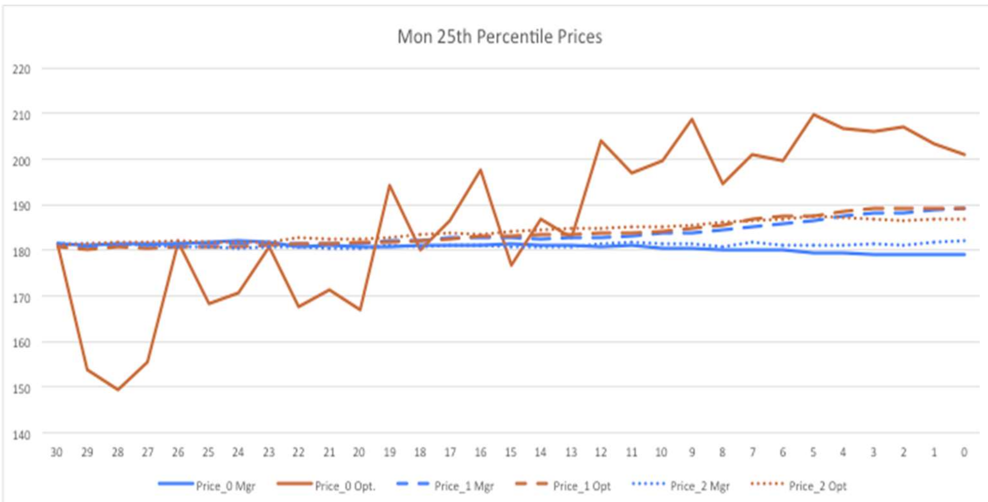


Figure 2-7 - Optimal Price Path for Slow Day
Prices for Monday 25th percentile cell shows dramatic variations for optimal case.

Notice the many price changes from day to day in the optimal policy as compared to the relatively stagnant pricing policies used by managers. These differences are driven primarily by two effects. The first is the negative correlation in daily level bookings with lagged daily bookings. This is the effect we interpreted as inter-day booking cannibalization. The second is the day of week differences in baseline bookings. Combined, these two effects cause optimal prices to have much higher variation than managerial pricing. As a comparison to the slow period, the price path of 75th percentile

Fridays shows that managers are consistently underpricing the hotel throughout the booking window (Figure 2-8). Summarily, we conclude with some caution that seasonal suboptimality across stay dates is driven by agency issues while DyP suboptimality across booking the window is driven by cognitive limitations, mainly managers' anchoring bias. This finding adds to the experimental literature in documenting managerial shortcomings when faced with complex problems while suggesting that managerial heuristics can also be effective in setting general price levels across seasons. Therefore, we suggest that under incentive compatible scenarios managers should be allowed to set initial price levels from which optimization software learns idiosyncratic shocks to demand. However, the subsequent day to day alterations to price should be kept out of the hands of managers.

Figure 2-8 - Optimal Price Path for Busy Day
Prices for Friday 75th percentile cell show that managers consistently underprice the hotel throughout the booking window when expected to sell out.

2.6.2. Competitive Prices

Having established the main effect of approaching DyP through dynamic programming, we turn to examining the effect of the informational advantage in predicting competitor prices. In this scenario we do the same optimization and simulation scheme as in the base case, except we include the focal firm's expectations of competitors' prices according to the estimated competitors' pricing equations in the DyP problem. Intuitively, the dynamic program that describes the pricing problem allows the focal firm not only to stochastically control the booking process, but also allows the focal firm to stochastically control the competitors' prices. Therefore, beyond the direct effect of prices affecting bookings, we examine the effect of focal hotel prices affecting competitors' prices, which leads to an indirect effect on bookings and revenue. To quantify this effect, we compare revenue differences achieved between the simulations in the optimized base case and those achieved in the current case with anticipation of competitive prices. The results of the revenue gains are summarized in tables 10a and 10b. Expected gains in revenues range from negligible to 3.7%. While none of these gains are statistically significant due to the high variance in outcomes, the advantage can be seen as economically significant in expectation.

