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Channels of Impact: User Reviews When Quality Is Dynamic and Managers Respond

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Abstract. We examine the effect of managerial response on consumer voice in a dynamic quality environment. We argue that the consumer is motivated to write reviews not only because reviews may impact other consumers, but because reviews may impact the management and the quality of the service. We examine this empirically in a scenario in which reviewers receive a credible signal that the service provider is listening. Specifically, we examine the “managerial response” feature allowed by many review platforms. We hypothesize that managerial responses will stimulate reviewing activity and, in particular, will stimulate negative reviews that are seen as more impactful. This effect is further heightened because managers respond more and in more detail to negative reviews. Using a multiple-differences specification, we show that reviewing activity and particularly negative reviewing is indeed stimulated by managerial response. Our specification exploits comparison of the same hotel immediately before and after response initiation and compares a given hotel’s reviewing activity on sites with review response initiation to that on sites that do not allow managerial response. We also explore the mechanism behind the effect using an online experiment.

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1. Introduction

Many Internet sites rely extensively on user contributions. User-generated online reviews have become an important resource for consumers making purchase decisions; retailers such as Amazon rely on reviews to help match consumers with products, and information portals like TripAdvisor and Yelp have user-generated reviews at the core of their business models. While many types of platforms rely on user reviews, there is a substantial amount of variation in the details of platform design. For example, some sites verify that reviewers purchased the product, while others do not. Some platforms allow reviewers to edit reviews after posting them; some do not. In this paper, we are interested in the role played by a feature adopted by some platforms that allows managers to respond publicly to consumer reviews. We examine the effect of managerial response on consumer expression of voice.


To understand the effect of managerial response on reviewing behavior, we consider what motivates consumers to expend time and energy to post reviews.

In particular, we are interested in drivers of word of mouth that are affected by the presence of managerial response in a dynamic-quality setting. We argue that in this setting, managerial response especially enhances the desire to have impact (Hirschman 1970, Wu and Huberman 2008), the ability to influence the audience’s actions.

The previous literature on online reviews has primarily focused on an environment where product quality is time invariant, studying physical products such as books, movies, digital cameras, etc. Here, we study a product category for which product quality is dynamic: hotels. For static-quality products, customer reviews are most naturally thought of as an avenue for customers to share information with each other. By contrast, for dynamic-quality goods and services, managerial investments may alter product quality over time. In such cases, the consumer may reasonably view both the management and other consumers as audiences for the review. Reviewing could be motivated by an intent to impact the manager, not just other







Figure 1. (Color online) A TripAdvisor Hotel Review with Managerial Response


"If you need strong wifi, this is not the hotel for you."



 Reviewed July 26, 2015

Nothing but trouble with the wifi connection, and the front desk staff could not resolve it. Not sure if it was lack of training or caring, but I am quite displeased with my stay. Unfortunate too, as it is a quality property, clean, etc. Just can't get any work done there, which is a big issue for me.

Stayed July 2015, traveled on business

 Value	 Rooms
 Location	 Cleanliness
 Sleep Quality	 Service

Review collected in partnership with Hampton 

Helpful?  **Thank Coskier303**  Report

[Ask Coskier303 about Hampton Inn Manhattan-Chelsea](#)

This review is the subjective opinion of a TripAdvisor member and not of TripAdvisor LLC.

Jessica D, General Manager at Hampton Inn Manhattan-Chelsea, responded to this review, July 30, 2015

Thank you so much for your review. I apologize that the internet access was of concern. We have contacted our internet provider to troubleshoot any problems, in order to offer better service in the future. If you plan to travel to the area again in the future, please consider giving us another opportunity to prove we have corrected your concerns. Thank you so much.

[Report response as inappropriate](#)

This response is the subjective opinion of the management representative and not of TripAdvisor LLC.

consumers.¹ (See Figure 1 for an example of a hotel review on TripAdvisor and the managerial response that followed.)

The entry of the firm into the conversation potentially changes the nature of the discourse, which in turn affects the customers' incentives to post reviews. The response functionality transforms a peer-to-peer review system into a hybrid peer review/customer feedback system. We study whether managerial response stimulates consumer reviewing and changes the nature of the reviews posted. Understanding the effect of managerial actions on consumer voice sheds further light on what motivates consumers to post feedback, which in turn has implications for all three actors (platforms, managers, and consumers); that is, understanding these incentives can aid in optimal platform design, help firms improve their response strategy, and help consumers of reviews make better decisions.

We examine managerial response in the empirical setting of midtier to luxury hotels. The primary hypothesis that we examine is whether and how public managerial response communication stimulates reviewing activity. The basic idea is the following: because the manager is listening, consumers' feedback is more likely to elicit a response and to impact the product's future quality, which in turn increases the motivation to post a review. Specifically, we investigate whether the introduction of managerial responses leads consumers to write more reviews, and whether it leads them to put more effort into reviewing, as measured by writing longer reviews. In addition, as we discuss at length below (Section 3), we hypothesize that managerial response activity disproportionately stimulates negative review production since negative feedback may be seen as particularly impactful by reviewers.

In particular, we study whether reviewing activity changes for a hotel following the first day of posting of managerial responses on three websites that allow managers to respond to reviews: TripAdvisor, Expedia, and Hotels.com. Of course, in testing our hypotheses, we are faced with an identification challenge. Clearly, hotels that post managerial responses are different from hotels that do not. The decision to commence posting responses is an endogenous decision of the manager. It is possible, for example, that managers begin responding to reviews when something is going on at the hotel that leads the manager to anticipate more reviews, and more negative reviews being posted in the future.

To handle this identification challenge, we employ an extension of the techniques that were used to handle similar identification challenges in Chevalier and Mayzlin (2006) and in Mayzlin et al. (2014). Specifically, our identification strategy has four components.

First, we undertake an “event study” technique in which we examine reviewing activity for a given hotel for very short (six week) time windows before and after the posting of the first managerial response. Therefore, we are not identifying the impact of review responses by straightforwardly comparing hotels that do and do not post responses; we are examining the change for a given hotel over time. Furthermore, by examining only the before and after change surrounding a discrete event in a very short time window, we are discarding changes that may derive from longer-run investments in facilities, position, or quality of the hotel.

Second, we undertake specifications in which the reviewing changes on each of the focal sites on which managers may post responses are measured, controlling for reviewing changes on other sites where managerial responses are not allowed. Specifically, managerial responses are not allowed on the popular booking sites Priceline and Orbitz, and our reviewing activity changes are measured from specifications that control for the changes in reviewing activity on Priceline and Orbitz. Thus, if a manager undertakes her first response on TripAdvisor in anticipation of some physical change in the hotel that will lead to negative reviews, the controls for changes in Priceline and Orbitz reviews should remove that source of review changes. This is similar to the approach used in Chevalier and Mayzlin (2006) and Mayzlin et al. (2014), though the appropriate “treatment” and “control” sites differ across the papers.

Third, all of our specifications are conducted measuring the change in the hotel’s reviews relative to changes in average reviews in the geographic area on the same reviewing site. For example, when we are measuring changes in TripAdvisor reviews around the commencement of managerial response, we are measuring the change in reviewing activity for the hotel relative to other hotels in the local area. This differencing

strategy will prevent us from attributing the changes in reviewing activity on TripAdvisor to the managerial response by the hotel if, in fact, the change in reviewing activity was caused by, for example, increased TripAdvisor advertising in the local area. This is a variant of a strategy that was employed in Mayzlin et al. (2014).

Finally, given the prominence of TripAdvisor as a review site, one may be concerned that a hotel that starts to respond on TripAdvisor may in fact also make physical TripAdvisor-specific investments. For example, TripAdvisor reviewers may especially value faster Wi-Fi, and the hotel’s first online review response (a virtual TripAdvisor-specific investment) may be accompanied by Wi-Fi upgrades (a physical TripAdvisor-specific investment). Because of this concern, we obtain data from two other sites that allow responses (Expedia and Hotels.com) in addition to TripAdvisor, as we discuss in Section 5.

In sum, this “multiple-differences” strategy controls for many of the underlying sources of the identification challenge. In Section 5, we discuss in more detail the extent to which remaining confounding effects can be eliminated and our results can be interpreted as causal. We find that reviewing activity for a given hotel increases on TripAdvisor in the six-week window following a managerial response relative to the six weeks prior and relative to the same hotel on Priceline and Orbitz, and relative to the TripAdvisor reviews of other hotels in the geographic area in the same six-week window. We also find, relative to the controls, a statistically significant decrease in review valence and a statistically significant increase in the length of reviews. We have many fewer managerial response episodes for Expedia and Hotels.com. However, we conduct the same exercise for these platforms. For these sites, as with TripAdvisor, we find an increase in reviewing activity following the posting of a managerial response. For Expedia, we also find a significant decrease in review valence, and for Hotels.com, a significant increase in review length. We also explore further the decrease in review valence result using our large TripAdvisor sample. While we are cautious about interpreting this particular set of specifications causally, it suggests that responding only to negative reviews increases negative reviewing effort.

In Section 8, we also provide further evidence on the mechanism behind our findings of increased reviewing activity and a decrease in review valence following managerial response. First, using human coders, we demonstrate that more negative hotel reviews indeed contain information that is more helpful to managers. Using an online behavioral experiment in which we manipulate the hotel experience (negative, mixed, or positive) and in which we also manipulate the managerial response environment, we provide evidence

that managerial response particularly stimulates posting by customers who had mixed experiences at a hotel. We demonstrate that providing information that the manager can use and eliciting manager feedback are important motivations that are stimulated by managerial response.

Our paper contributes to the recent literature on how firm intervention impacts consumer voice (see Ma et al. 2015, Proserpio and Zervas 2017). As we elaborate below (Section 9) in more detail, our setting and identification strategy are different from those of Ma et al. (2015), which gives rise to important differences in consumer incentives and overall results. While our setting is the same as that of Proserpio and Zervas (2017), our paper differs from theirs both methodologically and in the data that we use. Our result that managerial response leads to a decrease in review valence starkly contrasts with their result that review valence increases following the initiation of managerial response.

