Spillover Effects of Online Reviews: Evidence From the Hotel Industry

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Abstract

Do online consumer reviews have spillover effects on the sales of competitors? We study this question using a natural experiment where a major hotel group introduced its own review system to all the hotels within its portfolio. Using a modified Synthetic Control Method, we analyze the monthly financial performance data of reviewed and competing hotels before and after the review system was introduced. We find that the review system has significant economic impacts on both reviewed and competing hotels, and that the effects are highly heterogeneous. Surprisingly, the correlation between the economic impact on reviewed and competing hotels is significantly positive: If the occupancy rate of a reviewed hotel increases by 1%, its competitors' occupancy rate increases by 0.39%. The positive correlation can be explained by the information spillover. Under this mechanism, consumers update their beliefs about competing hotels based on the reviews for reviewed hotels. We explore alternative explanations, but none can fully explain the positive correlation. Our results suggest that, besides monitoring their own reviews, managers should also monitor competing products' reviews because of information spillover from the competitors' reviews.

Keywords: Online reviews, heterogeneous treatment effects, spillover effects, information spillover, Synthetic Control Method, natural experiment

1. Introduction

Over the past two decades, researchers have extensively investigated the effects of online reviews, or in a broader sense, electronic word of mouth, on sales. The research has focused on many product categories, including online books (Chevalier and Mayzlin 2006), movies (Chintagunta et al. 2010), restaurants (Wu et al. 2015, Luca and Zervas 2016), hotels (Hollenbeck 2018, Hollenbeck et al. 2019), technology, and home and garden products (Vana and Lambrecht 2021). Reviews are an important source of information for consumers to learn true product or service quality (e.g., Wu et al. 2015). Consequently, various review metrics, such as the valence, volume, and variance, are significantly correlated with the sales of the business entities under review (for a meta-analytic literature review, see Babić Rosario et al. (2016)). This stream of literature, however, has mostly been silent on the potential spillover effects of online reviews from one to other related businesses.

In this paper, we empirically study three research questions: First, are there any spillover effects of online consumer reviews on competitors' sales? Second, if spillover effects do exist, do they move in a particular direction? Specifically, we ask: if a firm's sales benefit or suffer from online reviews of its offering, will the sales of its rivals also benefit or suffer? Finally, what are the potential mechanisms for the spillover effects, if they exist?

Reviews can not only influence the sales of the reviewed business but also have spillover effects and affect the sales of competing businesses. If the reviews provide consumers with useful information that is common across the businesses, then the effects on the sales of the reviewed business and competitors are likely to move in the same direction. In this sense, reviews have a spillover effect similar to advertisements. Previous studies (Anderson and Simester 2013, Lewis and Nguyen 2015, Sahni 2016, Shapiro 2018) have documented the significance of spillover effects of advertising. Their findings are important for firms to determine optimal advertising strategies. From the firm's perspective, it is crucial to better understand the spillover effect of competitors' reviews and strategically engage in active online reputation management (e.g., Proserpio and Zervas 2017) or other marketing plans to stimulate sales. Therefore, our study has significant managerial implications.

We collaborate with a major international hotel group (henceforth, the "company") to achieve our research objectives. In 2012, the company implemented a review system on its website that enabled guests to review its affiliated hotels after completing their stay. Though hotel reviews were already available at external websites such as TripAdvisor.com and Expedia.com, this policy change offers consumers a new channel for finding additional reviews about the company's hotels (henceforth, "reviewed hotels"). Our study utilizes this change as a natural policy experiment.

Individual hotels could not opt out of the review system. Therefore, the policy change can be regarded as exogenous to the individual demand shocks for any reviewed hotel and for other hotels in the same geographical market (henceforth, "competing hotels"). This institutional feature facilitates the inference of the causal effects of the policy change.

We obtain the financial performance data of every reviewed hotel from the company before and after the implementation of the review system. To infer the spillover effects of the reviews on competing hotels, we first ask the company for a complete list of its competitor hotels. We then obtain from Smith Travel Research (STR), a leading hotel industry research firm, the financial performance data of every competitor on the list (for the same period before and after implementation of the review system) in each geographical market. To explore the underlying mechanisms for our findings, we further collect data on reviews not only from the review system of reviewed hotels but also from TripAdvisor.com, the leading travel review platform.

We modify the Synthetic Control Method (SCM) proposed by Abadie (2021) and estimate the treatment effect (henceforth, "TE") on the occupancy rate of reviewed hotels, as well as the spillover effect (henceforth, "SE") on the occupancy rate of competing hotels. Since the role of reviews is to inform consumers, high-quality hotels are likely to benefit from the policy change, while low-quality hotels could be negatively affected. The effects could thus be substantially heterogeneous across hotels. Therefore, we first estimate the TE for *every* reviewed hotel, using hotels that are located in the same state but outside a 15-km (9.3-mile) radius of the reviewed hotel ("donor hotels") as controls. We then estimate the SE for *every* competing hotel located within a 15-km radius of each reviewed hotel, also using donor hotels as controls. Our estimation thus recovers the full heterogeneity of TEs and SEs. This is a rare practice in the previous literature, which predominantly focuses on estimating the average effects. Finally, we use the estimated TEs and SEs to explore how the occupancy rate of a competing hotel is affected if the occupancy rate of the corresponding reviewed hotel decreases or increases because of online reviews.

We find that the empirical distributions of the estimated TEs and SEs can be approximated by normal distributions with large variances. For TEs, while the average is -0.15% and is statistically insignificant, the standard deviation is 7.80%. This implies that while the average treatment effect is negligible, many of the reviewed hotels are substantially affected by the reviews. We then turn to the SEs, which are the focus of our study. The average SE across all competing hotels is -0.46%. Though the average effect is statistically significant, the magnitude is quite small. However, the standard deviation is large, at 7.95%, which is comparable to the distribution of the TEs. For the top 10% and 25% of the competing hotels in terms of their SEs, the average occupancy rates increase by 9.02% and 4.54%, respectively. Consequently, their average monthly revenues increase by $41,413 and $27,586, respectively. The bottom 10% and 25% of hotels' average occupancy rates drop by 9.94% and 5.31%, respectively, implying average revenue reductions of $41,413 and $27,586. Overall, the results show that the spillover effects are economically significant for many competing hotels.

Based on our estimation results, we then test how the estimated TE and SE are correlated for a reviewed hotel and a competing hotel. We find that the correlation between TEs and SEs is 0.38 and statistically significant. A simple regression shows that if one of the reviewed hotels experiences a 1% increase (decrease) in the occupancy rate, its competing hotels, on average, also gain (lose) 0.39% sales of room nights. This finding is surprising, because hotels within the same geographic market are normally considered as substitutes for one another. Our results, however, suggest a complementary relationship, as both reviewed hotels and their competing hotels either benefit from or are hurt by the reviews.

We explore potential mechanisms that drive the positive correlation between TEs and SEs. We focus on *information spillovers* from online reviews, which help consumers learn about the attributes that reviewed and competing hotels share. In particular, we examine location information: as reviews provide positive (negative) information about a reviewed hotel's location, they will increase (decrease) the attractiveness of competing hotels nearby, causing the positive correlation between TEs and SEs.

To explore this mechanism, we first note from the data that the average distance between reviewed and competing hotels is less than half the average distance between reviewed and other hotels in the same geographic market (not regarded as competitors by the company). Next, we use the Latent Dirichlet Allocation (LDA) to extract topics from the posted reviews. We find that the higher the location topic score in the reviews, the larger the correlation between the TE on a reviewed hotel and its competing hotels' SEs. We also find that the impact of the location topic score on the correlation decreases as the distance between a pair of hotels increases, providing additional evidence supporting the location-information spillover effect of online reviews.

We further examine several other potential explanations. First, we show that the room capacity of reviewed hotels cannot fully explain our findings. Then we rule out the explanation that the reviewed hotels that experience positive or negative TEs strategically adjust prices and thus affect the demand of competitors. After that, we examine whether online reviews drive consumers to search for competing hotels – Lewis and Nguyen (2015) and Sahni (2016) show that display ads induce consumers to search for competing businesses as well as advertised ones. Our examination, using data from TripAdvisor.com, provides suggestive evidence that consumers jointly search for reviewed hotels and their competitors.

Our paper contributes to the literature on electronic word of mouth (eWOM) by documenting spillover effects from online reviews. Unlike in previous literature, we allow for the full heterogeneity of both spillover and treatment effects across individual businesses. Doing so allows us to establish the counterintuitive finding that TEs and SEs are positively correlated. We provide evidence for the mechanism underlying the positive relationship. We believe that information spillovers from online reviews are important in other empirical contexts beyond the hotel industry.

The rest of this paper proceeds as follows. In Section 2, we review the related literature and discuss our contribution. Section 3 details our conceptual framework. Section 4 describes the data and summary statistics. Section 5 details our empirical approach. In Sections 6 and 7, we discuss our findings and the potential mechanisms. Section 8 concludes.

2. Literature Review

This paper is related to the aforementioned eWOM literature, where the early research predominantly focuses on investigating the impact of aggregate review metrics on product sales or stock market performance (e.g., Chevalier and Mayzlin 2006, Chintagunta et al. 2010, Zhu and Zhang 2010, Tirunillai and Tellis 2012). Wu et al. (2015) measure the economic value of different information components of reviews. Recently, the focus has shifted to understanding the impact of individual reviews on purchasing (e.g., Vana and Lambrecht 2021). Researchers also investigate fake reviews (e.g., Mayzlin et al. 2014, Luca and Zervas 2016, He et al. 2022), as well as the representativeness of online reviews (e.g., Schoenmueller et al. 2020, Karaman 2021, Brandes et al. 2022).

In the context of the hotel industry, Hollenbeck (2018) shows that the value of chain affiliation has decreased due to the growth of online reviews. Hollenbeck, Moorthy, and Proserpio (2019) document that an increase in online ratings leads to a decline in ad spending, implying that online ratings can substitute for advertisements. Recently, Proserpio and Zervas (2017), Chevalier et al. (2018), and Wang and Chaudhry

(2018) have investigated the relationship between a firm's use of management responses and its online reputation.

Unlike the above works, our study focuses on the spillover effects of online reviews. To our knowledge, Chae et al. (2017) is the only paper related to this focus. They show that using seeded online posts (i.e., giving free products to selected customers to encourage them to review the products) reduces the number of posts discussing the firm's other products and the number of posts discussing products from competing firms. Our paper differs from Chae et al. (2017) in three ways. First, we study generic reviews instead of seeded WOM, a type of ad campaign. Second, we study the full heterogeneity of TEs and SEs from the reviews. Third, and perhaps most important, we study the effect on sales rather than on posts, which is more relevant from a business perspective.

Given our research focus, this paper also relates to the research on the spillover effects of a firm's actions on its competitors. On one hand, conventional wisdom says that a firm's action that yields beneficial outcomes will hurt its competitors. Chae et al. (2017), for example, show that seeded WOM negatively impacts competing products in the same category. On the other hand, previous research documents that positive spillover effects from marketing actions may exist. Lewis and Nguyen (2015), for example, show that online display ads make consumers subsequently search for their own brands *and* competing brands in the same category. Sahni (2016) uses a field experiment to show that the display ads on a restaurant search platform positively affect the sales leads of competing restaurants with similar cuisine. Anderson and Simester (2013) find that when a company advertises its own products to its competitor's customers, those customers end up buying more of the competitor's products. Shapiro (2018) shows that television advertising for prescription drugs has positive spillovers on demand for competing products.

The contrapositive has also been explored: previous research documents that negative events to a firm bring about negative spillovers to competing firms. For instance, Ozturk et al. (2019) find that as Chrysler's bankruptcy filing news spread, consumers became uncertain about its competitors' viability, which reduced sales of competing brands. Borah and Tellis (2016) show that automobile recalls raise negative chatter about competing products in the same category.

Our paper also contributes to the literature on firm agglomeration, which demonstrates the spillover effects from the colocation of multiple firms or stores. The benefits of agglomeration stem from consumers' needs from complementary categories (e.g., gas station and grocery.) Consumers can reduce travel costs if firms are colocated (Arentze et al. 2005, Sen et al. 2012). Other studies argue that agglomeration could have two opposing effects: (1) it can intensify price competition (Baum and Haveman 1997), and (2) it allows consumers to compare quality and prices; as such, when agglomerate, they can attract more customers (Vitorino 2012).

Hotels are a prime example of services greatly impacted by such effects. For example, Baum and Haveman (1997) argue that new hotels tend to locate near established hotels that are similar in price but different in size to take advantage of the positive effect of colocation while avoiding price competition. Chung and Kalnins (2001) show that chain and large hotels contribute to positive spillovers, and that independent and smaller hotels are likely to benefit from their proximity. Our study of the effects of online reviews on both reviewed hotels and their colocated competing hotels contributes a novel finding to this stream of literature.