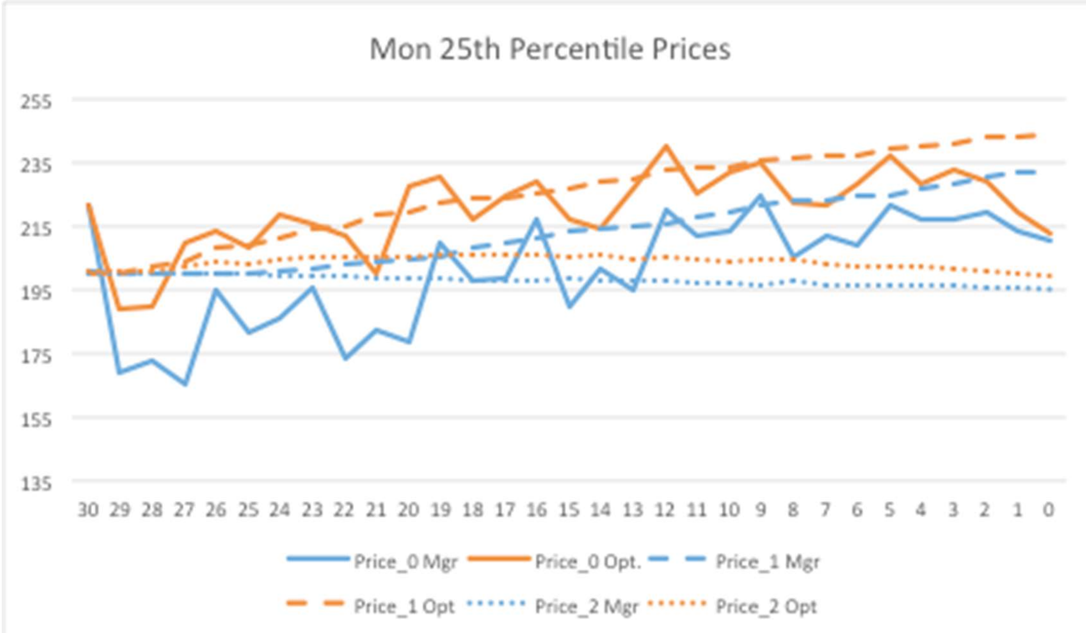


Figure 2-9 - Competitve vs. Base Optimized Cases
Competitive optimal and base case optimal prices show similar patterns, but the competitive optimal prices are strictly higher. This pattern takes advantage of the understanding that by raising the focal price, the manager can influence competitors to also raise their prices in a way that benefits the focal hotel in the long run.

To illustrate the differences in pricing trends between the base and competitive cases, we turn to the price trends for 25th percentile Monday illustrated in Figure 2-9. While there is no significant difference in the patterns of the two pricing trends, we find that when considering competitors' prices, focal hotels tend to price higher, thus driving up competitors' prices as well. Notice that competitors' prices are higher throughout the booking window in the competitive case. The competitors' response to the focal hotel's increased prices leads to a slightly decreased price elasticity and thus higher prices throughout the market and booking window. For this particular scenario, the expected gain in revenues is 3.71% (Table 2-9).

	25%	50%	75%
Mon	6,613.97	4,010.39	3,517.59
Tue	5,886.72	2,985.61	2,270.76
Wed	5,625.27	577.68	1,573.30
Thurs	642.31	1,659.27	548.10
Fri	610.67	108.86	411.54
Sat	1,910.91	789.58	242.66
Sun	414.35	5,251.24	668.20

Difference in revenues – competitive vs. base optimal pricing case.

	25%	50%	75%
Mon	3.71%	2.35%	1.52%
Tue	3.06%	1.69%	0.97%
Wed	3.13%	0.31%	0.63%
Thurs	0.33%	0.81%	0.24%
Fri	0.24%	0.04%	0.19%
Sat	0.72%	0.28%	0.09%
Sun	0.20%	2.76%	0.28%

% difference in revenue, competitive vs. base case.

Table 2-9 - Competitive vs. Base Simulation Gains

This result contributes to the literature by documenting economically significant potential gains in revenues when managers exercise an informational advantage by predicting competitors' prices. While the main effect of systematically solving the DyP through dynamic programming dwarfs the gains to predicting competitors' prices, this effect remains of interest in markets where managers price more closely to optimal levels where even a 2% gain in revenues represents a systematic advantage. Moreover, in markets where price volatility is higher, there should be more significant gains to anticipating those changes in competitors' prices. Finally, given the partial equilibrium nature of our study, our findings represent an empirical upper bound on the gains to competitive pricing strategies when all competitors are fully rational.

2.6.3. Online Reviews

To utilize the online reviews, we must first model the evolution of reviews in a parsimonious way so as to limit its effect on the dimensionality problem in the dynamic program. We choose to model the average rating of the top 25 reviews as an Ornstein-Uhlenbeck (OU) process, a mean reverting autoregressive process. Conceptually, an OU process (Eq. 2-11) is a random walk where there is a tendency to a stable long run average. λ_i represents the mean reversion tendency for each hotel, i, μ_i represents the long run mean for each hotel, and W is a Wiener process. The OU process represents online ratings well if one buys the assumption that the latent quality of the hotel is stable over time. In the hotel setting, it is not difficult to imagine such an assumption holding true as the room quality does not change over the course of a year and the service standard should remain consistent given stable managerial expectations.

Eq. 2-11
$$dR_{it} = \lambda_i \left(\mu_i - R_{it}\right) dt + \sigma_i dW_{it}$$

Such a process can be estimated via OLS through the regression of ratings on lagged ratings (Eq. 2-12). The parameters of this equation can be used to calibrate the parameters of Eq. 2-11using the identities in Eq. 2-13.