Our paper proceeds as follows. Section 2 reviews the literature. Section 3 presents the theoretical development in more detail. Section 4 describes our data and provides summary statistics about our sample. Section 5 describes our methodology. Section 6 provides our basic results. Section 7 presents results of robustness analyses. Section 8 presents evidence from an online experiment and text analysis on the mechanism outlined in the theory section (Section 3). Section 9 discusses our paper's relationship to previous literature, and Section 10 concludes.

2. Related Literature

What drives a consumer to engage in word of mouth in the first place, and, in particular, which motivations to post are influenced or enhanced by managerial response? Berger (2014) differentiates between two types of drivers of word of mouth: those that are self-driven versus those that are audience driven. As an example of self-driven motivation, consider the desire to vent feelings of anger: Wetzer et al. (2007) shows that consumers who experience anger engage in negative word of mouth to vent feelings or to take revenge. While there are many possible motivations behind posting of reviews (and we do in fact study anger and the desire to vent feelings in Section 8), we argue that managerial response especially enhances audience-driven motivations, and, in particular, the desire to have impact.

Several papers have examined impact as a motivation to post. Wu and Huberman (2008) provide evidence that individuals are more likely to post reviews on Amazon when their reviews will have a greater impact on the overall average review; that is, reviewers are more likely to post reviews when their opinion differs more from the consensus and when there are fewer reviews. Given the overall positive valence

of reviews on review sites, the impact hypothesis is consistent with the findings of Moe and Trusov (2011). They examine data from a beauty products site and demonstrate that reviews become increasingly negative as ratings environments mature. Godes and Silva (2012) test the hypotheses of Wu and Huberman (2008) using book data from Amazon.com and show that low-impact reviews are more likely to be posted when reviewing costs are low. Specifically, they demonstrate that the sequential decline in ratings is more pronounced for high-cost than for low-cost reviews.² Notably, these papers, in using books and beauty products as their empirical settings, have focused on environments in which later reviews necessarily have more limited impact because the underlying true quality of the product has gradually become known. However, products with a substantial service component such as hotels and restaurants provide potentially quite different reviewing environments, as the quality of service can evolve over time. In dynamic-quality settings, consumers can influence the audience by alerting the audience to changes in product quality. Dynamic quality settings also create the possibility, as we discuss in Section 3, of reviews having an impact on the manager and potentially the decisions that she undertakes to improve quality.

The desire to improve quality may be driven by altruism on the reviewer's part in that the reviewer undertakes a costly effort to write a review to help the manager. Past literature has studied altruism as a driver of word of mouth. Sundaram et al. (1998) conduct interviews where respondents are asked to recall recent episodes of word of mouth. For both positive and negative word of mouth, respondents listed altruism as one of the major motivators of word of mouth. Hennig-Thurau et al. (2004) survey an online panel of German opinion platform users to investigate the motivations behind the generation of electronic word of mouth. They find that one of the major factors that drives posting is "concern for other consumers" (Hennig-Thurau et al. 2004, p. 42). Note, however, that the desire for impact may not necessarily be driven by altruism. For example, if the reviewer is motivated by the desire to elicit a response, the motivation in this case would not be altruistic. Indeed, the desire to improve quality may be entirely selfish if the customer intends to visit the hotel in the future; Hirschman (1970) discusses the possibility that an unhappy customer may exercise "voice" to improve her own well-being. For this reason, in Section 3, we focus on impact rather than altruism.

Our paper is also related to recent literature on platform design and mechanisms for eliciting consumer feedback. Klein et al. (2016) shows that an increase in transparency in the review solicitation mechanism on eBay leads to a decrease in strategic bias in buyer ratings and an increase in welfare. Several papers

document that many consumers who use an Internet site do not post reviews. For example, Brandes et al. (2015) show that only 13% of buyers posted a review on a European hotel booking portal. Nosko and Tadelis (2014) show that 60% of consumers leave feedback on eBay, while Fradkin et al. (2015) show that about two-thirds of consumers leave reviews on Airbnb. The results of both Nosko and Tadelis (2014) and Fradkin et al. (2015) suggest that eliciting negative feedback from consumers may be particularly difficult. For example, Nosko and Tadelis (2014) suggests that consumers that have had negative experiences are less likely to leave feedback. Similarly, Horton and Golden (2015) demonstrates a positive skew in reviewing on the temporary-labor site ODesk.

Next, we consider the nascent literature on the impact of managerial response on consumer voice. Ma et al. (2015) examine the effect of a firm's service intervention in response to a compliment or a complaint on Twitter on the consumer's subsequent Twitter comments. The firm is a telecommunications firm that provides telecommunications, Internet, and wireless services. Ma et al. (2015) find that redress seeking is a major driver of complaints, and hence an intervention may actually encourage future complaints. Note that there are important differences between our studies. First, the identification strategies are very different—the earlier study builds a dynamic choice model of voice behavior and intervention on one platform only. Second, in the study by Ma et al. (2015), half of customer complaints were responded to. (For example, the customer complained that the Internet was not working, and the firm sent a representative to fix the service.) By contrast, in our setting, an intervention such as better staff training may help other customers, but probably not the poster of the review. Hence, our results apply to settings where a response may be a form of communication and not involve an actual service intervention, and in settings where the intervention would not benefit the complainer directly.

Several papers in this area have examined the effect of managerial response to hotel reviews. The papers of which we are aware are those by Park and Allen (2013), Ye et al. (2008), Proserpio and Zervas (2017), and Kim et al. (2015). Park and Allen (2013) use a case study of four luxury hotels and examine why management chose to be active or not in review responses. Kim et al. (2015) use proprietary data from an international hotel chain and show a correlation between responses to negative comments in online reviews and hotel performance. Ye et al. (2008) conduct an experiment similar to ours and that by Proserpio and Zervas (2017). Using data from two Chinese travel agents, Ye et al. (2008) show that reviewing activity and valence increase for hotels that post manager responses on the travel site that allows responses relative to the travel

site that does not. However, the number of manager responses is quite low.

The closest paper to ours is that by Proserpio and Zervas (2017). This paper examines Texas hotels, comparing the reviews in the time period before and after a hotel's initiation of managerial response on TripAdvisor. The identification scheme is similar to ours; however, these authors use Expedia as a control for TripAdvisor, constraining the sample to hotels that do not use Expedia's response function. Interestingly, the authors find that valence of reviews increases following managerial response. We elaborate on the differences between the two studies in Section 9.

Finally, since online reviews in the presence of managerial response can be thought of as a hybrid complaint/word of mouth system, our paper relates to the literature on customer complaint management (see Hirschman 1970; Fornell and Wernerfelt 1988, 1987). We discuss these papers in more detail in Section 3.

3. Theoretical Relationship Between Managerial Response and Subsequent User Reviews

As we discuss in Section 2, there are many possible motivations for posting reviews, ranging from self-driven (such as venting anger) to audience driven (such as impact). The dynamic-quality setting increases the possibility that reviews will impact quality, which, as we argue below, is further enhanced by managerial response. Hence, here we focus on impact and examine how managerial response affects this motivation.

Consider the effect of initial managerial response on the incentive to post in a dynamic-quality setting. The primary audience for a review in the period before the initiation of managerial response is potential customers who are considering the product. A review may impact a potential customer's purchase decision. Hence, the impact motivation is present in this period and forms the potential reviewer's baseline incentive to post.

The first managerial response credibly signals to potential reviewers that the manager is listening to consumer feedback. Hence, in the "after" period, in addition to potential customers, the audience for a review also consists of the manager; that is, while the firm always has the ability to collect and analyze customer reviews,³ the ability to respond allows the firm to credibly signal that it is reading reviews and responding to suggestions therein. Since the review may now also help the manager and impact product quality (which is variant in this setting), we expect to see an *increase* in the impact motivation of potential reviewers over the baseline. We expect this increase to lead to increases in both the incidence and quality of reviews.

Hypothesis 1. *Managerial response increases the probability that a review will be posted.*

Hypothesis 2. *Managerial response increases the effort put into posting reviews, operationalized here as the length of reviews posted.*

The dynamic nature of the product is an essential condition for the results above to hold, since in this setting, reviews can impact the manager's actions. Firms may, of course, be an audience for reviews in a static setting as well in that they may consider reviews in designing future products. However, given that the products being reviewed will not change as a function of the review, the owner or manager of the product is likely not considered by consumers to be the primary audience for the review. By contrast, in a dynamic setting, the manager can take direct actions to improve quality.

Our next hypothesis is based on another application of the impact principle. In an environment with managerial response, there are two reasons why reviewers may perceive that negative reviews will have more potential impact than positive reviews and thus be differentially incented to post negative versus positive reviews.

First, let us consider the potential review's impact on product quality. Note that reviewers who point out a product's flaw expect to have a bigger impact on subsequent product quality than reviewers who bring up positive points. Negative reviews of managerially dependent hotel attributes implicitly suggest a potential change in the manager's behavior. For example, a negative review may result in a manager fixing the bathrooms or training front desk staff. Positive reviews do not. This reasoning is very consistent with that of Hirschman (1970), who proposed that an unhappy loyal customer may exercise voice to improve the product. In Section 8, we provide supporting evidence for the assumption that more negative reviews are more helpful to managers for both short- and long-term changes.

Second, let us consider the potential review's impact on managerial response behavior. One of the primary motivations for a manager to respond to a review may be to encourage potential consumers to view the experience described in a negative review as unlikely to be repeated. Indeed, much of the online discussion about managerial response strategies emphasizes the importance of responding to negative reviews and advice about how to respond to them.⁴ We will demonstrate that, overall, more negative reviews are more likely to receive managerial responses on reviewing platforms than are more positive reviews, and that responses to negative reviews tend to be much longer (and therefore presumably more substantive) than the responses to more positive reviews. Why would a managerial

response be desirable to a reviewer? Seeing one's review acknowledged may be satisfying. Gans et al. (2017), who examine the effect of competitive structure on voice, predict that the goal of voice is to elicit a response. More generally, if we consider response itself to be a type of managerial action, a review that elicits a response from the manager is more impactful than a review that does not elicit a response. Hence, this general pattern in response behavior magnifies the differential impact of negative reviews.