3. Conceptual Framework

This section provides a conceptual framework of Bayesian learning under which consumer reviews affect the occupancy rates of the reviewed hotel (TE) and its competing hotels (SEs).[1] Further, the framework uses information spillovers to explain why SEs and TE are positively correlated, i.e., the occupancy rates of the reviewed hotel and competing hotels increase or decrease together.

Let hotel r be the reviewed hotel and $\mathcal{C}$ be the set of r's competing hotels, which have multiple attributes like those of hotel r. For example, they are proximate, so the attractiveness of the location applies to both r and its competing hotels. Let $\mathcal{O}$ be the set of other hotels in the same market. The attributes of hotels in $\mathcal{O}$ are less like those of hotel r.

[1] Other frameworks could possibly explain information spillovers. We focus on Bayesian learning to be consistent with previous literature (Erdem and Keane 1996, Ching et al. 2013, Ching and Lim 2020).

For consumer i, assume the utility of staying at hotel h (the reviewed hotel, one hotel in $\mathcal{C}$, or one hotel in $\mathcal{O}$) is:

$$u_{ih} = \beta_h + \xi_h + \varepsilon_{ih} \tag{1}$$

where β_h represents qualities of attributes that the consumer knows without reading the reviews (e.g., room rates, location) and ξ_h are qualities of attributes that the consumer has uncertainty about but can learn from the reviews (e.g., convenience, safety, attractiveness of the hotel's location). We assume that the true values of ξ_h are symmetrically distributed around zero and that consumers have an unbiased belief about the average of ξ_h being zero for all h's before reading the reviews. Furthermore, consumers know that reviewed hotels are more similar to competing hotels than other hotels in terms of attributes. Therefore, consumers have prior on $\boldsymbol{\xi} = \begin{pmatrix} \xi_r \\ \boldsymbol{\xi_{\mathcal{C}}} \\ \boldsymbol{\xi_{\mathcal{O}}} \end{pmatrix}$, where $\boldsymbol{\xi_{\mathcal{C}}}$ ($\boldsymbol{\xi_{\mathcal{O}}}$) is a vector consisting of $\xi_c, \forall c \in \mathcal{C}$ ($\xi_o, \forall o \in \mathcal{O}$), and the prior belief is normally distributed as follows: $\boldsymbol{\xi} \sim N(\vec{0}, \Sigma)$. ρ_{jk} captures the covariance between hotel pairs of (j,k) in Σ. We assume[2] that $\rho_{rc} > \rho_{ro} = 0$. For brevity, we fix the variances for all h as 1.

The consumer chooses a hotel to maximize their expected utility. Without reviews, the expected utility of staying at hotel h is $E(u_{ih}) = \beta_h + \varepsilon_{ih}$. Assume that the idiosyncratic error term ε_{ih} has type I extreme value distribution, and none of the hotels has reached the maximum capacity. Accordingly, the market share of hotel h without the review system is

$$s_h = \frac{\exp(\beta_h)}{\exp(\beta_r) + \sum_{c \in \mathcal{C}} \exp(\beta_c) + \sum_{o \in \mathcal{O}} \exp(\beta_o)} \tag{2}$$

Suppose hotel r implements a review system, and the consumer receives a signal, R_r, from the reviews about the true value of hotel attribute ξ_r. Assume that the reviews are unbiased but consist of noise such that $R_r \sim N(\xi_r, \sigma^2)$. Therefore, we can apply the Bayesian updating rule (DeGroot 2005): the consumer will update their belief on ξ_r by reading the reviews, and the posterior belief on ξ_r will be distributed as $N(\mu_{r1}, \tau_{r1}^2)$, where

$$\mu_{r1} = \frac{1}{1+\sigma^2} R_r \text{ and } \tau_{r1}^2 = \frac{\sigma^2}{1+\sigma^2} \tag{3}$$

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[2] The rest of the discussion also holds if $\rho_{rc} > \rho_{ro} \geq 0$.

Further, since consumers believe that ξ_r and ξ_c are correlated, they will update their belief on ξ_c, and the posterior mean is

$$\mu_{c1} = \frac{\rho_{rc}}{1+\sigma^2} R_r = \rho_{rc}\mu_{r1} \tag{4}$$

In other words, information in the reviews spills over to competing hotels because consumers are aware that competing hotels share similar attributes with the reviewed hotel.

Therefore, the market share of the reviewed hotel after the review system is

$$s_r(R_r) = \frac{\exp(\beta_r+\mu_{r1})}{\exp(\beta_r+\mu_{r1})+\sum_{c\in C}\exp(\beta_c+\rho_{rc}\mu_{r1})+\sum_{o\in O}\exp(\beta_o)} \tag{5}$$

if none of the hotels has reached its maximum occupancy. Similarly, the market share of competing hotel *c* will be

$$s_c(R_r) = \frac{\exp(\beta_c+\rho_{rc}\mu_{r1})}{\exp(\beta_r+\mu_{r1})+\sum_{c\in C}\exp(\beta_c+\rho_{rc}\mu_{r1})+\sum_{o\in O}\exp(\beta_o)} \tag{6}$$

We can obtain several results from this conceptual framework:

Result 1: *Given that consumers have an unbiased prior belief on ξ_r (i.e., $E(\xi_r) = 0$) and R_r is distributed as $N(\xi_r, \sigma^2)$, about half of the reviewed hotels will experience a positive treatment effect.*

Result 2: *There will be spillover effects on the occupancy rate of competing hotels. Whether the spillover effect on competing hotels is positive or negative depends on R_r and the magnitude of ρ_{rc}.*

Result 3*: If ρ_{rc} is large enough, the correlation between the spillover effects on competing hotels and the treatment effects on reviewed hotels will be positive. Further, the larger ρ_{rc} is, the larger the correlation will be.*

A numerical example: We present a numerical example to illustrate how the treatment and spillover effects can be positively correlated. Assume there are three hotels in a local market: one reviewed, one competing, and one other. Further, assume that $\beta_h = 0$ for all three hotels. Therefore, before the review system is enabled, the market share of each hotel is one-third and the occupancy rates are equal. Now consider the consequences of implementing the review system when the reviewed hotel receives positive (i.e., $\mu_{r1} = 1$) or negative reviews (i.e., $\mu_{r1} = -1$).

(1) $\rho_{rc} = 0.2$.

When $\mu_{r1} = 1$, the reviewed hotel's market share will increase from 33.33% to 55.03%. The market share of the competing hotel will decrease from 33.33% to 24.73%. However, if $\mu_r = -1$, the market share of hotel *r* will drop to 16.82%, whereas the market share of hotel *c* will increase from 33.33% to 37.44%. That is, even though ρ_{rc} is positive, the market shares of competing and reviewed hotels will move in opposite directions because of ρ_{rc}'s small magnitude, leading to a negative correlation between TE and SE.

(2) $\rho_{rc} = 0.7$.

When $\mu_{r1} = 1$, the market share of hotel *r* will increase to 47.42% and hotel *c*'s market share will also rise to 35.13%. However, if $\mu_r = -1$, the market shares of hotels *r* and *c* will decrease to 19.73% and 26.63%, respectively. Since ρ_{rc} is sufficiently large, the market shares of reviewed and competing hotels move in the same direction, resulting in a positive correlation between TE and SE.

4. Data and Statistics

In this section, we first describe the data source and the company's policy change. Then we describe how we classify hotels in our analysis. Finally, we present some summary statistics.

4.1. Data

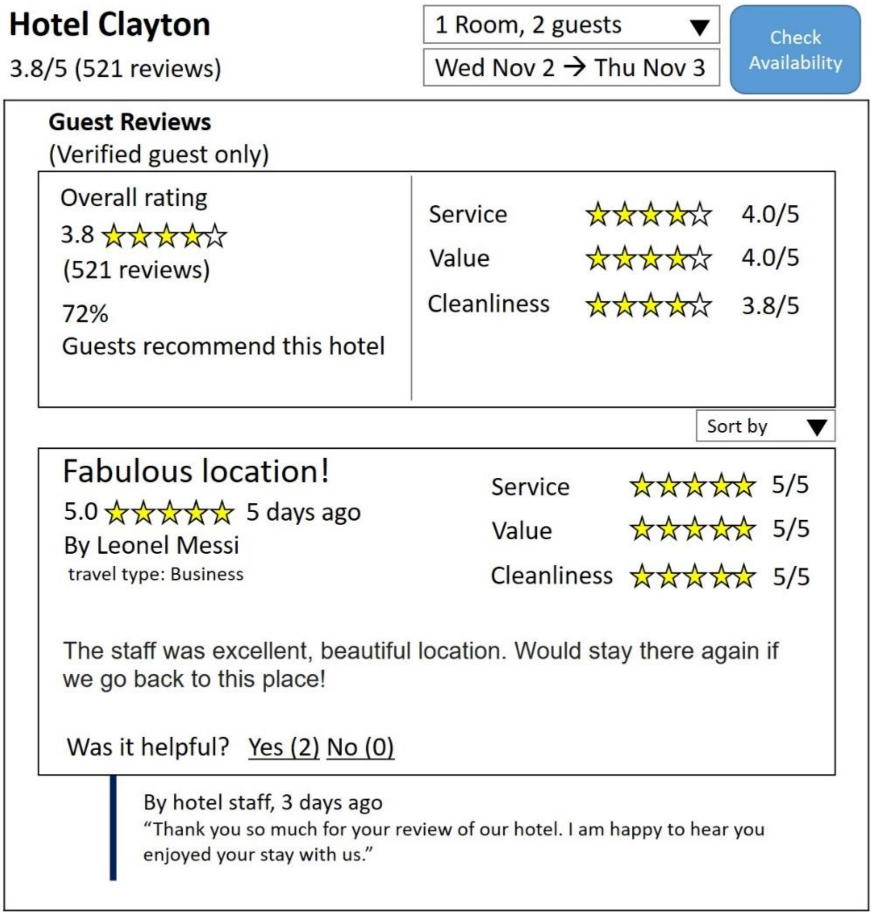
To study the effects of reviews, we compile a unique dataset from three sources, including (1) a major international hotel group (the "company"), (2) TripAdvisor.com, and (3) Smith Travel Research (STR), a research firm that collects market data on the hotel industry worldwide.

The company is one of the major international hotel groups, operating approximately 5% of all hotels in the United States. These hotels in the United States account for 68% of the company's hotel portfolio. Even though the company has a significant worldwide presence, we focus on these hotels located in the United States. The company has at least one affiliated property in almost all metropolitan statistical areas defined by U.S. Census Bureau.

The company hosts separate websites for each hotel in its portfolio. From the company's home page, customers can search and access individual hotel websites, which contain detailed information on each property (including location, amenities, availability, and prices) before making a reservation.

On June 1, 2012, the company launched an online review system that enabled guests to post reviews about their stays in any of the affiliated hotels. A reviewer is required to submit an overall rating, as well as ratings on various dimensions (e.g., service, value, cleanliness) of their stay; ratings are on a 1-to-10 scale. The reviewer also needs to write a review title and at least 50 characters of text for the review, then indicate the purpose of their trip. Figure 1 illustrates a hypothetical example of a review from a hotel's website.

Figure 1. Review Section in a Hotel Webpage



Note that the company implemented the review system on all affiliated hotels' websites; individual hotels could not opt out. This salient feature implies that the review system is exogenous to the demand shocks of any affiliated and nonaffiliated hotels in a given geographical market.

The company provided us with the monthly financial performance data for each of the 2,586 *reviewed* affiliated hotels from January 2010 to December 2015 (72 months). As such, we have data for 29 months before and 43 months after the review system was enabled. For each hotel, we observe (1) the total number of rooms in the hotel multiplied by the number of days in a given month, (2) the sum of the daily number of rooms sold in a given month, and (3) total monthly revenue. Using these observations, we calculate the average daily room rate (henceforth, ADR) for each month [dividing (3) by (2)], the monthly occupancy rate [dividing (2) by (1)], and the average daily revenue per available room (henceforth, RevPAR) for each month [dividing (3) by (1)].

The company also gave us a list of all hotels it competes with, which (the company told us) is compiled based on property managers' feedback and industry reports prepared by third-party researchers. Based on the list, we identify 8,432 hotels in the United States. We then obtain from STR the property-level financial performance data for these hotels from January 2010 to December 2015 (for the same variables described in the previous paragraph).

In addition, we scrape the text and ratings of each reviewed hotel from the company's website. From TripAdvisor.com, we extract reviews of the reviewed hotels and potential competitor hotels and their Expedia star ratings, which attempt to objectively represent the variety and quality of services and amenities offered by a hotel, ranging from 1 (lowest) to 5 (highest).