Eq. 2-12
$$R_{it} = b_{i0} + b_{i1} R_{it-1} + \varepsilon_{it}$$

Eq. 2-13
$$\lambda_i = -\frac{\ln(b_{i1})}{dt}, \quad \mu_i = \frac{b_{i0}}{1 - b_{i1}}, \quad \sigma_i = sd\left(\varepsilon_i\right)\sqrt{\frac{-2\ln\left(b_{i1}\right)}{dt\left(1 - b_{i1}^2\right)}}$$

In our application, d_t, the unit of change in time will be equal to 1, the daily change. Table 2-10 summarizes the coefficients of the linear regression and the corresponding coefficients of the OU process.

Given these parameters of the OU representation of average ratings, we perform a similar optimization and simulation exercise as in the previous section. We consider the revenue gains for a focal hotel that solves its DyP problem with the expectation of the mean reverting ratings embedded against the focal hotel that solves the DyP problem without making expectations over ratings, i.e. assumes ratings at any given point in the booking window will remain at the same level until the end of the booking window. Note that in either scenario, the simulations are done assuming that ratings follow the OU process. To illustrate the gains in revenue, we perform the optimization and simulation on the Monday 25th percentile cell[3]. With the initial condition that average ratings of all hotels start at 4.1, we find no qualitative differences in pricing, but observe a 2% gains in revenue above the competitor case. We see this as anecdotal evidence that even a simple time series model of hotel ratings can be sufficient in improving revenues. Note that the potential gains to predicting changes in online reviews depend on the magnitude of departure of all competitors' reviews from their long run means. The larger the departure, the more accurate mean reversion predictions become, and therefore the more there is to gain from this prediction.

[3] This is the initial condition under which we found the greatest gains in revenues. All other tested conditions were negligible.

	R0	R1	R2
b0	0.9480	0.9853	0.9536
b1	0.2310	0.0685	0.2054
std[e]	0.0626	0.0353	0.0504
lambda	0.0534	0.0149	0.0475
u	4.4458	4.6456	4.4240
sigma	0.0205	0.0061	0.0156

Table 2-10- OU Parameter Estimates

2.7. Discussion

In the current study, we estimate a demand and pricing system for a focal hotel in order to compare managerial pricing policies with optimal ones. We find that there are significant improvements to managerial pricing rules when policies are optimized. Generally, hotel managers price too low and do not alter their prices enough in anticipation of interday trends in bookings. Moreover, managers do not capitalize on historic trends in bookings by day of week. While there is no clear evidence as to what type of heuristic or rational rule the managers are using as this cannot be identified empirically, we suggest that managers are conservative in their pricing due to concerns about occupancy over revenue. In support of this hypothesis, we show that when occupancy is not a salient measure of managerial performance, i.e. during slow periods, managers actually price on average very close to optimal levels. Admittedly, it is not shocking that managers are not performing optimally, what is a bit surprising is the room for improvement that is available.

While there may be other reasons for managers to maximize a mixture of occupancy and revenue, such as marginal casino and retail spend at the hotel due to additional occupancy, gains in hotel revenues above 35% suggest that these reasons are not the only ones at play. Moreover, the hotel profit margin is the highest across all products sold by our focal resort. Therefore, one would expect room revenue maximization to be the primary interest of the manager. Most importantly, the large improvements that we observe leave little doubt that there are economically significant gains to be made despite some frictions that are omitted that could detract from our findings. Among these include the Lucas critique. Since we do not have individual purchase data, it is not feasible to model the consumer demand from a utility maximizing structural equation. However, as argued by Heching et al (2002), managers can use our relatively straightforward methodology more easily and update parameters to the reduced form models regularly. Another shortcoming of our study is the lack of length of stay and cancellations in both the econometric and optimization models. Unfortunately, we did not have access to length of stay or cancellation data for the entire span of the dataset, only aggregated accounting data for final stayed guests. This problem can only be addressed in a future study with more granular data.

In addition to the main result of significant improvements to revenue above managers' current pricing policies through a dynamic programming, we find that informational advantage can be gained by predicting competitors' prices and review ratings' mean reverting drift. While theoretical papers have spoken to competitive settings in DyP, no studies to date have considered the impact of online word of mouth on DyP decisions. Furthermore, we contribute to instrumental variables methodology by suggesting a new type of instrument in average ratings for cases where prices are independent of these ratings. This can have potentially many applications to markets where prices and reviewer sentiment fluctuate while latent quality stays stable such as in the case of cruise ships and online retailing (eBay, Amazon, etc.).

In future studies, we hope to obtain individual level data to facilitate the structural modeling of demand in order to address the Lucas critique. Additionally, if sales data for competitors can be obtained, we could pursue and validate more complex models of competitors' pricing rules as a function of latent demand. The final goal of these pursuits is to be able to predict in equilibrium how optimal price setting would behave given some structural model of consumer demand. Such an effort could demonstrate not only the short term gains that managers can achieve by switching to a more optimal pricing rule, but also demonstrate the long run equilibrium gains (or losses) when all managers begin to price more strategically.

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