This effect is also very much related to the idea of "audience tuning" (Berger 2014, p. 597); that is, the sender of word of mouth may change the information that she shares based on the needs and desires of her audience. In this sense, when the manager publicly becomes an audience member, reviewers are more likely to share more negative reviews that are more likely to affect change in managerial behavior, including response and possibly changes in product quality. In Section 8, we provide experimental evidence that managerial response increases both the motivation to receive a response from the manager and the motivation to give feedback to the hotel. We also show that managerial response differentially stimulates review posting by reviewers with mixed experiences, especially when the response targets more critical reviews.

Hypothesis 3. *Managerial response decreases the valence of reviews posted.*

Of course, in some circumstances, reviewers are motivated to write negative reviews to solicit individual compensation, an idea that is also related to the work of Hirschman (1970). For example, Ma et al. (2015) find that redress-seeking is a major force in driving complaints on Twitter. In fact, Ma et al. (2015) find that a service intervention on the part of the firm may result in more complaints being posted on Twitter. There are indeed many situations in which this motivation may be operative, but we believe it is muted in this context since the platforms that we study use public reviews and public managerial responses. Offers of specific individual remuneration in these responses appear to be rare. However, this may be operable elsewhere. For example, Yelp is a prominent example of a reviewing platform that allows private communication. Yelp also (unusually) allows reviewers to change their reviews, and the private communication channel is often used to encourage reviewers to change reviews.⁵

4. Data

The starting point of our data collection efforts is the identification of 50 focal cities. Similar to Mayzlin et al. (2014), we identified the 25th to 75th largest U.S. cities to include in our sample. Our goal was to use cities that were large enough to have many hotels, but not

so large and dense that competition patterns among hotels would be difficult to determine. Using data available on the TripAdvisor website in mid-2014, we identified all hotels that TripAdvisor identifies as operating in these focal cities. We also obtained data from Smith Travel Research (STR), a market research firm that provides data to the hotel industry (www.str.com). STR attempts to cover the universe of hotels in the United States. We used name and address matching to hand-match the TripAdvisor data to the STR data.

From STR, we obtained many characteristics of hotels, including their class grading of hotels. STR grades hotels by brand and objective characteristics into six quality tiers. For this paper, we exclude the bottom two quality tiers. The excluded chains consist largely of roadside budget motel chains such as Red Roof Inn, Super 8, Motel 6, Quality Inn, and La Quinta Inns. We include hotels in STR's "upper midtier" range and higher. The upper midtier includes Holiday Inn, Hampton Inn, Fairfield Inn, and Comfort Inn. We focus on upper midtier hotels and higher because "economy class" and "midscale class" hotels have significantly fewer reviews per hotel, and hotel shoppers can perhaps be expected to be less quality sensitive. Our sample of hotels is more homogeneous. Furthermore, the data provider that we used for data on reviews has much better coverage for upper midtier hotels and higher. In total, we obtain a sample of 2,104 hotels that match between STR and TripAdvisor in the upper midtier or higher categories.

Finally, our main source of review data was Revinate, a guest feedback and reputation management solutions provider. Among other services, Revinate provides client hotels a Review Reporting Dashboard. Client hotels can view daily social media feeds from all major reviewing sites on one page, view the equivalent feeds for their competitors, and respond to reviews from multiple sites from the single interface. To provide this service, Revinate has invested in creating robust matching of the same hotel across multiple reviewing platforms.

Revinate has excellent coverage of the 2,104 hotels in our target sample. Revinate has substantial market share; they serve more than 28,000 client hotels worldwide.⁶ Many large chains subscribe to Revinate services for all of their hotels. Crucially for us, they track not only their clients, but a large group of client competitors. Overall, of the 2,104 hotels in our target sample, we are able to obtain Revinate data for 88% of them, for a total of 1,843 hotels.

Even with this excellent coverage, the imperfect coverage presents a selection bias. However, note that the hotels that we track contain both Revinate clients and nonclients. The 261 hotels that we could not track through Revinate are clearly not Revinate clients. Thus, our data, as is, are unrepresentative in that they

underweight nonclients. In the analysis that follows, we will undertake weighted specifications in which the nonclients receive more weight to equate the weight on nonclients in the sample to the weight of nonclients in the overall population. Thus, in our specifications, each observation from a client receives a weight of 1, while each observation from a nonclient receives a weight of 1.04. Note that because Revinate's coverage is extensive, the extra weight assigned to nonclients is relatively small. All our results are substantially the same with or without the weighting scheme.

The Revinate data contain full text review information with date and time stamps for every review for the sites that Revinate tracks for our 1,843 hotels. We examine the flow of reviews for a six-year period; the earliest review in our sample was posted on January 1, 2009, and the latest review was posted on December 8, 2014. Revinate also collects the full text of all managerial responses, again with date and time stamps. The time period we study is well suited to our question. Managerial response increased in popularity over the time period of our data. In early 2010, *USA Today* reported that fewer than 4% of negative reviews on TripAdvisor get a response (according to TripAdvisor), but that utilization of the function increased 203% in 2009 (Yu 2010). There are a few issues with the data that we received from this provider. Because of a peculiarity of the way that Booking.com displays review data, our review data for Booking.com do not contain older reviews for the site. For this reason, we do not use Booking.com data at all in our analyses. Furthermore, because of a reporting format change at Hotels.com, we were unable to obtain the date of managerial response after sometime in the 2011 period. Our summary data here include all Hotels.com data, but our analysis requiring the response date uses only the earlier period data.

Our primary analysis compares pre-managerial response reviewing to post-managerial response reviewing. However, since our data have a starting point and an end point, there will be some truncation of the time period; that is, there are 31 hotels where the initial managerial response occurred less than six weeks from the beginning of our data set and six hotels where the initial managerial response occurred less than six weeks before the end of our data set. For these hotels, either the before or the after period is less than six weeks. Because all of our analysis compares the difference between the before and after periods across platforms, and given that the exact same truncation occurs for all the platforms, we do not exclude the truncated before or after periods. However, our results are robust to excluding these hotels from our sample.

Table 1 contains summary statistics that describe the reviewing and response data for our sample of hotels

Table 1. Summary Statistics—Reviews

	Expedia	Hotels.com	Orbitz	Priceline	TripAdvisor
No. of reviews					
Revinat noncustomer	252,781	223,450	94,321	256,143	624,555
Revinat customer	106,207	81,122	36,973	93,841	265,944
Response share					
Revinat noncustomer	0.056	0.015	0	0	0.457
Revinat customer	0.132	0.041	0	0	0.517
Weighted	0.078	0.022	0	0	0.474
Mean rating					
Revinat noncustomer no response	4.165	4.237	3.892	3.988	4.139
Revinat customer no response	4.158	4.241	3.891	4.011	4.194
Weighted no response	4.163	4.238	3.892	3.994	4.155
Revinat noncustomer response	3.963	4.131			4.0259
Revinat customer response	3.950	4.015			4.102
Weighted response	3.959	4.101	0.000	0.000	4.048
Weighted: response versus no response					
Percentage difference (%)	−4.9	−3.2			−2.6
For the universe of hotels that had responded five times before the date of this review					
Mean rating					
Revinat noncustomer no response	4.163	4.234	3.887	3.989	4.135
Revinat customer no response	4.156	4.238	3.888	4.012	4.190
Weighted no response	4.161	4.235	3.887	3.995	4.151
Revinat noncustomer response	3.964	4.131			4.026
Revinat customer response	3.949	4.015			4.102
Weighted response	3.960	4.101			4.048
Weighted: response versus no response					
Percentage difference (%)	−4.8	−3.2			−2.5

Note. All weighted means are weighted to overrepresent Revinat noncustomers.

for five of the most popular booking and reviewing sites: Expedia, Hotels.com, Orbitz, Priceline, and TripAdvisor.

Table 1 reveals several interesting stylized facts about the data. First, note that there are no review responses on Priceline and Orbitz because they do not allow responses. TripAdvisor, Expedia, and Hotels.com allow responses. In our sample, roughly half of TripAdvisor reviews receive responses, while only about 8% of Expedia reviews receive responses, and only 2% of Hotels.com reviews receive responses.⁷

Revinat customers are much more likely to respond to reviews than noncustomers. This is likely partly due to selection; they have demonstrated their interest in social media management by becoming customers. However, this is also likely due to the causal impact of the Revinat platform. The platform makes it very easy to respond to reviews. Note that the customer versus noncustomer review response rates are most disparate for non-TripAdvisor sites. This makes sense because the Revinat interface makes it equally easy to view all of the sites and post all of the responses; non-Revinat customers may have a greater tendency to monitor only the perceived most influential site, TripAdvisor. Our reweighting of customers versus noncustomers is important to achieve representativeness.

For our purposes, it is important to note the disparity between the valence of reviews that are responded to and reviews that are not responded to. Reviews that are responded to average 4.0 for TripAdvisor versus 4.2 for reviews that do not receive responses. This disparity is greater for the other sites.

The differences in the valence of reviews responded to versus not responded to is largely due to the reviews selected for response rather than the characteristics of the hotels that respond to reviews. Limiting the sample of hotels to only hotels that have responded to at least five prior reviews (frequent responders) produces similar summary statistics. In unreported specifications, for each of the three sites that allow responses, we take the sample of all reviews as observations and regress the indicator variable for *manager responded* on the review rating and hotel fixed effect. The coefficient for the review rating is strongly negative and significant. This suggests that hotels are more likely to respond to their more negative reviews.

Table 2 provides summary data on review length of each of the sites. Clearly, there are differences across sites in typical review length. For example, reviews on Priceline are particularly short, and reviews on TripAdvisor are particularly long. More negative reviews tend to be significantly more detailed across all sites.

Table 2. Review Length and Managerial Response Length

	Expedia	Hotels.com	Orbitz	Priceline	TripAdvisor
Review stars ≤ 3 review length	473.81	359.92	464.87	324.86	964.68
Review stars > 3 review length	362.46	229.83	347.81	231.36	683.18
Percentage difference (%)	–23.5	–36.1	–25.2	–28.8	–29.2
Review stars ≤ 3 response length	518.89	514.18			703.01
Review stars > 3 response length	387.27	361.04			516.22
Percentage difference (%)	–25.4	–29.8			–26.6

Notes. All means are weighted to overrepresent Revinate noncustomers. Review length is measured in number of characters.