Finally, we collect data on several other characteristics of every hotel in the United States: class (e.g., economy, luxury), year opened, number of floors, hotel amenities (e.g., restaurants, fitness center, meeting space), location type (e.g., suburban or small metro), city, state, GPS coordinates, brand name, and management type (i.e., franchise, direct chain management, or independent). We use these characteristics throughout our analysis to calculate, for example, distances among hotels using the GPS coordinates.

4.2. Treated and Donor Hotels

Both the *reviewed* hotels and their *competing* hotels (henceforth, both are labeled as *treated* hotels) could be affected by the reviews. To define the latter, we focus on the aforementioned list of 8,482 competitor hotels. If any hotel on this list is located far from all of the reviewed hotels, there should not be any spillover effects from the reviews, since the hotel is in another geographical market. We thus add another criterion to determining a competing hotel: it must also be located within a 15-km (9.3-mile) radius of at least one reviewed hotel of a similar class. With this criterion, the number of competing hotels reduces to 7,926.

Next, we explain how we define *control* units in our empirical application. The first step is to identify hotels that are not affected by the reviews so that we can use them to infer TEs for reviewed hotels and SEs for competing hotels. Conceptually, we can use hotels that are not reviewed and competing hotels. However, if a hotel is within a 15-km radius of a reviewed hotel, its sales could still be affected by the reviews, even though it is not identified by the company as a competitor. As such, we exclude from the analysis all hotels within a 15-km radius of at least one reviewed hotel.

We are also concerned that if we use hotels whose attributes are substantially different from the reviewed or competing hotels as the control, the estimated TEs and SEs could be imprecise. For example, if reviewed and competing hotels offer upscale facilities to attract business travelers but control hotels target leisure travelers by offering family-oriented amenities, using the latter to predict sales of the former (after the review system was enabled) may lead to incorrect inferences. Therefore, we include an additional criterion in the selection of control units: hotels should be similar to reviewed and competing hotels in many aspects but must not be in the same geographical market as treated hotels. This selection criterion suggests that we should use the competitor hotels identified by the company but located outside a 15-km radius of all the reviewed hotels.[3] We will show below that this set of hotels is more similar to the reviewed and competing hotels than other hotels on various hotel characteristics. In all, we find 234 hotels that satisfy such criteria; we label them as *donor hotels* (Abadie et al. 2010).

Next, we assign donor hotels to each of the reviewed and competing hotels. We restrict donor hotels to be in the same state as the reviewed or competing hotels. This is because state-level shocks such as state regulations and other policies are likely to similarly affect hotels in the same state. We note that, under this criterion, a reviewed hotel and its competing hotels may have different donor hotels if they locate in different states.

[3] We have also tried a 10-km radius to define competing hotels and identify donor hotels. The results are qualitatively the same.

With well-defined reviewed, competing, and donor hotels, we further filter out some hotels from the analysis. First, we exclude all reviewed hotels with fewer than five donor hotels. This is because a sparse donor pool may result in noisy inference. Next, we exclude reviewed hotels near airports. This is because we cannot find donor hotels near airports. Hotels farther from airports, however, may not be appropriate donors, because their customers can be very different. Finally, we also remove reviewed hotels renovated in any month during the sample data period to avoid biased estimates for their TEs. For competing hotels, we keep only those within a 15-km radius of their corresponding reviewed hotels that are not filtered out from the analysis. We also drop donor hotels if their corresponding reviewed or competing hotels are also removed from the analysis. With these additional filters, 964 reviewed hotels and 2,740 competing hotels remain; each of these reviewed hotels has 3.35 competing hotels on average. In our final dataset, there are 3,227 unique pairs of reviewed and competing hotels, and 102 donor hotels. Each reviewed or competing hotel has 7.57 donor hotels on average (minimum: 5, maximum: 12).

To ensure that the remaining reviewed and competing hotels are representative, we compare their characteristics with hotels excluded from the analysis. We find that the characteristics are very similar (see Online Appendix A for the comparison). Therefore, the selection criteria described above do not introduce any detectable bias.

4.3. Summary Statistics

Table 1 compares a battery of hotel characteristics for reviewed, competing, and donor hotels. As a reference, we also list the characteristics of hotels that are not considered as competitors by the company and are located outside a 15-km radius of every reviewed hotel. We observe that donor hotels are, on average, more like treated hotels than other hotels are. For instance, 96.47% of reviewed hotels, 87.26% of competing hotels, and 98.04% of donor hotels are franchised, while only 26.47% of other hotels are managed by franchisees.

However, even though donor hotels are similar to treated hotels, they are located very far from their corresponding reviewed hotels, with an average distance of 272 km. We observe that the average distance between reviewed and competing hotels is 3.52 km—much shorter than the average distance of 7.29 km between reviewed hotels and other hotels within a 15-km radius of any reviewed hotels. This observation suggests that hotels in a competing relationship tend to be located very close to each other. Therefore, given the average distance between donor hotels and treated ones, they are very unlikely to be competitors; as a result, donor hotels would not be exposed to spillover effects. In sum, we establish that donor hotels satisfy two important criteria as control units: (1) having similar characteristics as treated hotels and (2) not being subject to spillover effects.

Table 1. Hotel Characteristics

Variable	**Reviewed Hotels**	**Competing Hotels**	**Donor Hotels**	**Other Hotels Outside 15km**
Class*	3.03 (0.46)	2.95 (1.03)	2.34 (0.88)	1.92 (1.35)
Age**	22.26 (11.33)	25.49 (12.44)	24.85 (9.95)	43.98 (28.12)
Number of rooms	110.64 (62.89)	110.28 (69.94)	72.49 (30.31)	46.54 (66.64)
With restaurant	22.61%	22.19%	15.69%	27.0%
All suites	19.09%	22.74%	5.88%	8.12%
Indoor corridor	98.86%	90.99%	89.22%	37.34%
Total meeting space (sq. ft.)	2,453.73 (5,382.78)	2,300.16 (6,989.65)	1,244.43 (2,885.21)	1,113.67 (4,570.86)
Largest meeting space (sq. ft.)	1,414.59 (2788.75)	1,232.36 (3143.18)	752.67 (1227.02)	600.87 (1873.39)
Number of floors	4.19 (2.66)	3.97 (2.63)	2.70 (0.84)	2.19 (1.42)
Franchised hotel	96.47%	87.26%	98.04%	26.47%
Independent hotel	0%	1.97%	0.98%	72.11%
Interstate	16.08%	15.11%	36.28%	15.53%
Small metro	22.72%	20.70%	50.0%	71.96%
Suburban	53.53%	56.86%	13.73%	6.62%
Urban	7.68%	7.36%	0%	0.20%
Distance*** (km)		3.52 (3.61)	272.03 (189.13)	295.93 (613.08)
N	964	2,740	102	12,823

Notes. Each value represents the average across each type of hotel, and the values in parentheses are standard deviations. *****Class: 1 = Economy, 2 = Midscale, 3 = Upper Midscale, 4 = Upscale, 5 = Upper Upscale, 6 = Luxury. **Age is 2021 minus the year established. ***Distances for competing and donor hotels are the average distances from the corresponding reviewed hotel. The distance for other hotels outside the 15-km radius is the average distance from the closest reviewed hotel.

Table 2 shows rating metrics and occupancy rates for reviewed, competing, and donor hotels, which are measured before the introduction of the review system. On average, treated hotels have more TripAdvisor reviews, higher average ratings, higher Expedia star ratings, and higher occupancy rates than donor hotels. Though we suspect that donor hotels are more like treated hotels than other hotels outside the 15-km radius, we do not have data on these variables for other hotels to use for reference, as we do in Table 1.

Table 2. Ratings and Occupancy Rate

Variables	**Reviewed Hotels**	**Competing Hotels**	**Donor Hotels**
Number of reviews in TripAdvisor	29.81	31.72	19.42
	(36.19)	(46.26)	(21.12)
Average rating in TripAdvisor	3.95	3.80	3.73
	(0.52)	(0.63)	(0.77)
Variance of rating in TripAdvisor	1.26	1.22	1.15
	(0.63)	(0.59)	(0.72)
Expedia star rating	2.65	2.63	2.38
	(0.37)	(0.43)	(0.37)
Occupancy rate (Occ)	62.55%	60.89%	53.85%
	(11.10%)	(12.72%)	(12.48%)

Notes. Each value represents the average across each type of hotel, and the values in parentheses are standard deviations. We measure the values in this table using pretreatment data.

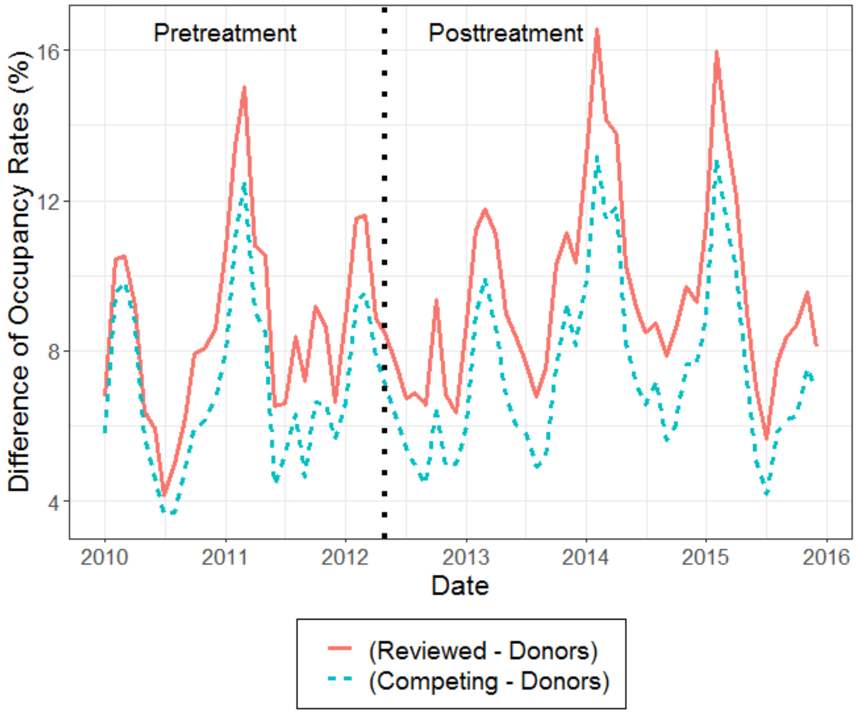
In Table 3, we compare the average occupancy rates for reviewed, competing, and donor hotels before and after the treatment. After the treatment, reviewed and competing hotels' average occupancy rates increase by 5.75% ($p < 0.01$) and 5.28% ($p < 0.01$), respectively, compared to the pretreatment period. We note that donor hotels' average occupancy rate also significantly increases, by 4.87% ($p < 0.01$), despite not being affected by the treatment, suggesting that the treated hotels' increase in occupancy rates may be outcomes of concurrent exogenous shocks in addition to TEs and SEs. Therefore, to identify the net effects of reviews, it is crucial that we use the donor hotels as control units.

Table 3. Pretreatment and Posttreatment Occupancy Rates

	Pretreatment Occupancy	Posttreatment Occupancy	Difference
Reviewed hotels	62.55% (11.10%)	68.30% (9.47%)	5.75% ***
Competing hotels	60.89% (12.72%)	66.18% (11.83%)	5.28% ***
Donor hotels	53.85% (12.48%)	58.73% (12.74%)	4.87 ***

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

Figure 2. Trends in Occupancy Rate Differences



Notes. The solid line captures the difference between the average monthly occupancy rates of reviewed and donor hotels. The dashed line represents the difference between the average monthly occupancy rates of competing and donor hotels. The black dashed line indicates when the company implemented the review system.

A simple comparison of averages reported in Table 3 suggests that the effects may be positive, but it cannot reveal the heterogeneity of the effects. One way to capture heterogeneity is to conduct the analysis at the individual hotel level. This can be achieved by estimating a Difference-in-Differences (DID) regression for each treated hotel directly using the corresponding donor hotels as controls. However, Figure 2 suggests that the parallel trends assumption does not hold on average, and it is highly unlikely that the parallel trends assumption is satisfied for all hotels individually. Moreover, it is impractical to check whether the parallel trends assumption holds for each one of the 3,704 treated hotels. For this reason, the DID is not ideal for analysis at the individual hotel level. Instead, we use the method described in the next section.

5. The Synthetic Control Method (SCM) and Estimation

The launch of the review system serves as a natural experiment, allowing us to use the SCM proposed by Abadie (2021) to infer the TEs and SEs. The approach uses donor hotels to predict the counterfactual outcome for treated hotels had they not been treated in the posttreatment period. The inference is based on the information of both the outcomes and the match of characteristics between donor and treated hotels in the pretreatment period. The SCM is more flexible than the DID approach, since it relaxes the restrictive assumption of parallel trends between treated and control units. To recover the full heterogeneity in the effects of the reviews, we apply the SCM for each of the 964 reviewed hotels and 2,740 competing hotels (in total, 3,704 treated hotels).