Table 2 also provides summary data on review response length for the three sites that allow review responses. Managers tend to provide longer review responses on TripAdvisor versus the other two sites. Across all sites, managers appear to put more effort into responding to negative reviews. Table 2 shows that for all three sites that allow responses, responses to more positive reviews (greater than three stars) are 25% to 30% shorter than responses to more negative reviews.

5. Methodology

As discussed above, we consider the hotels' adoption of managerial response on a particular site to potentially present a discrete change in reviewer incentives. Thus, our methodology focuses on changes in reviewing activity in a very tight time window around the day that responses are first posted by the hotel.

In Table 3, we examine summary statistics on the behavior of hotels on the day of first managerial response posting. The first thing to note about Table 3 is that managers frequently respond to more than one review the first time that review responses are posted. The average star rating of reviews responded to, unsurprisingly, is more negative than that of the overall population of reviews. For example, for TripAdvisor, of the 1,807 hotels that post responses, 641 of the first-day responses are to reviews with an overall average star rating of strictly less than three.

Our identification scheme relies on a differences methodology. Our primary specifications examine the six-week windows before and after the posting of first managerial response. We undertake robustness specifications in Section 7, but describe our primary measurement strategy here.

We will describe the platforms in which the manager initially posts a response as the treatment platforms. These are TripAdvisor, Expedia, and Hotels.com, which we will consider separately in separate specifications (since the response posting time windows are different for the three sites). The control platforms are Orbitz and Priceline.

First, to control for contemporaneous factors that may cause within-platform changes in reviews in a geographic area, we straightforwardly difference the before versus after review measurements from the before versus after review measurements for the geographic area. We construct the geographic mean for each TripAdvisor geocode imposing no restrictions on the hotels included in the mean calculation. Our measure of review changes measures the difference over time from the geographic mean for both treatment and control platforms. Thus, for example, in all specifications that use the number of TripAdvisor reviews in a time window, the number of TripAdvisor reviews for the observation hotel for a specific time window is calculated as the difference between TripAdvisor reviews in the time window minus the average number

Table 3. Characteristics of First Day of Responses

	Expedia	Hotels.com	TripAdvisor
Reviews responded to the first day			
Average star Revinate noncustomer	3.54	3.78	3.12
Average star Revinate customer	3.65	3.56	3.20
Average star weighted	3.57	3.72	3.14
Total number responded Revinate noncustomer	1.91	1.69	1.94
Total number responded Revinate customer	1.99	1.32	2.04
Total number responded weighted	1.93	1.60	1.97

of reviews for all other hotels in the same city for the same time window.

We have two platforms that we use as controls, Orbitz and Priceline. These controls are meant to capture other physical investments in quality that the hotel makes concurrently with response adoption. An important issue in using one platform as a control for another is that the platforms certainly may cater to different populations. This might be particularly true for TripAdvisor versus the other platforms, as TripAdvisor is primarily a review platform, while Expedia, Orbitz, and Priceline are booking platforms. In addition, the scales of the platforms are very different. In including two controls, we allow the data to “choose” the combination of platforms that are the best controls. Also, calculating a control-platform-specific coefficient captures differences in scale across platforms. Thus, for any review measurement constructed for our treatment sites TripAdvisor, Expedia, and Hotels.com, we construct the corresponding measure for both Orbitz and Priceline and use these as control variables in our regression specifications.

Table 4 summarizes the cross-sectional correlation in number of reviews, review valence, and review length across sites but within hotels. Our identification strategy is predicated on the idea that hotel characteristics will be similarly measured across sites. Table 4 suggests high correlation among the sites for all of the measures. The correlation across sites is largest for review valence and smallest for review length. Hotels that inspire longer reviews on one site tend to receive longer reviews on other sites, but the effect is modest in magnitude. Our two control sites, Orbitz and Priceline, are less correlated with each other across each of the measures than are any other pair of sites. This suggests

that there is plausibly different information about the hotel captured by using each of them as a control.

Recall that our review measures of interest are change in the number of reviews between the six-week windows (to test Hypothesis 1), change in the valence of reviews (to test Hypothesis 3), and change in the length of reviews (to test Hypothesis 2). For each measure, M , for hotel i in city j , our simple estimating equation is

$$\begin{aligned} & (M_{ij}^{\text{Treat}} - \bar{M}_j^{\text{Treat}})_{\text{Post}} - (M_{ij}^{\text{Treat}} - \bar{M}_j^{\text{Treat}})_{\text{Pre}} \\ &= \alpha + [(M_{ij}^{\text{Priceline}} - \bar{M}_j^{\text{Priceline}})_{\text{Post}} - (M_{ij}^{\text{Priceline}} - \bar{M}_j^{\text{Priceline}})_{\text{Pre}}] \beta_1 \\ & \quad + [(M_{ij}^{\text{Orbitz}} - \bar{M}_j^{\text{Orbitz}})_{\text{Post}} - (M_{ij}^{\text{Orbitz}} - \bar{M}_j^{\text{Orbitz}})_{\text{Pre}}] \beta_2 \\ & \quad + \epsilon_{ij}. \end{aligned} \quad (1)$$

In this equation, *Pre* denotes the six-week period prior to first managerial response on the treatment site for hotel i , and *Post* denotes the six-week period following the first managerial response on the treatment site. The treatment site is $\text{Treat} \in (\text{TripAdvisor}, \text{Expedia}, \text{Hotels.com})$, and \bar{M}_j denotes the city-average variable. Note that for each specification, α is our variable of interest, as it is the change in the variable net of the changes in the controls. For example, consider the change in number of reviews for TripAdvisor following the first response. The variable α measures the extent to which the number of reviews posted on TripAdvisor increases above and beyond corresponding changes in the number of reviews on Priceline and Orbitz, as well as corresponding geographic averages. In the tables that display our estimation results (Tables 7–13), we refer to α as the “treatment effect.”

Our identification strategy is helpful in overcoming several potential endogeneity challenges. (See Table 5 for the summary of endogeneity concerns and our solutions to these concerns.)

When will our strategy fail? The primary weakness of our strategy is that it is possible that a hotel-specific, time-specific, platform-specific factor is correlated with both the initiation of managerial response for hotel i and with the future review process for hotel i on that specific platform. We find the possibility of one category of such confounds slightly more plausible for Expedia and Hotels.com than for TripAdvisor. This is because Expedia and Hotels.com are both booking sites, rather than purely review sites.⁸ It is possible, for example, that hotels systematically simultaneously commence participation in hotel-specific promotions on Expedia or Hotels.com and initiate managerial responses on those sites. Such promotions might plausibly lead, through an increase in platform-specific bookings, to an increase in reviewing activity on those sites. By contrast, even if a hotel undertook some kind of promotion on TripAdvisor, the consumer would click out to a different site to book the reservation.

Table 4. Correlations Within Hotel and Across Sites

	TripAdvisor	Expedia	Hotels.com	Priceline	Orbitz
Review count correlations					
TripAdvisor	1.00				
Expedia	0.78	1.00			
Hotels.com	0.63	0.58	1.00		
Priceline	0.38	0.34	0.31	1.00	
Orbitz	0.67	0.41	0.29	0.24	1.00
Average star correlations					
TripAdvisor	1.00				
Expedia	0.81	1.00			
Hotels.com	0.71	0.80	1.00		
Priceline	0.72	0.77	0.72	1.00	
Orbitz	0.63	0.66	0.60	0.59	1.00
Length correlations					
TripAdvisor	1.00				
Expedia	0.55	1.00			
Hotels.com	0.45	0.58	1.00		
Priceline	0.30	0.34	0.31	1.00	
Orbitz	0.34	0.41	0.29	0.24	1.00

Table 5. Our Methodological Response to Major Endogeneity Concerns

Endogeneity concerns (other changes that may be happening concurrently with response)	Our methodological response
The hotel made long-term quality investments	Our narrow time windows ensure that changes due to long-term investments will not be captured
The hotel made short-term quality investments	We use as control the change in reviews for the hotel on platforms that do not allow managerial response
TripAdvisor ran local promotions	We use as control the change in reviews for other hotels on TripAdvisor in the same geographic area
The hotel made physical and virtual investments that target TripAdvisor	We redo our analysis with Expedia and Hotels.com as treatment users

Hence, there is a weaker connection between promotion, the number of bookings, and the number of reviews. While this is a concern, we note three things about this concern. First, many of the plausible confounds that we can think of (such as promotions) might lead people to book more rooms in the short run, but the booking activity should somewhat more slowly work its way into staying and reviewing activity (since many people book for a stay occurring somewhat in the future). Second, it is not entirely clear why such a promotion would also lead people to be systematically differentially satisfied or unsatisfied with their experience; that is, there is not a natural prediction for review valence. Third, there is also not a natural prediction for review length.

A second scenario that would undermine our strategy is the possibility that hotels that commence review response on a site are “getting organized” about catering to the users of the site more generally. This might be a particular concern for TripAdvisor, since TripAdvisor has become so important in the industry. Several factors, we believe, mitigate this concern in our setting. First, using the same logic that TripAdvisor reviews are particularly important and salient in the industry, this should be less of an issue for Expedia and Hotels.com. Second, the natural bias stories of this type seem to cut in the opposite direction of our hypothesis and findings. If a hotel were launching a coherent TripAdvisor management system with immediate implications, it is hard to see how that would systematically lead to a decrease in review valence. Third, there is not a clear natural prediction of this possibility for review length.

6. Results

Table 6 presents summary statistics of the variables used to estimate Equation (1).

Table 6. Summary Statistics for Six-Week Difference Variables

	No. of reviews	Average stars	Average length
Summary statistics for first TripAdvisor (TA) response			
TripAdvisor average (sum six weeks before)	4.50 (8.29)	4.01 (0.82)	762.60 (412.21)
Diff. in diff. TA	1.27 (5.64)	−0.06 (0.94)	50.61 (514.00)
Diff. in diff. Orbitz	0.14 (2.96)	0.00 (2.35)	6.54 (344.55)
Diff. in diff. Priceline	0.12 (2.78)	0.05 (2.28)	3.56 (174.78)
Summary statistics for first Expedia response			
Expedia average (sum six weeks before)	4.97 (6.55)	4.19 (0.66)	351.13 (191.49)
Diff. in diff. Expedia	0.33 (4.59)	−0.07 (0.81)	9.94 (239.75)
Diff. in diff. Orbitz	−0.04 (2.20)	−0.13 (−3.34)	−5.76 (364.92)
Diff. in diff. Priceline	0.12 (3.64)	0.07 (2.20)	16.59 (255.96)
Summary statistics for first Hotels.com response			
Hotels.com (sum six weeks before)	9.49 (13.19)	4.25 (0.56)	236.77 (132.19)
Diff. in diff. Hotels.com	1.06 (8.57)	0.00 (0.61)	24.23 (207.88)
Diff. in diff. Orbitz	−0.04 (3.61)	0.30 (2.10)	−1.19 (337.62)
Diff. in diff. Priceline	−0.26 (4.24)	0.19 (2.16)	8.04 (192.40)

Notes. Standard deviations are in parentheses. Observations are weighted using the probability weight for Revinate customers versus noncustomers.

Table 7 provides estimates of Equation (1) where TripAdvisor is the treatment site. Column (1) examines the variable of primary interest to us, the change in the number of reviews for the sample of 1,807 first responders on TripAdvisor. This provides our primary test of Hypothesis 1. Note that both the Orbitz control and the Priceline control coefficients are positive and significant, at least at the 10% level. The number of reviews positively comoves across the sites. This is not surprising, as presumably all of the sites get more reviews in periods of particularly high occupancy for the hotel relative to the local area. Note that both Orbitz reviews and Priceline reviews also experience review increases over the period. The constant term is positive and statistically significant at the 1% level. This suggests that, net of the controls, the number of reviews increases by 1.2 reviews. The average number of reviews in the pre-review period is 4.5 (from Table 6), so this represents a substantial sudden increase in reviewing activity relative to the controls.

Column (2) examines average stars, which pertains to Hypothesis 3. When considering average stars,

Table 7. TripAdvisor Six-Week Changes in Reviewing Activity

Variables	(1) No. of reviews	(2) Avg. stars	(3) Avg. length	(4) Length 1-, 2-, 3- star reviews	(5) Length 4-, 5- star reviews
<i>Orbitz controls</i>	0.117** (0.059)	0.001 (0.011)	−0.015 (0.048)	0.039 (0.079)	0.007 (0.048)
<i>Priceline controls</i>	0.110* (0.061)	−0.003 (0.013)	−0.020 (0.076)	0.104 (0.224)	0.089 (0.074)
Constant (treatment effect)	1.240*** (0.130)	−0.064** (0.027)	50.783*** (14.781)	19.492 (32.402)	31.235** (15.548)
Observations	1,807	1,210	1,210	516	1,037

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

we restrict the sample to hotels that had reviews on TripAdvisor in both the pre- and post-six-week windows. We see that average stars decrease significantly for hotels that have commenced managerial response. This is consistent with Hypothesis 3 in Section 3. (We explore the mechanism behind this result in an experimental setting in Section 8.) Interestingly, our results contrast with those of Proserpio and Zervas (2017) in this regard. The point estimate is −0.06. This may seem small, but recall that the average number of stars obtained in the before period is 4.01, with a cross-sectional standard deviation of only 0.8. Thus, small movements in the average number of stars can significantly move a hotel up or down the rank ordering of hotels in a local area. An important issue to consider is that the Orbitz and Priceline controls are not statistically significant in the regression. The hotels also have essentially no average star movement on Priceline or Orbitz over the two six-week windows. This is to be expected if underlying quality at the hotel is, indeed, not significantly changing.

Column (3) displays results for the average length of review. These results pertain to Hypothesis 2. We restrict the sample to hotels that had reviews in both the before and after periods on TripAdvisor. Review

length has not changed significantly over the six-week windows for Priceline and Orbitz, suggesting that perhaps nothing has changed at the hotel that fundamentally leads consumers to want to leave longer reviews. However, reviews on TripAdvisor increase significantly. The point estimate of the increase is 51 characters. This is a large change given the average length of reviews on TripAdvisor for the period prior to the managerial response is 763 characters. Because we also find evidence of a change in review valence, we also examine whether review length changes even within review valence categories. Thus, we examine the change in review length for negative valence (one-, two-, and three-star) reviews and positive valence (four- and five-star) reviews separately. In each case, we must restrict the sample to hotels that have reviews in that category in both the before and after windows on TripAdvisor. This increase in reviewing effort is estimated to be positive both for negative and positive valence reviews, although it is statistically different from zero for only the four- and five-star reviews.

Table 8 provides estimates of Equation (1) where Expedia is the treatment site. Of course, the sample of review responses is much smaller. Interestingly, the number of reviews that the hotel has in the six weeks

Table 8. Expedia Six-Week Changes in Reviewing Activity

Variables	(1) No. of reviews	(2) Avg. stars	(3) Avg. length	(4) Length 1-, 2-, 3- star reviews	(5) Length 4-, 5- star reviews
<i>Orbitz controls</i>	0.135 (0.086)	0.006 (0.012)	0.026 (0.024)	−0.051 (0.054)	−0.005 (0.032)
<i>Priceline controls</i>	0.086* (0.052)	0.017 (0.013)	−0.029 (0.046)	0.007 (0.077)	−0.017 (0.053)
Constant (treatment effect)	0.329** (0.145)	−0.072** (0.030)	10.568 (9.055)	−30.860 (24.113)	9.557 (9.056)
Observations	984	709	709	275	652

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

* $p < 0.1$; ** $p < 0.05$.

Table 9. Hotels.com Six-Week Changes in Reviewing Activity

Variables	(1) No. of reviews	(2) Avg. stars	(3) Avg. length	(4) Length 1-, 2-, 3- star reviews	(5) Length 4-, 5- star reviews
<i>Orbitz controls</i>	0.412*** (0.132)	0.004 (0.019)	0.028 (0.038)	−0.036 (0.077)	−0.012 (0.038)
<i>Priceline controls</i>	0.159 (0.135)	−0.022 (0.019)	−0.032 (0.055)	0.128 (0.096)	−0.026 (0.065)
Constant (treatment effect)	1.116** (0.460)	0.001 (0.038)	24.515* (12.835)	12.047 (30.852)	19.924 (13.860)
Observations	332	265	265	136	256

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

** $p < 0.05$; *** $p < 0.01$.

prior to the first response is about the same for Expedia as for TripAdvisor, suggesting that responders on Expedia tend to be hotels that garner a lot of Expedia reviews. Despite the smaller number of observations, we find somewhat similar, albeit weaker, results. The increase in the number of reviews net of the controls is 0.3, about one-quarter of the magnitude of the effect estimated for TripAdvisor, but still significantly different from zero at standard confidence level. The decrease in review valence of 0.07 is very similar to the TripAdvisor results. However, the increase in review length is small and insignificant.

Table 9 provides estimates of Equation (1) where Hotels.com is the treatment site. Here, the sample of responding hotels is again quite small, as we have only 332 hotels that provide responses on Hotels.com or for which the date of the first managerial response date are available. Nonetheless, we do find a significant increase in the number of reviews posted, no measurable change in average stars, and a small (and significant at the 10% level) increase in review length overall.

In sum, we interpret the results in Tables 7–9 as demonstrating that reviewing activity increases following managerial response, that valence decreases (at least modestly), and that the length of reviews (a measure of reviewing effort) increases.

Should we conclude based on the valence result that a hotel is better off not responding to reviews? Given the popularity of response among hotels (including the hotel's competitors), not responding at all may not be feasible. Furthermore, it is quite likely (and untestable given current data) that consumer purchasing behavior responds differently to a given review depending on whether it has received a thoughtful response. Instead, we explore an aspect of the managers' response strategy that is under their control—the extent to which they respond to positive versus negative reviews. That is, so far we have hypothesized that perceived higher impact of negative reviews combined with the empirical regularity that negative reviews are more likely

to receive a manager response implies that managerial response results in a decrease in subsequent review valence. Another implication of our reasoning is that a manager who is more likely to favor responses to negative over positive reviews will amplify this effect further; that is, by disproportionately responding to reviews that contain criticisms, an individual manager signals to consumers that criticisms will be read by management, possibly responded to, and possibly acted on.

Below we explore whether we observe this regularity in the data. While, overall, more negative reviews are more likely to receive managerial responses and more likely to receive more substantive managerial responses, the extent that this is true will vary across managers and hotels. We explore whether the hotels that are more likely to respond to negative reviews are also more likely to experience a larger fall in subsequent review valence.

In Tables 10 and 11, we reestimate Equation (1) for TripAdvisor but separate the data into two groups. First, in Table 10, we consider the set of TripAdvisor respondees whose first-day responses are to reviews with an average star value of less than three. For example, this would include a hotel whose first-day responses included a two-star and a three-star review since the average of the two reviews is 2.5. Second, in Table 11, we consider the disjoint set of TripAdvisor respondees whose first-day responses are to reviews with an average star value of three or more. For the 641 hotels that respond to low average star reviews in Table 10, we see that in the six weeks after the first response, the number of reviews increases significantly, review valence decreases significantly, and average length increases. The decrease in review valence is roughly double the magnitude of our estimate of the review valence differences using the overall sample. On closer inspection of the pattern of review length increases, review length increases are positive but insignificant for the two valence categories. Overall,

Table 10. Six-Week Changes in Reviewing Activity for TripAdvisor Hotels Who Respond to Reviews with an Average Star Value of Less Than Three

Variables	(1) No. of reviews	(2) Avg. stars	(3) Avg. length	(4) Length 1-, 2-, 3- star reviews	(5) Length 4-, 5- star reviews
<i>Orbitz controls</i>	0.093 (0.071)	−0.004 (0.016)	−0.046 (0.075)	0.085 (0.112)	0.002 (0.077)
<i>Priceline controls</i>	−0.035 (0.055)	−0.000 (0.017)	−0.041 (0.108)	−0.091 (0.225)	0.107 (0.107)
Constant (treatment effect)	0.724*** (0.157)	−0.143*** (0.037)	62.186*** (20.537)	42.942 (41.472)	25.324 (20.336)
Observations	968	673	673	305	564

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

*** $p < 0.01$.

the results in this table are suggestive that managerial responses that concentrate on responding to negative reviews encourages more negative reviews and more detailed negative reviews from consumers.