5.1. The Model

For each treated hotel, suppose there are H donor hotels during the sample periods. There are T month periods. We denote the treated hotel as the first unit ($h = 1$) and the remaining $h = 2, \dots, H + 1$ are the donor hotels. The treatment (enabling the reviews) starts in period T_0 (i.e., June 2012). The pretreatment periods are from period 1 to period $\mathrm{T}_0 - 1$, and the posttreatment periods are from period T_0 to period T. Let Y_{ht}^R be the outcome (e.g., occupancy rate) for hotel h in period t if the hotel is treated, and Y_{ht}^N be the outcome if the hotel is untreated. In posttreatment periods, the TE (if the hotel is a reviewed hotel) or the SE (if the hotel is a competing hotel) in period t is $\alpha_{1t} = Y_{1t}^R - Y_{1t}^N$. However, we observe only Y_{1t}^R but not the counterfactual outcome Y_{1t}^N, which must be estimated using SCM.

Following Abadie et al. (2010), Y_{ht}^N of hotel h in (the pre or posttreatment) period t is specified by a linear factor model as follows:

$$Y_{ht}^N = \delta_t + \boldsymbol{\theta_t Z_h} + \boldsymbol{\lambda_t \mu_h} + \epsilon_{ht} \tag{7}$$

where δ_t is a time-specific factor that is common across all hotels, and $\boldsymbol{Z_h}$ is a $(K \times 1)$ vector of observed hotel characteristics. Furthermore, $\boldsymbol{\lambda_t}$ is a $(1 \times F)$ vector of time-specific common factors across hotels, and

$\boldsymbol{\mu_h} = (\mu_{h1}, \dots, \mu_{hF})'$ is an $(F \times 1)$ vector of hotel-specific factor loadings. Finally, the error term ϵ_{ht} represents unobserved demand shocks. In this specification, $\boldsymbol{\lambda_t \mu_h}$ captures a flexible time trend. The DID model is a special case that imposes $\boldsymbol{\lambda_t}$ to be constant for all t.

For the treated hotel (h=1), the outcome in the posttreatment periods will be

$$Y_{1t}^{R} = \alpha_{1t} + \delta_t + \boldsymbol{\theta_t Z_1} + \boldsymbol{\lambda_t \mu_1} + \epsilon_{1t} \tag{8}$$

where α_{1t} is the TE or SE.

For the treated hotel, Y_{1t}^{N} is unobserved in posttreatment periods. To infer Y_{1t}^{N} and α_{1t} for $t \geq T_0$, the SCM estimates weights $\boldsymbol{W} = (w_2, \dots, w_{H+1})'$ using pretreatment data such that $Y_{1t}^{N} \approx \sum_{h=2}^{H+1} w_h Y_{ht}^{N}$ where $\sum_{h=2}^{H+1} w_h = 1,\ w_h \geq 0$, and Y_{1t}^{N} and Y_{ht}^{N} are observed outcomes of treated and donor hotels for $t < T_0$. In Abadie et al. (2010), $\boldsymbol{W}$ also satisfies the conditions that $\boldsymbol{Z_1} \approx \sum_{h=2}^{H+1} w_h \boldsymbol{Z_h}$. We can forecast counterfactual values of Y_{1t}^{N} for $t \geq T_0$ using $\sum_{h=2}^{H+1} w_h Y_{ht}^{N}$ and infer the values of α_{1t} using $Y_{1t}^{R} - \sum_{h=2}^{H+1} w_h Y_{ht}^{N}$.

One potential issue of this specification is that Y_{1t}^{N} could be outside the convex hull of Y_{ht}^{N} for $t < T_0$ such that $Y_{1t}^{N} \neq \sum_{h=2}^{H+1} w_h Y_{ht}^{N}$. This is the case when the average Y_{1t}^{N} is larger or smaller than Y_{ht}^{N} for all donor hotels. To solve this issue, we modify equations (7) and (8) by adding a hotel fixed effect γ_h. The modified Equation (7) becomes

$$Y_{ht}^{N} = \gamma_h + \delta_t + \boldsymbol{\theta_t Z_h} + \boldsymbol{\lambda_t \mu_h} + \epsilon_{ht} \tag{9}$$

We then transform the model by subtracting the averages across pretreatment periods from both sides of Equation (9). The equation can be rewritten as

$$\tilde{Y}_{ht}^{N} = \tilde{\delta}_t + \boldsymbol{\tilde{\theta}_t Z_h} + \boldsymbol{\tilde{\lambda}_t \mu_h} + \tilde{\epsilon}_{ht} \tag{10}$$

where on the left side, $\tilde{Y}_{ht}^{N} \equiv Y_{ht}^{N} - \bar{Y}_h$, and $\bar{Y}_h = \frac{\sum_{t=1}^{T_0-1} Y_{ht}^{N}}{T_0 - 1}$. On the right side, $\tilde{\delta}_t = \delta_t - \bar{\delta}$, $\boldsymbol{\tilde{\theta}_t} = \boldsymbol{\theta_t} - \boldsymbol{\bar{\theta}}$, $\boldsymbol{\tilde{\lambda}_t} = \boldsymbol{\lambda_t} - \boldsymbol{\bar{\lambda}}$, $\tilde{\epsilon}_{ht} = \epsilon_{ht} - \bar{\epsilon}_h$, and $\bar{\delta} = \frac{\sum_{t=1}^{T_0-1} \delta_t}{T_0 - 1}$, $\boldsymbol{\bar{\theta}} = \frac{\sum_{t=1}^{T_0-1} \boldsymbol{\theta_t}}{T_0 - 1}$, $\boldsymbol{\bar{\lambda}} = \frac{\sum_{t=1}^{T_0-1} \lambda_t}{T_0 - 1}$, and $\bar{\epsilon}_h = \frac{\sum_{t=1}^{T_0-1} \epsilon_{ht}}{T_0 - 1}$.

Since the modification demeans the average outcome $\bar{Y}_h$ for every hotel, it ensures that $\tilde{Y}_{1t}^{N}$ stays within the convex hull of $\tilde{Y}_{ht}^{N}$ of donor hotels. The predicted Y_{ht}^{N} in posttreatment periods can be calculated as $\bar{Y}_1 + \sum_{h=2}^{H+1} w_h \tilde{Y}_{ht}^{N}$.

5.2. Estimation

To estimate TEs and SEs, we need to first estimate $\boldsymbol{W} = (w_2, \dots, w_{H+1})'$, and based on $\boldsymbol{W}$, we predict the outcome had the treated hotel not been treated, i.e., Y_{1t}^N for $t \geq T_0$. Following Abadie et al. (2015) and Abadie (2021), we incorporate out-of-sample validation for better inference. We divide pretreatment periods into training (January 2010 to May 2011) and validation (June 2011 to May 2012) periods. See Figure 3 for a graphical illustration. The starting point of the validation period is denoted by t_0. Let $\boldsymbol{X_1^{train}}$ be a $(L \times 1)$ vector of a treated hotel's observed variables in the training period, and $\boldsymbol{X_0^{train}}$ the corresponding $(L \times H)$ matrix of the same variables for donor hotels $h = 2, \dots, H+1$ (refer to Table 4 for the list of variables). If X_{l1}^{train} is the value of the lth variable in $\boldsymbol{X_1^{train}}$, and X_{lh}^{train} $(h = 2, \dots, H+1)$ is the value of the same variable for donor hotel h in $\boldsymbol{X_0^{train}}$, the optimal $\boldsymbol{W}$ minimizes the criterion function value:

$$\left\|\boldsymbol{X_1^{train}} - \boldsymbol{X_0^{train}}\boldsymbol{W}\right\|_{\boldsymbol{V}} = \left(\sum_{l=1}^{L} v_l \left(X_{l1}^{train} - w_2 X_{l2}^{train} - \dots - w_{H+1} X_{l,H+1}^{train}\right)^2\right)^{\frac{1}{2}} \tag{11}$$

$$\textit{subject to} \sum_{h=2}^{H+1} w_h = 1, \textit{ and } w_h \geq 0$$

In the above equation, v_l represents the relative importance of the lth variable. Variables with a greater prediction power on the outcome variable in the validation period would be assigned larger levels of importance. Specifically, $(v_1, \dots, v_L)'$ minimizes the following mean squared prediction error (MSPE):

$$\frac{1}{T_0 - t_0} \sum_{t=t_0}^{T_0-1} \left(\tilde{Y}_{1t}^{N,validation} - \sum_{h=2}^{H+1} w_h \tilde{Y}_{ht}^{N,validation}\right)^2 \tag{12}$$

We obtain $\tilde{Y}_{ht}^{N,validation} = Y_{ht}^N - \bar{Y}_h^{N,validation}$, where $\bar{Y}_h^{N,validation} = \frac{\sum_{t=t_0}^{T_0-1} Y_{ht}^N}{T_0 - t_0}$, and $\boldsymbol{W} = (w_2, \dots, w_{H+1})'$ from minimizing the criterion function value in Equation (11).

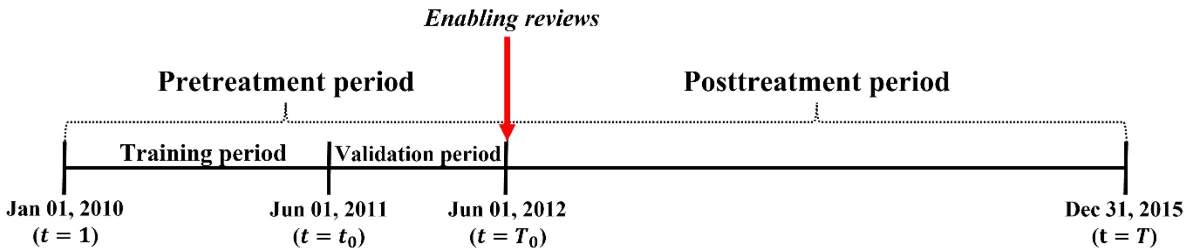
Given $\boldsymbol{W}$, we can forecast the values of Y_{1t}^N for $t \geq T_0$ using $\bar{Y}_1^{N,validation} + \sum_{h=2}^{H+1} w_h \tilde{Y}_{ht}^{N,validation}$. The synthetic control estimator for $h = 1$ in month t is

$$\hat{\alpha}_{1t} = Y_{1t}^R - \bar{Y}_1^{N,validation} - \sum_{h=2}^{H+1} w_h \tilde{Y}_{ht}^{N,validation} \tag{13}$$

and the average synthetic control estimator can be written as

$$\hat{\alpha}_1 = \frac{\sum_{t=T_0}^{T} \hat{\alpha}_{1t}}{T-T_0+1} \tag{14}$$

Figure 3. Training and Validation Periods



5.2.1. Implementation

There are 24 potential hotel variables to be included in $\boldsymbol{X}_{\boldsymbol{1}}^{\boldsymbol{train}}$ and $\boldsymbol{X}_{\boldsymbol{0}}^{\boldsymbol{train}}$ (see Table 4 for the complete list). Abadie (2021) argued that more variables may lead to better fit but can also result in overfitting and thus poor predictability in posttreatment periods. When choosing variables to be included for each treated hotel and the corresponding donor hotels, we adopt the following procedure proposed in Abadie (2021) to mitigate overfitting[4]:

1) Choose a treated hotel and its corresponding donor hotels.
2) Choose a set of variables. Find $\boldsymbol{W}$ that minimizes the criterion function in Equation (11) while $(v_1, \dots, v_L)'$ minimizes the training period MSPE between $\tilde{Y}_{1t}^{N,train}$ and $\sum_{h=2}^{H+1} w_h \tilde{Y}_{ht}^{N,train}$ (i.e., $\frac{1}{t_0-1}\sum_{t=1}^{t_0-1}\left(\tilde{Y}_{1t}^{N,train} - \sum_{h=2}^{H+1} w_h \tilde{Y}_{ht}^{N,train}\right)^2$), where $\tilde{Y}_{ht}^{N,train} = Y_{ht}^{N} - \bar{Y}_{h}^{train}$ and $\bar{Y}_{h}^{train} = \frac{\sum_{t=1}^{t_0-1} Y_{ht}^{N}}{t_0-1}$.
3) Calculate the validation period MSPE in Equation (12).
4) Repeat steps 2 to 3 for different sets of variables. Choose the set of variables that minimizes the MSPE in step 3.