For the 839 hotels that respond to higher average star reviews in Table 11, we see that in the six weeks after the first response, the number of reviews increases significantly, review valences are unchanged (the point estimate is positive), and average review length increases modestly. The contrast between Tables 10 and 11 is suggestive that negative reviewing activity is differentially stimulated when managers use the response function exclusively to respond to negative reviews. This makes sense in an environment in which consumers post reviews to have an impact on hotel quality.

It is important to recognize that caution must be undertaken in interpreting the first-day reviewing strategies because the decision of which reviews to respond to is an endogenous choice. However, several factors lead us to optimism that the results can be interpreted causally.

First, we undertake an analysis to examine whether the difference in the postresponse review valence of positive first-day responders and negative first-day responders is the result of a prerespone trend.⁹ For example, one concern with our findings is that hotels with declining review valence may be more likely to commence response to negative reviews than hotels with a rising or steady review valence. To examine this, we reestimate the regressions presented in Tables 10 and 11. However, instead of using the change from the six weeks before response initiation to the six weeks after response initiation, we shift the window back by six weeks to examine the prerespone initiation trend. We do not find any significant trends in number of reviews, average stars, or review length for the prerespone period for either positive first-day responders or negative first-day responders. Specifically, for average stars, the coefficient for the constant term (the prerespone trend in average stars) for positive first-day responders is −0.021, with a standard error of 0.038. For negative first-day responders, it is −0.006, with a

Table 11. Changes in Reviewing Activity for TripAdvisor Hotels Who Respond to Reviews with an Average Star Value of Three or More

Variables	(1) No. of reviews	(2) Avg. stars	(3) Avg. length	(4) Length 1-, 2-, 3- star reviews	(5) Length 4-, 5- star reviews
<i>Orbitz controls</i>	0.161 (0.104)	0.007 (0.016)	0.012 (0.061)	−0.008 (0.120)	0.012 (0.061)
<i>Priceline controls</i>	0.269** (0.113)	−0.009 (0.018)	−0.005 (0.108)	0.348 (0.402)	0.071 (0.105)
Constant (treatment effect)	1.806*** (0.210)	0.034 (0.040)	37.490* (20.990)	−9.838 (50.474)	38.204 (24.044)
Observations	839	537	537	211	473

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

standard error of 0.034. Thus, there is not a significant prerespone change in average star leading up to managerial response for either group of hotels, and there is no significant difference between the two groups. Thus, we rule out at least one important alternative hypothesis to the hypothesis that review response causes a change in subsequent review valence.

Second, in Section 8, we study this effect in an experimental setting that allows us to deal with the issue of causality.

7. Robustness

We undertake a number of robustness specifications; for the robustness specifications, we focus on TripAdvisor, as we have a larger number of responders on TripAdvisor.

First, we investigate using longer windows both before and after the managerial response. While the narrow 6-week window that we use in our base specifications is desirable to separate our hypotheses from longer-run changes in hotel quality, it raises the possibility that the reviewers have not had time to fully react to the initiation of managerial response by the end of the 6-week window. In Table 12, we undertake the basic specifications of Equation (1) for TripAdvisor, allowing a 10-week window before and after the managerial response. The cost of a longer window is that it is more plausible that long-run investments in hotel quality that could be systematically coincident with the advent of managerial response are being experienced by consumers. The benefit of a longer window is that, over short time periods, reviews and the correlation of the reviews across sites will be noisier.

The results in Table 12 look very similar to our base results in Table 7. The constant term in the number of reviews specification has increased from 1.24 to 2.27. Recall that we are measuring changes in reviews in levels; if the treatment effect of managerial response is permanent, we would anticipate roughly a 67% increase in the coefficient given the 67% increase in the time

period. Our estimates represent an 83% increase in the number of reviews, and we certainly cannot reject a 67% increase in the number of reviews. The average star measures are nearly identical in Tables 7 and 12, as are the review length results.

We conduct a few other tests to investigate possible sources of misspecification. First, our empirical design uses an event study framework in which we look at narrow windows before and after the posting of managerial response. This design envisions the posting as a discrete shift in reviewer behavior. However, a plausible alternative explanation is that our empirical observations represent a continuation of a trend that commenced prior to the review response date; that is, for some reason, reviews were getting more numerous, longer, and more negative over time for the hotels that responded relative to those that did not (and on TripAdvisor relative to the other platforms). Therefore, a shift that we attribute to managerial response may instead arise simply due to a time trend.

To address this, we devise an alternative specification that specifically takes out the possible time trend by differencing out all of the variables with respect to their lags. If the changes that we observe are due to the time trend alone, the detrended data should no longer yield significant results. We refer to the (6- or 10-week) period after managerial response as “post,” the (6- or 10-week) period before managerial response as “pre,” and the (6- or 10-week) period prior to that as “pre-pre.” Hence, the left-hand side of the specification in Equation (1) becomes

$$\begin{aligned} & [(M_{ij}^{\text{Treat}} - \bar{M}_j^{\text{Treat}})_{\text{Post}} - (M_{ij}^{\text{Treat}} - \bar{M}_j^{\text{Treat}})_{\text{Pre}}] \\ & - [(M_{ij}^{\text{Treat}} - \bar{M}_j^{\text{Treat}})_{\text{Pre}} - (M_{ij}^{\text{Treat}} - \bar{M}_j^{\text{Treat}})_{\text{Pre-Pre}}]. \quad (2) \end{aligned}$$

The independent variables are also differenced accordingly. We perform this specification for both the 6-week windows and the 10-week windows described above. The basic results for number of reviews, average stars, and length are presented in Table 13. The

Table 12. TripAdvisor Specifications—Longer (10-Week) Time Window

Variables	(1) No. of reviews	(2) Avg. stars	(3) Avg. length	(4) Length 1-, 2-, 3- star reviews	(5) Length 4-, 5- star reviews
<i>Orbitz controls</i>	0.108* (0.055)	0.008 (0.010)	−0.034 (0.047)	0.059 (0.061)	0.039 (0.043)
<i>Priceline controls</i>	0.205* (0.105)	0.005 (0.011)	0.015 (0.063)	0.052 (0.121)	0.024 (0.061)
Constant	2.270*** (0.209)	−0.059** (0.023)	35.761*** (13.188)	14.992 (26.845)	29.455** (12.769)
Observations	1,807	1,385	1,385	738	1,248

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 13. Robustness: Time-Shifted Control Specifications

Variables	(1) 6-week No. of reviews	(2) 6-week Avg. stars	(3) 6-week Avg. length	(4) 10-week No. of reviews	(5) 10-week Avg. stars	(6) 10-week Avg. length
<i>Orbitz controls</i>	0.092* (0.051)	−0.005 (0.011)	0.042 (0.045)	0.056 (0.052)	−0.001 (0.010)	−0.011 (0.045)
<i>Priceline controls</i>	−0.013 (0.058)	−0.001 (0.011)	−0.004 (0.070)	0.154** (0.066)	0.002 (0.010)	0.002 (0.059)
Constant (treatment effect)	1.171*** (0.175)	−0.058 (0.045)	83.544*** (25.319)	1.940*** (0.301)	−0.120*** (0.040)	55.137** (21.673)
Observations	1,807	1,025	1,025	1,807	1,165	1,165

Notes. Robust standard errors are in parentheses. Regressions are weighted to overrepresent Revinate noncustomers.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

results suggest that our specifications are robust to this new specification, although the average star specification for the 6-week horizon is not statistically different from zero. Note that the average star specification for the 10-week window is still negative and significant. As discussed above, we also conducted this analysis separately for hotels that responded to negative reviews on the first day and hotels that responded to positive reviews on the first day, and we did not find a more negative preexisting trend for hotels that responded to negative reviews.

We also investigate the possibility that the reviewing activity that we document here does not represent new increases in the posting of less-positive reviews, but rather a migration of reviews across sites. For example, this could occur if the initiation of managerial response makes customers less eager to post on other sites and more eager to post on TripAdvisor. To examine this, we calculate the total sum of reviews on each of the five major reviewing sites (TripAdvisor, Expedia, Orbitz, Hotels, and Priceline). We construct the difference in reviews in the pre-TripAdvisor-response window and the postresponse window. As before, we construct a double difference, measuring this over time relative to the average in the geographic area. Using this measure, we examine whether the total number of reviews across sites grows relative to other hotels in the geographic area. We find that the increase in reviews is similar to what we obtain by focusing on TripAdvisor alone. Thus, we do not believe our results stem from a shift in reviews across sites.

Finally, in the original specifications, we difference changes with respect to geographic averages. We also reestimate our main TripAdvisor specification, where we difference with respect to geographic-tier averages. The results remain qualitatively the same (see the online appendix).

In the online appendix, we discuss and present a few additional robustness specifications.

8. Mechanism Behind the Results

In this section, we analyze the mechanism behind our main result, the fall in average review valence following the initiation of managerial response. In particular, analysis of the review text enables us to test the assumption made in Section 3 that negative reviews are more impactful on manager's actions than positive reviews. In addition, an online experiment allows us to examine (1) whether reviewers are motivated by the impact of their reviews on hotels and (2) the effect of the presence and the type of managerial response on the likelihood of posting by reviewers with different hotel stay experiences.

8.1. Analysis of the Text of Reviews

Here we present empirical evidence for our assumption that negative reviews are more impactful on manager's actions than positive reviews. To investigate this question, we had a team of six coders rate a random subsample of our TripAdvisor reviews.¹⁰

Each review was assessed by three coders on whether it contained information that was (1) helpful to the manager planning improvement to the hotel over the longer term, (2) helpful to the manager in the very short term, and (3) helpful to customers selecting a hotel. Coders were instructed that comments helpful to the manager in the short run reflected issues that could be improved nearly instantly (cold coffee at breakfast, etc.), while long-run advice would reasonably take a week or more to implement (replace carpeting in a room, etc.). Raters were also instructed that comments about fixed characteristics of hotels, such as location, may be helpful for customers selecting a hotel, but unhelpful to management. Each answer was given on a seven-point Likert scale from "very unhelpful" to "very helpful." Note that since our instructions focus on changes that the hotel manager can make based on the reviews, managerial "helpfulness" of a review measures potential impact. Raters were shown the text of the review, but not the star rating given by the original reviewer.

Table 14. Mean Helpfulness Ratings Across Different Star Reviews

	1-star reviews	2-star reviews	3-star reviews	4-star reviews	5-star reviews
Mean manager helpful long term	3.04	2.96	2.49	1.71	1.34
Mean manager helpful short term	4.04	3.73	2.97	1.97	1.46
Mean customer helpful	4.68	4.68	4.48	4.45	4.42
Observations	151	180	454	983	1,387

Table 14 presents the helpfulness scores, averaged for each review across the three different raters.¹¹ Clearly, we see that the helpfulness of the reviews to the manager is monotonically decreasing with the increase in the rating of the review, for both the short term and the long term. All means for managerial helpfulness are statistically different across adjacent stars, with the only exception being the one-star and two-star long-term managerial helpfulness means, which are not significantly different from each other. Hence, we find that the more negative reviews are potentially more impactful on managerial actions. By contrast, for customer helpfulness, the only adjacent star ratings with statistically different means are the two-star and three-star reviews; we do not observe the same decline in helpfulness for customers.

8.2. Online Experiment

An experiment allows us to examine reviewer motivations and the effect of managerial response on the likelihood of posting by reviewers with different hotel stay experiences. We expose 1,202 U.S.-based participants on the Amazon Mechanical Turk platform to a hypothetical scenario followed by a survey. In all cases, the subjects were asked to imagine that they recently stayed at a hotel in San Diego, with the quality of the stay randomly varying across conditions: *Negative*, *Mixed*, or *Positive*. Roughly speaking, the negative condition represents a truly terrible experience, the mixed condition is a mediocre experience, and the positive condition is a very positive experience.¹²

We also randomly varied the presence and the nature of managerial response. Half of the subjects were randomly assigned to the *No Response* condition, and half were told that the manager responded to previous reviews. Among the latter subjects, who were told that the manager replied to reviews, half were simply told that the manager replied to reviews (*Response*), while the other half were also told that that reviews that mentioned problems were more likely to receive a response (*Negative-Only Response*). Hence, we have three disjoint response conditions: *No Response*, *Response*, and *Negative-Only Response*. See Tables A.1 and A.2 in the appendix for more details on the scenarios.

Following the scenario description, the subjects were asked, on a nine-point Likert scale (1 = very unlikely to 9 = very likely), how likely are they to post a review

of the hotel. Next we asked the subjects, “How important are the following factors in determining your decision to post?” The subjects were given a table of several motivations (see Table A.3 in the appendix for more details on the questions), which they were asked to rate using a 1 (“not important at all”) to 9 (“very important”) scale. We consider the following motivations: (1) provide constructive feedback to the hotel, (2) receive a response, (3) help customers, (4) blow off steam, (5) punish the hotel, and (6) feeling of anger.

Let us start with the analysis of motivations behind posting. Table 15 contains the results of six different specifications where we estimate (using an ordered logit specification) the subject’s rating of the importance of each motivation on indicators for whether the subject was in the *Response* condition or the *Negative-Only Response* condition. The coefficients reported are in odds-ratio format, and the results are relative to the omitted *No Response* indicator.

First note that we observe an increase in the motivation to receive a response in both response conditions relative to *No Response*, which we would certainly expect to occur. However, this is not the only motivation that increases. The results suggest a large and significant increase in the motivation to give feedback to the hotel following both types of managerial response. Hence, it appears that managerial response indeed increases the motivation to provide the hotel with feedback, which supports our hypothesis that reviewers view managers as more of the audience of their reviews in a managerial response environment. By contrast, managerial response does not significantly increase the motivation to help other customers and actually decreases the motivation to punish the hotel in the *Negative-Only Response* condition.

The fact that response to negative reviews lowers the motivation to punish the hotel is certainly good news (in the negative-only treatment) from the point of view of the responding hotel. However, it appears that it is the motivation to provide feedback that results in a decrease in average stars following managerial response.¹³ To explore further the mechanism behind this decrease, we turn to the effect of managerial response on the likelihood to post reviews. Overall, in all treatments, the response to this question has a mean of 6 and is highest in the negative experience condition. Table 16 demonstrates how the likelihood

Table 15. The Effect of Managerial Response on Reviewer Motivation to Post

Variables	(1) Provide feedback	(2) Receive response	(3) Help customers	(4) Blow off steam	(5) Punish hotel	(6) Anger
<i>Response</i>	1.832*** (0.231)	1.727*** (0.214)	1.038 (0.131)	0.835 (0.106)	0.885 (0.113)	0.955 (0.121)
<i>Negative-Only response</i>	1.604*** (0.196)	1.731*** (0.216)	1.024 (0.127)	0.835 (0.102)	0.751** (0.094)	0.830 (0.102)
Observations	1,202	1,202	1,202	1,202	1,202	1,202
R-squared	0.025	0.023	0.000	0.003	0.005	0.002

Notes. The table shows odds ratio estimates from ordered logit specifications. Estimated cut points are omitted for brevity. The dependent variable in each specification is the Likert measure for the motivation type listed in the column header. Standard errors are in parentheses.

** $p < 0.05$; *** $p < 0.01$.

to post varies across the conditions. The table presents three ordered logit specifications, one for the subsample of each hotel experience type, where the likelihood to post is regressed on the same set of indicator variables that we used in Table 15. Coefficients are reported as odds ratios.

From Table 16, we see that response where targeting of critical reviews is not emphasized (*Response* condition) has comparable and significant increases in both the *Positive* and the *Mixed* conditions. By contrast, managerial response that targets critical reviews (*Negative-Only* condition) only significantly increases the likelihood to post in the *Mixed* experience condition. Given the high average star of hotel reviews overall, increasing only the posting of reviews by customers with mixed experiences is likely to lower average review valence.¹⁴

There are two important takeaways from Table 16. First, these results are broadly consistent with our empirical findings; in Tables 10 and 11 we show that our result that the initiation of managerial response leads to a decrease in average review stars is driven entirely by hotels with managers who focus their responses on

negative reviews. Second, the experiment allows us to examine the mechanism behind the result—different types of responses differentially stimulate reviewers with mixed versus positive experiences.

9. Relationship to Previous Literature

In this section, we highlight the contribution of our paper and reconcile the findings with the existing literature: Ma et al. (2015) and Proserpio and Zervas (2017).

Ma et al. (2015) finds that a service intervention by the firm may actually encourage negative redress-seeking tweets. This is, in spirit, related to our finding that a managerial response results in lower-valenced reviews. Despite the seeming similarity, there are also important differences between the two settings and the resulting mechanisms; that is, while Ma et al. (2015) examines concrete service interventions on behalf of the complainer (such as restoring Internet service), here, we examine communication that may or may not involve an intervention, and where the intervention would not benefit the complainer directly. Also, as we discuss above, while it is possible that redress seeking is present in our setting, it is clearly not as central a motive as it is in Ma et al. (2015). There are many online platforms where word of mouth is exchanged, and where a service intervention is either not possible (because of the anonymous nature of the forum) or is not advisable (perhaps because the firm does not want to encourage excessive redress seeking), but a firm may still be able to respond to feedback. In this sense, our setting is broad.

Proserpio and Zervas (2017) study a phenomenon similar to ours but have a very different finding. They find an increase in review valence on TripAdvisor relative to Expedia following a managerial response on TripAdvisor. By contrast, we find a decrease in review valence following the initiation of managerial response, a substantively different result with different managerial implications. There are methodological and conceptual differences between the two papers. Unfortunately, we were not successful in pinpointing exactly the driver

Table 16. The Effect of Managerial Response on Likelihood of Posting a Review

Variables	(1) Negative hotel experience	(2) Mixed hotel experience	(3) Positive hotel experience
<i>Response</i>	1.105 (0.237)	1.962*** (0.424)	1.865*** (0.412)
<i>Negative-Only response</i>	1.088 (0.236)	1.677*** (0.358)	1.274 (0.266)
Observations	400	401	401
R-squared	0.001	0.031	0.023

Notes. The table shows odds ratio estimates from ordered logit specifications. Estimated cut points are omitted for brevity. The dependent variable for each specification is the Likert measure of likelihood to post. Each column represents a different experimental subsample. Standard errors are in parentheses.

*** $p < 0.01$.

of the difference in empirical results—we still found a decrease in valence even when we made sampling and methodological choices similar to theirs (please see discussion below).

First, the two papers propose very different mechanisms behind the results. Proserpio and Zervas (2017) suggest that managerial response decreases the posting of negative reviews since reviewers are worried that their reviews will be more scrutinized. They also suggest that once hotels start responding, they attract reviewers who are inherently more positive in their evaluation. By contrast, we argue (and provide supportive experimental evidence in Section 8) that negative reviews are more likely to be stimulated by managerial response since potential reviewers perceive negative reviews to be more impactful.

Second, there are important methodological differences between our papers. In particular, Proserpio and Zervas (2017) use TripAdvisor, as we do, but use Expedia as a control site. We use Priceline and Orbitz as controls because neither of these allow managerial responses. In fact, we use Expedia in one of our treatment analyses since it allows managerial response. While managerial response is less frequent on Expedia than TripAdvisor, it is not negligible. In Proserpio and Zervas's (2017) sample of Texas hotels, 17.4% of the hotels that receive any Expedia reviews eventually post a reply and have to be discarded from their study; in our sample, the majority of hotels with Expedia reviews eventually post at least one reply. More fundamentally, since both sites allow managerial response, in the sample in Proserpio and Zervas (2017), a hotel chooses to post a reply on TripAdvisor and not on Expedia. This raises endogeneity concerns. For example, it could be the case that a hotel that responds on TripAdvisor but not on Expedia also favors TripAdvisor over Expedia customers in other ways, which would result in more reviews, and more positive reviews, arriving on TripAdvisor compared to Expedia. In our paper, these concerns are lessened since (1) our control sites do not allow managerial reviews, and (2) we investigate several treatment sites besides TripAdvisor; that is, as we argue above, the concern that the effect is entirely driven by managers catering to the needs of TripAdvisor visitors becomes less plausible when applied to three different platforms. This endogeneity issue is an *a priori* concern and may indeed be an issue in their sample. However, in the online appendix, we conduct an analysis in which we use our sample and analyze TripAdvisor as a treatment site and Expedia as a control. We actually find results that are very consistent with the results that are presented here; following the initiation of managerial response, review valence decreases on TripAdvisor relative to Expedia.