However, it is very time consuming to calculate MSPEs for all possible combinations of hotel variables. We also have to repeat the procedure for all 3,704 hotels. Efroymson (1960) suggested an automatic procedure for variable selection in regression analysis in cases with many potential predictive variables, known as the "stepwise regression." In each step of this regression, a variable is added to or subtracted from

[4] Because we carry out the variable selection separately for each treated hotel, the variables included vary from one treated hotel to the next.

the set of predictive variables to be used in the estimation. The procedure continues until another step of adding or subtracting a variable does not decrease a chosen model fit criterion (i.e., MSPE in our application). We follow this procedure in the variable selection. The details are available in Online Appendix B.

After obtaining $\boldsymbol{X}_1^{train}$ for every treated hotel and $\boldsymbol{X}_0^{train}$ for its donor hotels, we take the following steps to estimate the TE or SE:

1) Find $\boldsymbol{W}$ that minimizes the criterion function in Equation (11), and $(v_1, \dots, v_L)'$ that minimizes the MSPE in the validation period in Equation (12).
2) Obtain $\hat{\alpha}_{ht}$ from Equation (13) using $\boldsymbol{W}$ from step 1 and calculate $\hat{\alpha}_h$ from Equation (14).
3) Repeat this procedure for all treated hotels.

The estimation procedure recovers the full heterogeneity of TEs for the 964 reviewed hotels and SEs for the 2,740 competing hotels.

6. Results

In this section, we first discuss the hotel variables selected in the SCM across hotels and their weights $\boldsymbol{W}$. We then report the estimated distributions of TEs and SEs. Finally, we examine the relationship between the TE of a reviewed hotel and the SEs of its competing hotels.

6.1. Weights and Selected Variables in the SCM

For each reviewed hotel, there are 3.35 competing hotels on average. We find that the SCM typically assigns high weights for three donor hotels (on average 0.58, 0.26, and 0.09) and very low (near zero) weights for the remaining donor hotels.

When implementing the SCM, 24 hotel variables are available for the optimization of $\boldsymbol{W}$ (Equation 11). These variables include reviews and ratings, room price, facilities, and average demeaned occupancy rates in each season (i.e., summer, fall, winter, and spring). Table 4 presents summary statistics for these variables and their comparison between treated and donor hotels. Treated hotels have higher average ratings and a higher average number of reviews. They also have more rooms, floors, and meeting space on average. The average demeaned occupancy rates vary between peak and off-peak seasons, and treated hotels have a smaller seasonal fluctuation than donor hotels (the positive values in summer indicate the peak season).

We apply the variable selection procedure described in Section 5.2.1 to determine variables to be included in $\boldsymbol{X}_{\boldsymbol{1}}^{\boldsymbol{train}}$ of each treated hotel. On average, 3.50 variables are selected for a hotel. The most frequently selected variables are the average demeaned seasonal occupancy rates reported in the last four rows of Table 4. We also find that the average and variance of ratings at TripAdvisor, RevPAR, small metro location, number of floors, and indoor corridor dummy variable are often included in the SCM.

Table 4. Hotel Variables in the Training Period and Selection

Variables	**Treated Hotels**	**Donor Hotels**	**Selection Percentage**
Number of reviews in TripAdvisor	12.06 (35.40)	10.06 (5.98)	12.42%
Average rating in TripAdvisor	3.84 (0.56)	3.80 (0.31)	19.25%
Variance of rating in TripAdvisor	1.17 (0.59)	1.15 (0.21)	18.36%
Average RevPAR	51.68 (19.46)	43.23 (9.45)	16.36%
Average ADR	86.51 (18.28)	82.18 (9.87)	13.74%
Class	2.90 (0.86)	2.34 (0.42)	15.58%
Expedia star rating	2.57 (0.36)	2.40 (0.15)	16.66%
Age	23.01 (9.93)	23.66 (5.08)	16.52%
Number of rooms	101.06 (48.25)	73.43 (15.22)	15.79%
With restaurant	19.30%	24.69%	11.91%
All suites	25.79%	14.88%	12.85%
Indoor corridor dummy	95.04%	81.22%	17.47%
Total meeting space size	1954.13 (4303.97)	1526.43 (1289.21)	10.99%
Largest meeting space size	1014.78 (1560.18)	751.67 (514.09)	15.52%
Number of floors	3.61 (2.20)	2.74 (0.39)	16.98%
Number of hotels in the same submarket	111.34 (70.85)	169.11 (73.20)	16.17%
Percentage of major-hotel-group hotels* in the same submarket	81.74% (11.97%)	78.72% (8.56%)	16.50%
Franchised hotel	97.66%	81.04%	2.73%
Small metro	30.22%	45.0%	18.98%
Suburban	49.99%	28.73%	12.66%
Average demeaned occ rate in summer	3.90% (10.47%)	5.11% (7.77%)	21.90%
Average demeaned occ rate in fall	-2.49% (7.99%)	-3.39% (4.51%)	27.00%
Average demeaned occ rate in winter	-11.02% (9.20%)	-13.17% (5.76%)	27.24%
Average demeaned occ rate in spring	0.05% (6.25%)	-2.84% (4.42%)	22.06%

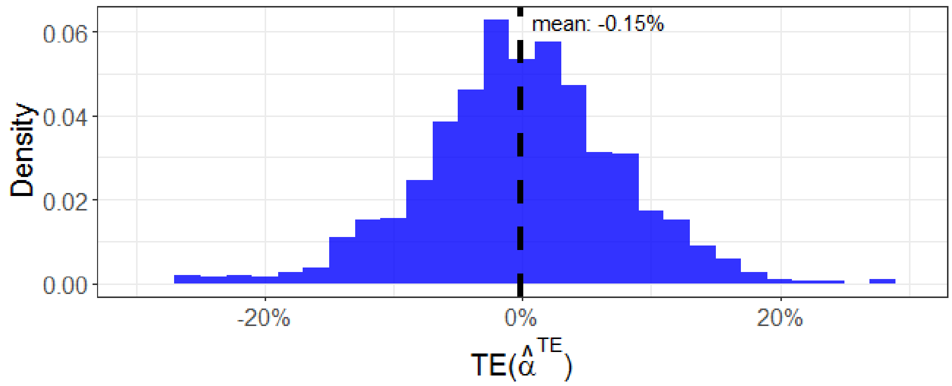
Notes. Summary statistics for each variable are calculated using the observations of treated hotels (donor hotels) whose $\boldsymbol{X}_{\boldsymbol{1}}^{\boldsymbol{train}}$ ($\boldsymbol{X}_{\boldsymbol{0}}^{\boldsymbol{train}}$) includes the variable. Standard deviations are in parentheses.
*These groups are Choice, IHG, Hilton, Marriott, and Wyndham.

6.2. Treatment Effects

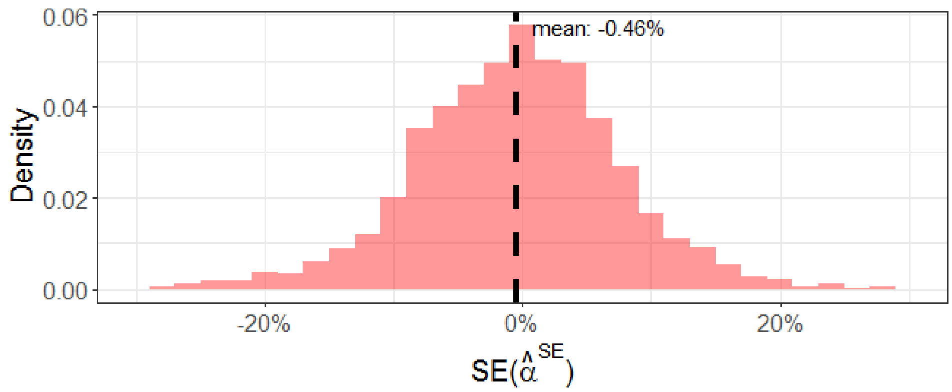
We obtain the TEs using Equation (14) and report their distribution in Panel (A) of Figure 4. The distribution can be approximated by a normal distribution with a mean of -0.15%, which is insignificant (90% CI: [-0.52, 0.33]) and a standard deviation of 7.80%. A 0.15% decrease in occupancy rate, on average, corresponds to a drop of $1,153 in monthly revenue.[5] Even though the TE is statistically insignificant, its large standard deviation indicates that the reviews have a considerable impact on many reviewed hotels.

Figure 4. Distributions of TEs and SEs

(A) Distribution of TEs



(B) Distribution of SEs



The left column of Table 5 reports the distribution of TEs. For hotels with TEs at the 90th percentile and the 75th percentile of the distribution, the reviews increase their occupancy rates by 9.19% and 4.49%, respectively. Correspondingly, these hotels' monthly revenue increases by $40,039 and $28,907, respectively. The reviews also have a substantial negative impact on the bottom 10% and 25% of hotels. Their occupancy rates decrease by more than 9.79% and 4.68%, and their monthly revenues decline by

[5] To obtain the confidence interval of the average, we use the bootstrap resampling method.

$48,679 and $32,046 per hotel, respectively. In sum, the reviews yield economically meaningful changes for the majority of reviewed hotels.

Table 5. Percentiles of TEs and SEs

	TE	SE
10th percentile	-9.79% [-10.71, -8.92]	-9.94% [-10.49, -9.41]
25th percentile	-4.68% [-5.19, -4.33]	-5.31% [-5.83, -5.15]
40th percentile	-2.01% [-2.35, -1.50]	-2.09% [-2.51, -1.75]
Median	-0.10% [-0.74, 0.33]	-0.28% [-0.66, 0.13]
60th percentile	1.79% [1.16, 2.09]	1.52% [1.16, 1.87]
75th percentile	4.49% [4.08, 5.23]	4.54% [4.20, 4.86]
90th percentile	9.19% [8.43, 9.98]	9.02% [8.58, 9.65]

Notes. 90% confidence intervals from the bootstrap resampling method are in brackets.

The findings are consistent with the conceptual framework presented in Section 3. Consumers know the average of the unknown hotel qualities ξ_r but not the exact value of each individual hotel. To resolve this uncertainty, consumers use the reviews as an unbiased but noisy signal (i.e., R_r) to update their belief about individual hotel's ξ_r. If ξ_r is above (below) average, consumers are more (less) likely to receive favorable signals from the reviews and update their beliefs accordingly. Because ξ_r are symmetrically distributed, half of the hotels with above-average values get positive TEs, while the other half get negative TEs.

We must note that the quality of a reviewed hotel depends not only on its own attributes but also on certain factors shared with competing hotels nearby (e.g., a hotel's neighborhood, community, and local safety). When reviewers write about their experiences about these common factors, readers are likely to extrapolate that competing hotels within the same geographical market have these same features (i.e., $\rho_{rc} > 0$). Consequently, consumers who read the reviews will also use the signal to update their beliefs about competing hotels' unknown qualities (i.e., $\mu_{c1} = \frac{\rho_{rc}}{1+\sigma^2} R_r$), leading to the spillover effects discussed next.

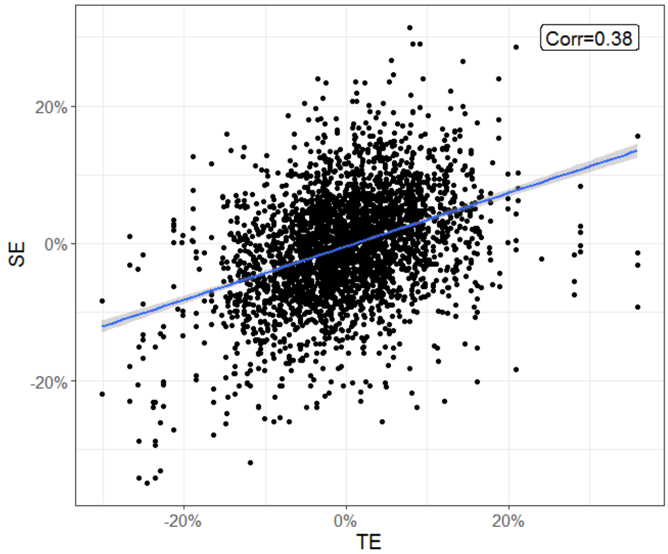
6.3. Spillover Effects (SEs)

We present the distribution of SEs – calculated using Equation (14) – in Panel (B) of Figure 4. The distribution can be approximated by a normal distribution with a mean of -0.46% and a standard deviation of 7.95%. The mean SE translates into a $1,913 decline in monthly revenue. Although small in magnitude, the average spillover effect is statistically significant (90% CI: [-0.84, -0.19]). The right column of Table 5 presents the distribution of SEs. We use the bootstrap resampling method to obtain the confidence intervals at different percentiles of SEs. Specifically, we draw 964 samples from the set of all reviewed hotels with replacement, and then we pick their corresponding competing hotels to calculate the confidence intervals. The rationale behind drawing reviewed hotels along with their competing hotels is that both reviewed and competing hotels are affected by the reviews. In addition, our focus is on studying the relationship between TEs and SEs. Therefore, we cannot treat reviewed and competing hotels independently.