Finally, there are a number of differences between our paper and Proserpio and Zervas's (2017) in how

our samples are constructed. For example, we focus on middle tier to luxury tier hotels (eliminating, effectively, motels); we have a national sample, as opposed to their sample of Texas hotels; and our time window in which we measure the impact of responses initiation is much shorter. In the online appendix, we conduct a number of additional analyses to explore how our results change if we undertake changes to our sample to make it more closely resemble that of Proserpio and Zervas (2017). We find that our result that review valence decreases in the presence of managerial response is quite robust to these changes.

While we are not certain what drives the differences between the results in the two papers, we can speculate on ways in which the results can be reconciled. In Section 8, we find that response that does not favor negative reviews stimulates the likelihood of posting of positive reviews, which is consistent with Proserpio and Zervas (2017). By contrast, managerial response to negative reviews only does not stimulate the posting of positive reviews. Perhaps the present paper and Proserpio and Zervas (2017) find different results because the two data sets reflect these two response strategies with different intensities.

10. Conclusion

Allowing management to respond to user reviews has become a common feature of reviewing platforms, especially platforms geared to services such as hotels. We argue that allowing managerial response can fundamentally change the nature of the reviewing platform if users view themselves to be in a dialogue with management rather than only leaving information for future customers.

Frequently, managers attempt to use the response function to mitigate the impact of criticism, often by promising change. However, the prior literature suggests that consumers post reviews to have an impact on others and that they are more motivated to post when they perceive that they can have more impact. These observations lead to our hypothesis that the managerial response function promotes reviewing generally and promotes the production of critical reviews specifically. Our empirical results rely on a multiple-difference strategy to address endogeneity issues. Our empirical results, along with some additional experimental evidence, are generally supportive of the hypothesis that managerial response encourages critical reviewing.

While stimulating negative reviews is not a favorable outcome from the point of view of the firm, we do not claim that responding to reviews is a poor managerial strategy. Note that we do not study the impact of managerial response on actual bookings. It is possible that managerial responses do lead potential customers to view a hotel's negative reviews in a more favorable light and thus lead potential customers to be more

likely to book the hotel conditional on the reviews. This is an interesting area for future research.

Indeed, as we discuss in this paper, the dilemma facing the manager is a tough one. On one hand, a managerial response to a negative review may neutralize the possible negative effect of the original review on future bookings. On the other hand, as we point out, by responding, the firm also runs the risk of encouraging further critical reviews, which of course may hurt future bookings. Based on our study, we would suggest that one way to navigate this dilemma is to avoid selectively targeting negative reviews for response.

These results also have implications for the growing literature on online collaborative information creation. Our results suggest that seemingly small tweaks to the platform design can have measurable implications for consumer reviewing behavior and potentially the utility of reviews for future consumers.

Finally, our results contribute to the literature on the effect of managerial response on customer voice. While ours is not the first paper to address this issue, we believe that our setting, sampling strategy, and methodology contribute to robustness and more general applicability of our results.

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Appendix A

In Tables A.1–A.3, we show the details of the information shown to subjects in our online experiment.

Table A.1. The Quality of Stay Conditions

Condition	Scenario text
Negative	You spent the last four days at a hotel in San Diego. You did not enjoy your stay: the location was not convenient, the hotel room was poorly decorated, the bed was not very comfortable, the bathroom was too small, the breakfast buffet was over-priced given its limited selection, the front desk staff was not courteous, and the maid service fell short as well.
Mixed	You spent the last four days at a hotel in San Diego. There were certain aspects of the stay that you enjoyed: the location was nice, the hotel room was tastefully decorated, the bed was comfortable, and the bathroom was large. However, you also felt that the breakfast buffet was over-priced given its limited selection, the front desk staff was not courteous, and the maid service fell short as well.
Positive	You spent the last four days at a hotel in San Diego. You enjoyed your stay: the location was nice, the front desk staff was courteous, the hotel room was well-maintained and tastefully decorated, the bed was comfortable, the bathroom was large, the hotel restaurant food was tasty and reasonably-priced, and the maid service was very professional.

Table A.2. Managerial Response Conditions

Condition	Scenario text
No response	You see that about 120 reviews have been previously posted for the hotel on TripAdvisor.
Response	You see that about 120 reviews have been previously posted for the hotel on TripAdvisor. You also see that since April the manager of the hotel has started to reply to some of the reviews. For example, one previous review mentioned that the breakfast food was cold, and the manager replied that she would talk to her staff about keeping the food warm.
Negative-only	You see that about 120 reviews have been previously posted for the hotel on TripAdvisor. You also see that since April the manager of the hotel has started to reply to some of the reviews. For example, one previous review mentioned that the breakfast food was cold, and the manager replied that she would talk to her staff about keeping the food warm. You also notice that the reviews that mentioned problems during the customer's stay were more likely to receive a response from the manager than the reviews that did not list any problems.

Table A.3. Measures on Reviewer Motivations

Question text	Source
I wanted to give constructive suggestions to the hotel on how to improve its service.	Adapted from item on participation scale in Eisingerich et al. (2014)
I wanted to receive a response from the manager to my review.	New
I wanted to help other consumers with making a decision.	Adapted from item on helping receiver scale in Wetzer et al. (2007)
I had to blow off steam.	Adapted from item on venting scale in Wetzer et al. (2007)
I wanted to punish the hotel in some way.	Adapted from item on revenge scale in Gregoir et al. (2010)
I felt angry.	Adapted from item on anger scale in Gregoir et al. (2010)

Endnotes

¹There is a sense in which the quality of physical products such as books or beauty products could change over time. A book could become dated, or a product's attributes could become dominated by a newly introduced product. However, these changes are not a result of managerial investments as with hotels and restaurants, and thus the impact issues we discuss are not completely relevant.

²In a context distinct from product reviews, Zhang and Zhu (2011) provide support for the impact hypothesis using data from Chinese Wikipedia postings. Zhang and Zhu (2011) show that contributions to Chinese Wikipedia by contributors outside mainland China declined dramatically when the site was blocked to readers in mainland China. This suggests that contributors receive social benefits from posting their contributions; reducing the size of potential readership reduces the benefits of contributing.

³The fact that consumer reviews contain managerially useful information is illustrated by White (2014), who discusses the trend of hotels using customer reviews as "blueprints" for renovation.

⁴See, for example, the many articles that TripAdvisor has written in its "TripAdvisor Insights" article series on the topic of managerial responses to negative reviews, <https://www.tripadvisor.com/TripAdvisorInsights/w637>.

⁵See, for example, the Yelp Official Blog, <http://officialblog.yelp.com/2011/03/tactics-for-responding-to-online-critics-new-york-times-boss-blog.html>.

⁶This number was obtained from a conversation with Revinate executives in January 2016.

⁷Toward the end of our data period, in the summer of 2013, Hotels.com and Expedia, who have a common owner, initiated some review sharing on the two sites. This data sharing was not reflected in Revinate's data collection. While we found instances where some reviews from Expedia (which were marked as "Expedia-verified") appeared on Hotels.com, we did not find examples of the reverse occurring. We also found that the policy was not consistent across all hotels—while in one instance only a small subset of all available Expedia reviews was displayed on Hotels.com, in another instance it was a bigger subset. There are several reasons why we think that this merger was not a major issue for us. First, for unrelated reasons, as discussed above (Section 4), we do not use postmerger data for Hotels.com, so this is not an issue for our Hotels.com estimation. Second, we did not see examples of Hotels.com reviews displayed on Expedia, which suggests that this is not a major issue for our Expedia.com estimation. Finally, this occurred relatively late in our data set.

⁸Note that the booking versus information-only site distinction also leads to differences in how the platform can elicit reviews. For example, Expedia, Orbitz, and Priceline send reminders to their customers to review their recent stays. By contrast, many of the reviews posted on TripAdvisor describe trips that were booked on other platforms. Hence, the majority of the reviews on TripAdvisor were posted spontaneously and not because of a reminder. We also expect these differences to affect the timing of review posting across sites. Since there are many observable and unobservable differences across platforms, it is important for us to take differences over time since they keep the platform constant.

⁹We thank an anonymous reviewer for raising this point.

¹⁰Coders were undergraduate students at a U.S. university. Each coder worked roughly 60 hours at this task. Coders were instructed that they would be evaluated based on their speed, but also the extent to which their evaluations correlated with the other raters'.

¹¹Measures of intersubject reliability are quite modest: Krippendorff's alpha measure averaged 0.29 for the helpfulness questions. The literature suggests that this measure tends to be lower when the raters have more category choices (here, seven) and for rating tasks evaluating emotional or opinion text (see Antoine et al. 2014).

¹²In a pretest, the average satisfaction with the stay was 2.05 out of 9 in the negative condition, 4.74 in the mixed condition, and 8.44 in the positive condition. Note that the mixed condition is calibrated to be below average: it is equivalent to 2.63 out of 5 stars.

¹³As another check on our proposed mechanism that posters are motivated by the impact of their reviews, we conduct an exploratory latent Dirichlet allocation topic analysis to investigate whether the topics of reviews change after managerial response is initiated. We find that the largest increase after the initiation of managerial response is in the propensity of reviews to discuss issues that are related to staff and service quality, topics that we would argue are under managerial control.

¹⁴Interestingly, while consumers are most likely to post a review in the *Negative* hotel experience condition, we see no significant marginal effect of response on posting in that condition, although coefficient estimates are positive. These results are related to the findings of Proserpio and Zervas (2017, p. 645). They suggest a mechanism in which fewer negative reviews will be posted in managerial response environment because "unsatisfied consumers become less likely to leave short indefensible reviews." Our results that punishment is a less powerful motivator following the initiation of managerial response accords with their proposed mechanism, but we do not find support that those with a negative experience are *less* likely to post in a managerial response environment.

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