Table 5 shows that the occupancy rates of competing hotels with their SEs at the 90th percentile and the 75th percentile increase by 9.02% and 4.54%, respectively. Their revenue increases are $41,413 and $27,586, respectively. The reviews also significantly affect competing hotels whose SEs are at the left tail of the distribution. The occupancy rates for the 10th percentile and the 25th percentile competing hotels decline by 9.94% and 5.31%, respectively. Correspondingly, their monthly revenues, on average, decrease by $41,839 and $32,043. These findings answer our first research question and establish that SEs do exist after the review system, and that they are economically consequential for most of the competing hotels.

Having established the existence and economic impacts of SEs, we now investigate the second research question, namely the correlation between a reviewed hotel's TE and its competing hotels' SEs. We are particularly interested in whether TE and SE are positively correlated. This investigation helps us understand how reviews of the reviewed hotel affect the demand of its competitors.

Figure 5. Relationship between TE and SE



Notes. The correlation between TE and SE is calculated based on 3,227 unique pairs of reviewed and competing hotels. The solid blue line represents the regression line of SE on TE; the gray band shows the 90% confidence interval.

Figure 5 illustrates the overall distribution of 3,227 unique pairs of reviewed hotels' TE and competing hotels' SE. The correlation between TE and SE is 0.38 and statistically significant (90% CI: [0.34, 0.42]). We also run an ordinary least squares regression to further document the relationship between TEs and SEs. We regress the SE of a competing hotel on the corresponding reviewed hotel's TE. The coefficient estimate is 0.39 and statistically significant (90% CI: [0.35,0.43]). The coefficient implies that, for a 1% increase in the occupancy rate of a reviewed hotel (a $3,096 increase in monthly revenue), each competitor will, on average, experience a 0.39% increase in the occupancy rate (a $1,199 increase in monthly revenue).

This is a surprising result. Because most consumers will choose only one hotel to stay in each night, hotels are typically viewed as substitutes. Our results, however, suggest that a type of "complementary" relationship exists: reviewed hotels and their competing hotels both benefit from or are hurt by the reviews. This result is consistent with the colocation effects documented in Baum and Haveman (1997), Chung and Kalnins (2001), and Kalnins and Chung (2004). Our study identifies a novel factor that causes the colocation effect: online reviews.

6.4. Robustness Checks

To check the robustness of our findings, we first investigate whether the treatment effects depend on hotel quality. One might argue that high-quality hotels are well known to consumers before the review system and subsequently their TEs may be smaller than low-quality hotels. To check this possibility, we classify reviewed hotels as high vs low quality based on their TripAdvisor ratings using a median split at the rating of 3.96. Then we compare the TE distributions of the two groups as well as the SE distributions of their competing hotels. In Panel (A) of Table 6, we find that the treatment and spillover effects are heterogeneous regardless of hotel quality. Moreover, the Kolmogorov-Smirnov test establishes that the distributions of the effects are the same ($p = 0.75$ for TE and $p = 0.74$ for SE). In addition, the correlations reported in Panel (B) of Table 6 are significant and similar in magnitude to the correlation reported in Section 6.3. We conclude that the effects of reviews are robust to different hotel qualities.

Table 6. Summary Statistics of TEs and SEs for High-Quality and Low-Quality Hotels

(A) Percentiles and Mean				
	TE (High*)	TE (Low*)	SE (High†)	SE (Low†)
10th percentile	-9.86%	-9.53%	-10.53%	-9.44%
25th percentile	-4.80%	-4.67%	-5.59%	-5.26%
40th percentile	-2.12%	-1.76%	-2.30%	-1.94%
Mean	-0.36%	0.07%	-0.56%	-0.48%
Median	-0.36%	-0.03%	-0.16%	-0.36%
60th percentile	1.59%	1.87%	1.53%	1.53%
75th percentile	4.38%	4.75%	4.66%	4.46%
90th percentile	9.11%	9.50%	9.55%	8.60%
Kolmogorov-Smirnov test	$p = 0.75$		$p = 0.74$	
(B) Correlations				
Correlation between	0.43			
TE (High*) and SE (High†)	[0.37, 0.48]			
Correlation between	0.34			
TE (Low*) and SE (Low†)	[0.27, 0.40]			

Notes. *High (Low) corresponds to reviewed hotels with their TripAdvisor average rating ≥ (<) 3.96. †High (Low) corresponds to competing hotels of which reviewed hotels' TripAdvisor average rating ≥ (<) 3.96. 90% confidence intervals from the bootstrap resampling method are in brackets.

Further, we check the robustness of our findings by separately examining the short-term and long-term effects of the reviews. We divide the posttreatment period into short term and long term: (1) the first year after the treatment (June 1, 2012, through May 31, 2013) and (2) the remaining months (June 1, 2013 through December 31, 2015). Table 7 shows the four distributions. We can observe that the distributions of the short-term effects are similar to those of the long-term effects. Moreover, the correlations between TEs and SEs are significantly positive in both time frames. The findings highlight that the effects of implementing reviews are immediate and last for at least several years, and so does the positive relationship between TEs and SEs.

Table 7. Short-Term and Long-Term TEs and SEs

	TE (short)	SE (short)	TE (long)	SE (long)
10th percentile	-8.76%	-8.90%	-11.24%	-11.50%
25th percentile	-4.85%	-4.60%	-5.04%	-6.02%
40th percentile	-2.32%	-2.18%	-1.97%	-2.22%
Mean	-0.81%	-0.89%	0.11%	-0.30%
Median	-0.81%	-0.79%	0.06%	-0.07%
60th percentile	0.66%	0.58%	2.34%	2.05%
75th percentile	3.15%	3.10%	5.58%	5.46%
90th percentile	7.15%	6.66%	10.94%	11.04%
Correlation	0.33 [0.29, 0.37]		0.38 [0.35, 0.42]	

Notes. 90% confidence intervals from the bootstrap resampling method are in brackets.

7. Mechanisms

In this section, we discuss several potential mechanisms that can explain the positive correlation between TEs and SEs. The focus is on information spillovers, which have been described using the conceptual framework in Section 3. We further offer some empirical evidence to support the hypothesis. We then discuss several other potential explanations for our empirical findings.

7.1. Information Spillovers

Because reviewed hotels may have attributes that are similar or even identical to those of their competing hotels, one hotel’s reviews can illuminate the attributes of its competitors. When planning a hotel stay, consumers often consider location, for instance to ascertain proximity to tourist attractions. Therefore, reviews that discuss these common factors for a reviewed hotel will affect consumer preferences for nearby competing hotels.[6] For example, suppose many reviews mention that the hotel is downtown with easy access to many bars and clubs. If customers find this attribute attractive after reading the reviews, they may also consider other downtown hotels. As a result, the TE and SE move in the same direction.

To investigate this mechanism, we conduct text analysis on the reviews of reviewed hotels between June 1, 2012, and December 31, 2015. There were 225,997 reviews posted on their websites, with on average 234 reviews for each reviewed hotel. We first follow the standard procedures in the literature to preprocess the textual data. We then use the LDA from Blei et al. (2003) to extract underlying topics commonly mentioned in the reviews and measure how much each review is devoted to discussing each topic (*topic score*). LDA is widely used in marketing to analyze textual data (e.g., Tirunillai and Tellis 2014, Hollenbeck 2018). After estimating several LDA models, we settle on the one with seven topics (see Online Appendix C for the details). We label these topics based on their associated keywords: (1) Staff, (2) Service, (3) Room quality, (4) Location, (5) Amenities, (6) Food, and (7) Memorable experience. Table 8 lists the top 50 keywords for the location topic; among them are "location," "close," "restaurant," "easy," "walk," "place," and "convenient."

Table 8. Top 50 Location Topic Keywords

Hotel	Location	Brand*****	Brand*****	Would	Recommend	Brand*****	Close
Stay	Business	Restaurant	Easy	Walk	Place	Convenient	Lot
Parking	Area	Find	Park	Highly	Travel	Town	Access
Locate	Right	Near	Drive	Trip	Anyone	Many	Downtown
Within	Perfect	Road	Distance	View	City	Shopping	Safe
Away	Street	Stop	Highway	Brand*	Local	Property	Nearby
Airport	Across						

Notes. The top 50 keywords account for 76% of word usage for the location topic. *****Brand is a masked keyword related to the brand identity.

For each review, the estimated LDA model also computes a *location topic score*, which represents the proportion of the discussion dedicated to the location topic. Table 9 shows two examples. The first review consists of many keywords associated with the location topic; its location topic score is 61.5%. The second mostly discusses service and food; accordingly, its location score is only 4.0%.

[6] Table 1 shows that the average distance of competing hotels from reviewed hotels is 3.52 km, much shorter than the 7.32-km average distance of other hotels inside a 15-km radius.

Table 9. Examples of Reviews with High and Low Location Topic Scores

Location topic score	Reviews
61.5%	**Location** in **Downtown** Burbank. You can **walk** to **many** pubs, **restaurants** and **shopping**. Few Miles from Hollywood and Universal City.
4.0%	Outstanding staff. I arrive every Sunday night and your shuttle promptly picks me up from the **airport**. When I arrive, Scott at the front desk has my sign-in package all prepared so there is no waiting. Your two bar maids are truly professionals and know what customer service means. I get your delicious breakfast buffet every morning and Monica is always there to serve and without asking, brings me a cup of coffee to go. GREAT JOB!

Note. The words in bold have a high probability of being used to discuss the location topic.

We calculate the average of the location topic scores across all reviews. For each reviewed-competing hotel pair, we compute *pairwise correlation,* which is defined as a correlation between monthly TEs and monthly SEs.[7] We end up with 3,227 pairwise correlations. We then regress these correlations on the average location topic score of the reviewed hotel.

Column (1) of Table 10 shows that the pairwise correlation is significantly and positively correlated with the average location topic score in the reviews. As the proportion of the location topic score increases by 1 percentage point, the pairwise correlation will increase by 0.5 percentage points. This result supports the information spillover effect.

[7] Monthly TEs and SEs are calculated based on Equation (13).

Table 10. Relationship Between the Pairwise Correlation and Location Topic and Geographical Distance

	DV: Pairwise Correlation		
	(1)	(2)	(3)
Intercept	0.342 ***	0.393 ***	0.347 ***
	(0.030)	(0.006)	(0.043)
Location topic score	0.502 ***		
	(0.222)		
Distance (0–1km)		0.044 ***	-0.053
		(0.010)	(0.067)
Distance (1–2km)		0.016	0.091
		(0.014)	(0.089)
Distance (0–1km) × Location topic score			1.049 ***
			(0.380)
Distance (1–2km) × Location topic score			-0.215
			(0.556)
Distance (2–15km) × Location topic score			0.335
			(0.314)
N	3,227	3,227	3,227
$\mathbf{R^2}$	0.002	0.006	0.009

Notes. The numbers of hotel pairs within 1 km, 1–2km, and 2–15km are 1,157, 395, and 1,675, respectively. Standard errors are in parentheses. $*$:p < 0.1 $**$:p < 0.05 $***$:p < 0.01.

Furthermore, if the information spillover of the location is one of the mechanisms driving the positive correlation between TEs and SEs, the correlation should become weaker as the distance between reviewed and competing hotels increases. This is because location information from consumer reviews of a reviewed hotel will be less informative for more distant competing hotels. Therefore, we expect the correlation to get weaker as the distance increases.

Consistent with this intuition, column (2) of Table 10 shows that the pairwise correlation is stronger between the reviewed hotel and its competing hotel within a 1-km (0.6-mile) radius than that of the other hotel pairs which are 2 to 15 km apart from each other. Next, we further include the interactions between location topic score and distances between hotels, examining whether the impact of location topic scores depends on the distance between hotels. The results in column (3) of Table 10 show that the impact of location topic score is significant only when the reviewed and competing hotels are within one km of each other. Both regression results support the information spillover mechanism in explaining the positive correlation between TEs and SEs.

Though our analysis focuses on location factors, the information spillover effect of reviews may not be limited to the discussion of locations. Table 1 shows that reviewed and competing hotels are not only close geographically but also similar in other attributes, including class, facilities, and hotel management. Therefore, consumers may also learn about the quality of competing hotels' other attributes from reviews.

7.2. Other Potential Explanations

Another potential explanation for the positive correlation between TEs and SEs is that reviewed hotels sell out of rooms due to high demand caused by positive reviews. Consequently, it forces consumers to book at competing hotels in the area, resulting in a higher demand for competing hotels. To test this mechanism, we focus on the peak month of each reviewed hotel in the posttreatment months. The average occupancy rate in the peak month is 82.65% among all reviewed hotels, suggesting that the chance of selling out in these months is high. We then divide the reviewed hotels into four groups:

(a) the average TE is positive during the peak months and the average occupancy rate in the peak months is greater than 82.65%;

(b) the average TE is positive during the peak months and the average occupancy rate in the peak months is less than 82.65%;

(c) the average TE is negative during the peak months and the average occupancy rate in the peak months is greater than 82.65%;

(d) the average TE is negative during the peak months and the average occupancy rate in the peak months is less than 82.65%.

For each hotel group, we calculate the correlations between the TEs and SEs during the peak months. If the sold-out effect is the main mechanism of the positive correlation, we expect to observe two outcomes concurrently: (1) the correlation for group (b) is smaller than that of group (a), and (2) the insignificant correlation between TEs and SEs in groups (c) and (d) because reviewed hotels in these groups experience a decline in their occupancy rates.

Panel (A) of Table 11 reports the results. Consistent with the above discussion, the correlation of TEs and SEs of reviewed hotels in group (a) is larger than that in group (b) (0.38 vs. 0.29). However, the correlation of the latter is still significantly positive. In addition, we find that the correlations for groups (c) and (d) are also significantly positive. Though the findings support the idea that the sold-out effect results in positive correlation, it is clear that the sold-out effect is not the sole mechanism driving our results.

To further test this mechanism, we divide reviewed hotels into high and low occupancy rates based on a median split of occupancy rates (68.70%) across hotels and all posttreatment months rather than just the peak season. We then divide the treated hotels within each group based on whether the average TE is positive or negative. If the sold-out effect is the only explanation, we expect the correlation between TEs and SEs to be positive only for reviewed hotels with positive TEs and high occupancy rates. However, the results in Panel (B) of Table 11 show that the correlations are higher among reviewed hotels that experience negative TEs. Indeed, the correlation is the lowest for reviewed hotels with positive TEs and high average occupancy rates. Again, the implication is that the sold-out effect is unlikely to be the only explanation.

Table 11. Correlations of TE and SE for Hotels with High and Low Occupancy Rates

	(A) Peak Months		
Correlation Btwn. TE and SE	High Occ	Low Occ	Diff Btwn. High and Low Occ
Positive TE	0.38 [0.32, 0.44]	0.29 [0.23, 0.35]	0.10 [0.01, 0.18]
Negative TE	0.28 [0.17, 0.34]	0.30 [0.22,0.37]	-0.02 [-0.17, 0.07]
	(B) All Months		
Correlation Btwn. TE and SE	High Occ	Low Occ	Diff Btwn. High and Low Occ
Positive TE	0.09 [0.03, 0.17]	0.13 [0.06, 0.20]	-0.03 [-0.13, 0.07]
Negative TE	0.36 [0.25, 0.45]	0.31 [0.23, 0.39]	0.04 [-0.08, 0.18]

Notes. High (Low) Occ for Panel (A) indicates hotels with an average occupancy rate in peak months after the treatment $>$ ($\leq$) 82.65. High (Low) Occ for Panel (B) indicates hotels with an average occupancy rate in all months after the treatment $>$ ($\leq$) 68.70. 90% confidence intervals from the bootstrap resampling method are in brackets.

A third potential mechanism is that reviewed hotels may strategically adjust room rates after the review system launch. If a reviewed hotel observes that its occupancy rate drops, it may cut prices and thus reduce the occupancy rate of competing hotels by poaching their potential customers. Similarly, a reviewed hotel may raise its price if it observes that its occupancy rate rises, driving customers to its competing hotels. Such strategic pricing decisions can cause a positive correlation between TEs and SEs.

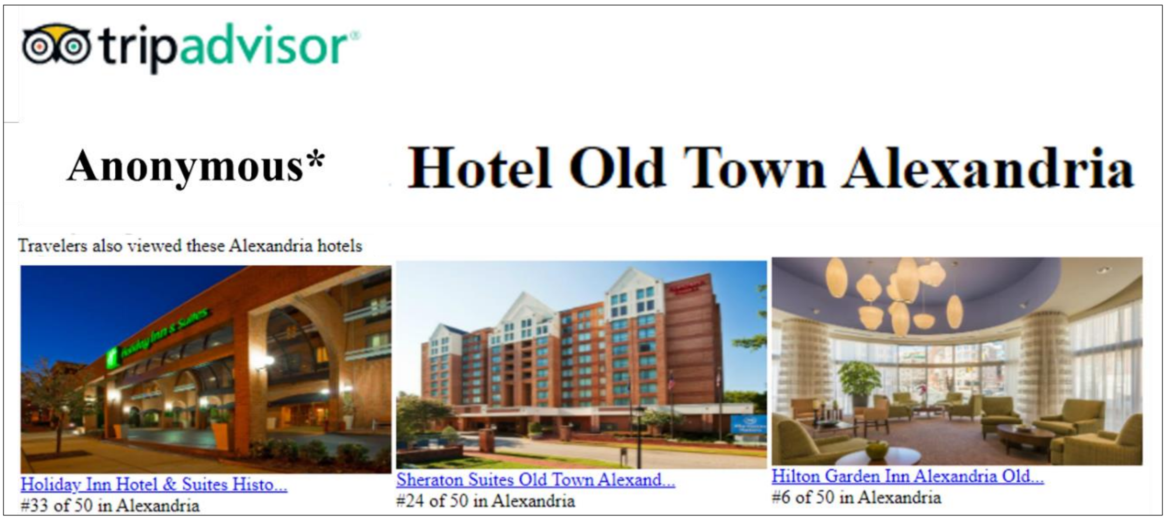
To test this explanation, we estimate the treatment effects of reviews on the ADR of reviewed hotels using the SCM. We then calculate the correlations between TEs on the occupancy rate and TEs on the ADR. We find that the correlation is -0.07 (90% CI: [-0.14, 0.10]). The insignificance of the correlation indicates that the TEs on the occupancy rate do not have much impact on room rates, perhaps showing that managers of reviewed hotels are not strategically setting prices according to the reviews.

We further calculate the correlation between TEs on the ADR and the SEs on the occupancy rate of competing hotels. The correlation is 0.01 and statistically insignificant ($p = 0.41$), suggesting that even if there are any price adjustments from reviewed hotels, they do not correlate with changes in the occupancy rates of competing hotels. The result again rules out the explanation that the strategic pricing decision of reviewed hotels is the driver of the positive correlation between TEs and SEs.

Finally, we consider the mechanism studied in Lewis and Nguyen (2015) and Sahni (2016). They show that online display ads induce consumers to search for other competing products. In our context, if consumers find a well-reviewed hotel, it may increase their interest in similar hotels. Consequently, consumers will further search for information about both the reviewed hotel and similar hotels in the area. In this case, the design of hotel aggregator platforms such as TripAdvisor can influence which hotels consumers search for. In particular, if reviewed hotels and their competing hotels are frequently placed together on webpages, consumers are more likely to also search for the competing hotels. This can lead to the positive correlation between TEs and SEs.

While we do not have data on how consumers search for hotel information, we look at the "travelers also viewed" section on a hotel's page on TripAdvisor.com (Figure 6) as indirect evidence for this explanation. This section displays a list of six hotels users typically search for along with the reviewed hotel. If consumers are likely to search for reviewed and competing hotels together, competing hotels will populate this section of the corresponding reviewed hotel.

Figure 6. Hotels Under the "Travelers Also Viewed" Section of a Reviewed Hotel



Notes. *We masked the hotel brand identity for anonymity.

We collect the hotel list of this section for each of the reviewed hotels on TripAdvisor.com. We then calculate the probability that a competing hotel appears in the "travelers also viewed" section by dividing the number of competing hotels listed in the section by the total number of competing hotels. Next, we calculate the probability of a competing hotel *randomly* appearing in the section by dividing $min(6, \#\text{ of hotels within a 15km radius})$ by the total number of hotels within a 15-km radius.[8]

Table 12 shows that the mean and the median of the probability that a competing hotel appears in the section are 60.3% and 60.0%, respectively, while the mean and the median of the probability that the list is populated randomly are 26.0% and 15.0%, respectively. We conduct the Wilcoxon signed-rank test[9] and reject the null hypothesis that the median difference between the two probabilities for each reviewed hotel is zero ($p < 0.001$). This finding indicates that, when searching for information about a reviewed hotel on TripAdvisor.com, consumers are more likely to find its competing hotels listed in the section. This suggests that when searches of reviewed hotels increase, it can lead to more searches of competing hotels, which may also explain the positive correlation between TEs and SEs.

We caution that the result of the test presented in Table 12 is only a necessary condition for the mechanism of consumer search. While it is consistent with the mechanism, unlike Lewis and Nguyen (2015), we do not observe how a consumer actually searches for hotel information; therefore, we cannot

[8] If the number of hotels within the 15-km radius is less than six, the chance of seeing these hotels in the section should be 100%.
[9] We use the Wilcoxon signed-rank test because the empirical distributions of the two probabilities are not normal.

provide direct evidence to either support the mechanism or rule it out as one of the explanations for our findings.

Table 12. Test of the Probability of Finding Competing Hotels on TripAdvisor's "Also Viewed" Section

Probability of a Competing Hotel Being in the Section				Probability of Being in the Section Randomly				Wilcoxon Signed-Rank Test
N	Mean	Median	SD	N	Mean	Median	SD	*p*-value
964	60.3%	60.0%	32.4%	964	26.0%	15.0%	27.1%	< 0.001

8. Conclusion

In this paper, we examine the effects of online consumer reviews on competing hotels as well as on reviewed hotels. We observe that the effects of online reviews are small on average. However, the effects are highly heterogeneous and significantly affect many reviewed and competing hotels' sales. We also establish that if a reviewed hotel's demand increases due to its reviews, its competing hotels are also likely to benefit from the reviews. Managers should recognize that demand for their own products is affected not only by their own reviews but also by their competitors' reviews. Thus, they should actively monitor reviews of competing products, especially those with which their own products share common features.

We show that the information spillover mechanism is the main driver of the positive correlation between treatment and spillover effects. According to this mechanism, the quality perceptions that consumers form about the reviewed hotel by reading reviews may spill over to its competitors. We find supporting evidence that if the reviews focus more on the locational features shared between the reviewed hotel and its competitors, the correlation between treatment and spillover effects increases. Moreover, we confirm that reviews on locational features increase the correlation only if reviewed and competing hotels are sufficiently close, which further strengthens the credibility of the information spillover mechanism.

Our research contributes to the eWOM literature by establishing the spillover effects of online reviews. We also introduce the information spillover as the mechanism behind the online reviews' spillover effects, which is a novel finding in this literature stream. The information spillover is prevalent and significantly affects firms' performance in other business contexts beyond the hotel industry. For instance, research shows that information from product recalls (Borah and Tellis 2016), clinical trials (Ching and Lim 2020), and Chapter 11 bankruptcy announcements (Ozturk et al. 2019) can affect the consumers' perceived quality of competing products in the automobile and pharmaceutical industries.

Our paper also adds to the literature on firm agglomeration. The hotel industry is one in which many service providers tend to cluster and as a result are subject to colocation effects. Our study establishes online reviews as a novel factor that affects the colocation effect.

Our study is not without limitations. For example, we cannot identify the source of the total demand change for reviewed and competing hotels, because we do not observe financial information on other nontreated hotels. One possibility is that reviews shift the demand from other hotels to the studied hotels, or vice versa. A second possibility is that reviews expand or contract the whole market.[10] Identifying where the demand change comes from remains an avenue for future research.

Another limitation is that even though we establish the heterogeneity of review effects, we do not investigate the factors driving these heterogeneous effects. For example, review characteristics could determine whether a hotel will experience a positive treatment effect or not. However, because other factors (e.g., hotel quality) can affect both occupancy rates and reviews, it is hard to establish causality – we leave this for future research.

Finally, examining the information spillover effect of reviews in other industries would be another important extension of this research.

Competing Interests

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or nonfinancial interest in the subject matter or materials discussed in this manuscript. The authors have no funding to report.

[10] We conduct an indirect test of the second possibility by using traveler types. Since WOM is likely to affect leisure travelers more than business travelers, the market expanding (contracting) as a result of the reviews could experience disproportionately increased (decreased) demand from leisure travelers. Though our analysis does not lend support to the market expansion/contraction explanation, we cannot rule it out, because this is not a direct test.

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ONLINE APPENDICES

ONLINE APPENDIX A. Treated Hotels Included in and Excluded From the Analysis

We compare the treated hotels included in the analysis to those excluded from the analysis to verify whether the included ones are representative of all treated hotels. We compare their characteristics before the review system was introduced on reviewed hotel web pages (i.e., January 2010 to May 2012). Table A1 shows that the characteristics of included treated hotels are similar to those of excluded hotels. Therefore, we conclude that the 3,704 treated hotels are representative.

Table A1. Hotel Characteristics of Treated Hotels Included in and Excluded From the Analysis

Variable	**Treated Hotels Included (n = 3,704)**	**Treated Hotels Excluded (n = 7,314)**
Class	2.97	2.88
	(0.92)	(0.96)
Age	24.65	24.97
	(12.24)	(13.39)
Number of rooms	110.37	112.31
	(68.17)	(78.47)
With restaurant	22.30%	24.34%
All suites	21.79%	18.13%
Indoor corridor	93.03%	92.14%
Total meeting space (sq. ft.)	2,340.13	2,445.37
	(6,608.81)	(6,549.91)
Largest meeting space (sq. ft.)	1,279.78	1,273.18
	(3,055.57)	(2,399.87)
Number of floors	4.03	4.15
	(2.64)	(3.27)
Number of hotels in the same submarket	117.37	122.17
	(82.49)	(76.98)
Percentage of major hotel groups* in the same submarket	17.43%	17.42%
	(5.88%)	(5.83%)
Franchise hotel	89.66%	89.37%
Independent hotel	1.46%	2.68%
Interstate	15.36%	17.37%
Small metro	21.22%	22.41%
Suburban	55.99%	37.57%
Urban	7.42%	7.290%
Number of reviews in TripAdvisor	29.54	34.66
	(43.31)	(64.85)
Average rating in TripAdvisor	3.85	3.84
	(0.57)	(0.60)
Variance of rating in TripAdvisor	1.24	1.20
	(0.57)	(0.58)
Expedia star rating	2.63	2.62
	(0.41)	(0.43)
Occupancy rate (Occ)	61.33%	60.54%
	(12.34%)	(13.52%)

Notes. Each value represents the average across each type of hotel. Standard deviations are in brackets.

*These groups are Choice, IHG, Hilton, Marriott, and Wyndham.

ONLINE APPENDIX B. Stepwise Variable Selection

The stepwise variable selection begins with no variable in $\boldsymbol{X}_{\boldsymbol{h}}^{\boldsymbol{trng}}$. At the first and the second round of the procedure, we subsequently add a variable to $\boldsymbol{X}_{\boldsymbol{h}}^{\boldsymbol{trng}}$, which provides the lowest MSPE in Equation (12) among all variables in each round. The variables considered can be found in Table 4. Then, in the following odd rounds, we add a variable to $\boldsymbol{X}_{\boldsymbol{h}}^{\boldsymbol{trng}}$ if this addition decreases MSPE. Likewise, in the even rounds the procedure subtracts a variable from $\boldsymbol{X}_{\boldsymbol{h}}^{\boldsymbol{trng}}$ if this subtraction decreases MSPE. If adding and removing a variable does not lower MSPE, the procedure will stop, and we use the selected variables for the estimation of $\boldsymbol{W}^*$and $\boldsymbol{V}^*$.

Let $\boldsymbol{\Omega}_{(\boldsymbol{p})}(\boldsymbol{\Psi}_{(\mathbf{p})})$ denote the set of all possible variables (not) included in $\boldsymbol{X}_{\boldsymbol{h}}^{\boldsymbol{trng}}$ up until the end of the pth round. Since no variable is included at the beginning of the procedure, $\boldsymbol{\Omega}_{(\mathbf{0})}$ is an empty set, and $\boldsymbol{\Psi}_{(\mathbf{0})}$ is the set of all variables. $\boldsymbol{X}_{(\boldsymbol{p})}^{\boldsymbol{trng}} = \left[X_{(p)1}^{trng}, \cdots, X_{(p)h}^{trng}, \cdots, X_{(p)H+1}^{trng}\right]$ denotes a variable chosen at pth round, where $X_{(p)h}^{trng}$ is the corresponding variable for hotel h chosen at pth round.

The stepwise variable selection proceeds as follows:

1. If $p = 1$,
   1.1. For each variable in $\boldsymbol{\Psi}_{(\mathbf{0})}$, run variable selection steps 2 and 3 described in Section 5.2.1.
   1.2. Include the variable with the lowest MSPE$(\equiv \text{MSPE}_{(1)})$, denoted by $\boldsymbol{X}_{(\mathbf{1})}^{\boldsymbol{trng}}$ into $\boldsymbol{\Omega}_{(\mathbf{0})}$. Then, $\boldsymbol{\Omega}_{(\mathbf{1})} = \boldsymbol{\Omega}_{(\mathbf{0})} \cup \left\{\boldsymbol{X}_{(\mathbf{1})}^{\boldsymbol{trng}}\right\}$, and $\boldsymbol{\Psi}_{(\mathbf{1})} = \boldsymbol{\Psi}_{(\mathbf{0})} \setminus \left\{\boldsymbol{X}_{(\mathbf{1})}^{\boldsymbol{trng}}\right\}$.
2. If $p = 2$,
   2.1. Add one variable in $\boldsymbol{\Psi}_{(\mathbf{1})}$ to the variable in $\boldsymbol{\Omega}_{(\mathbf{1})}$ and run variable selection steps 2 and 3 described in Section 5.2.1.
   2.2. Repeat above step 2.1 for each variable in $\boldsymbol{\Psi}_{(\mathbf{1})}$.
   2.3. Denote the variable with the lowest MSPE$(\equiv \text{MSPE}_{(2)})$, by $\boldsymbol{X}_{(\mathbf{2})}^{\boldsymbol{trng}}$.
      2.3.1. If $\text{MSPE}_{(2)} < \text{MSPE}_{(1)}$, add $\boldsymbol{X}_{(\mathbf{2})}^{\boldsymbol{trng}}$ to $\boldsymbol{\Omega}_{(\mathbf{1})}$. Then, $\boldsymbol{\Omega}_{(\mathbf{2})} = \boldsymbol{\Omega}_{(\mathbf{1})} \cup \left\{\boldsymbol{X}_{(\mathbf{2})}^{\boldsymbol{trng}}\right\}$, and $\boldsymbol{\Psi}_{(\mathbf{2})} = \boldsymbol{\Psi}_{(\mathbf{1})} \setminus \left\{\boldsymbol{X}_{(\mathbf{2})}^{\boldsymbol{trng}}\right\}$.

2.3.2. If $\text{MSPE}_{(2)} \geq \text{MSPE}_{(1)}$, the variable selection will stop, and $\boldsymbol{X_h^{trng}} = \boldsymbol{\Omega}_{(\mathbf{1})}$.

3. If $p = 2g - 1$ $(g \geq 2)$,

3.1. Add one variable in $\boldsymbol{\Psi}_{(\boldsymbol{p}-\mathbf{1})}$ to the variables in $\boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$ and run variable selection steps 2 and 3 described in Section 5.2.1.

3.2. Repeat above step 3.1 for each variable in $\boldsymbol{\Psi}_{(\boldsymbol{p}-\mathbf{1})}$.

3.3. Denote the variable with the lowest $\text{MSPE}\left(\equiv \text{MSPE}_{(\text{p})}\right)$, by $\boldsymbol{X_{(p)}^{trng}}$.

3.3.1. If $\text{MSPE}_{(\text{p})} < \text{MSPE}_{(\text{p}-1)}$, add $\boldsymbol{X_{(p)}^{trng}}$ to $\boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$. Then, $\boldsymbol{\Omega}_{(\boldsymbol{p})} = \boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})} \cup \left\{\boldsymbol{X_{(p)}^{trng}}\right\}$, $\boldsymbol{\Psi}_{(\boldsymbol{p})} = \boldsymbol{\Psi}_{(\boldsymbol{p}-\mathbf{1})} \setminus \left\{\boldsymbol{X_{(p)}^{trng}}\right\}$.

3.3.2. If $\text{MSPE}_{(\text{p})} \geq \text{MSPE}_{(\text{p}-1)}$, the variable selection will not update (i.e., $\boldsymbol{\Omega}_{(\boldsymbol{p})} = \boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$ and $\boldsymbol{\Psi}_{(\boldsymbol{p})} = \boldsymbol{\Psi}_{(\boldsymbol{p}-\mathbf{1})}$).

4. If $p = 2g$ $(g \geq 2)$,

4.1. Subtract one variable from $\boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$, run variable selection steps 2 and 3 described in Section 5.2.1.

4.2. Repeat above step 4.1 for each variable in $\boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$.

4.3. Denote the variable with the lowest $\text{MSPE}\left(\equiv \text{MSPE}_{(\text{p})}\right)$, by $\boldsymbol{X_{(p)}^{trng}}$.

4.3.1. If $\text{MSPE}_{(\text{p})} < \text{MSPE}_{(\text{p}-1)}$, subtract $\boldsymbol{X_{(p)}^{trng}}$ from $\boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$. Then, $\boldsymbol{\Omega}_{(\boldsymbol{p})} = \boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})} \setminus \left\{\boldsymbol{X_{(p)}^{trng}}\right\}$, and $\boldsymbol{\Psi}_{(\boldsymbol{p})} = \boldsymbol{\Psi}_{(\boldsymbol{p}-\mathbf{1})} \cup \left\{\boldsymbol{X_{(p)}^{trng}}\right\}$.

4.3.2. If $\text{MSPE}_{(\text{p})} \geq \text{MSPE}_{(\text{p}-1)}$, the variable selection will not update (i.e., $\boldsymbol{\Omega}_{(\boldsymbol{p})} = \boldsymbol{\Omega}_{(\boldsymbol{p}-\mathbf{1})}$ and $\boldsymbol{\Psi}_{(\boldsymbol{p})} = \boldsymbol{\Psi}_{(\boldsymbol{p}-\mathbf{1})}$).

5. Termination condition for steps 3 and 4: If both steps 3 and 4 do not have updates consecutively (e.g., no variable added to $\boldsymbol{\Omega}_{(\mathbf{2})}$ at the third round, no variable subtracted from $\boldsymbol{\Omega}_{(\mathbf{3})}$ at the fourth round, and thus, $\boldsymbol{\Omega}_{(\mathbf{4})} = \boldsymbol{\Omega}_{(\mathbf{3})} = \boldsymbol{\Omega}_{(\mathbf{2})}$. Or no variable subtracted from $\boldsymbol{\Omega}_{(\mathbf{5})}$ at the sixth round, no variable added to $\boldsymbol{\Omega}_{(\mathbf{6})}$ at the seventh round, and thus, $\boldsymbol{\Omega}_{(\mathbf{7})} = \boldsymbol{\Omega}_{(\mathbf{6})} = \boldsymbol{\Omega}_{(\mathbf{5})}$), the variable selection will stop, and $\boldsymbol{X_h^{trng}} = \boldsymbol{\Omega}_{(\boldsymbol{P})}$ where $\boldsymbol{P}$ is the last round run.

ONLINE APPENDIX C. The Latent Dirichlet Allocation (LDA) Model

C.1. The Model and the Estimation Procedures

The LDA model imitates the process of writing textual documents based on probabilistic rules (Blei et al. 2003). Specifically, the model consists of the observed textual data and the hidden parameters. The probabilistic rules connect the data to hidden parameters by defining how writers generate the observed text based on hidden parameters.

The hidden parameters include (1) the number of topics discussed throughout all documents; (2) the topic scores, which indicate how much a writer discusses each topic on a document; and (3) the conditional word probabilities for each topic, which represent how likely each word is to be chosen to describe a specific topic. In the LDA model, writers are assumed to probabilistically pick a topic (e.g., location) for each word based on parameter (2). Next, they choose a word based on parameter (3). They repeat this procedure word by word until the review is complete.

Before estimating the model, we preprocess the textual data. First, we clean textual data. Specifically, we remove punctuation marks and all stop words (e.g., "the," "and," "when"). Second, we convert all uppercase letters to lowercase. Third, we lemmatize the inflected forms of words and extract the base words (e.g., "playing," "plays," or "played" are replaced with "play"). For instance, if a reviewer writes "This hotel is in a nice area but far from major attractions," then the review is transformed into "hotel nice area far major attraction" for the analysis.

With the preprocessed textual data, we estimate the hidden parameters. Researchers should predetermine parameter (1). Next, given the number of topics, we maximize the likelihood function of the LDA model to estimate the hidden parameters (2) and (3) by using the Variational Inference algorithm. We repeat these steps with different numbers of topics (ranging from 4 to 13). As a result, for each number of topics, we obtain parameter (2) for each review and parameter (3) for every topic.

Next, we sort all words in descending order based on parameter (3), the select the words with the top 50 conditional word probabilities and call them *keywords* of the corresponding topic. We also give the corresponding topic a name that can represent its keywords. For instance, if keywords (e.g., location, close, restaurant, downtown) of a particular topic are coherently related to locational features, we call the topic "location." A clear location topic emerges for models with seven or more topics. For the models with six or fewer topics, the keywords related to the location are mixed with keywords for other hotel attributes within the same topic. For instance, one of the topics in the model with six topics has keywords including location, close, breakfast, and buffet. This topic clearly combines two different hotel characteristics (i.e., location and food).

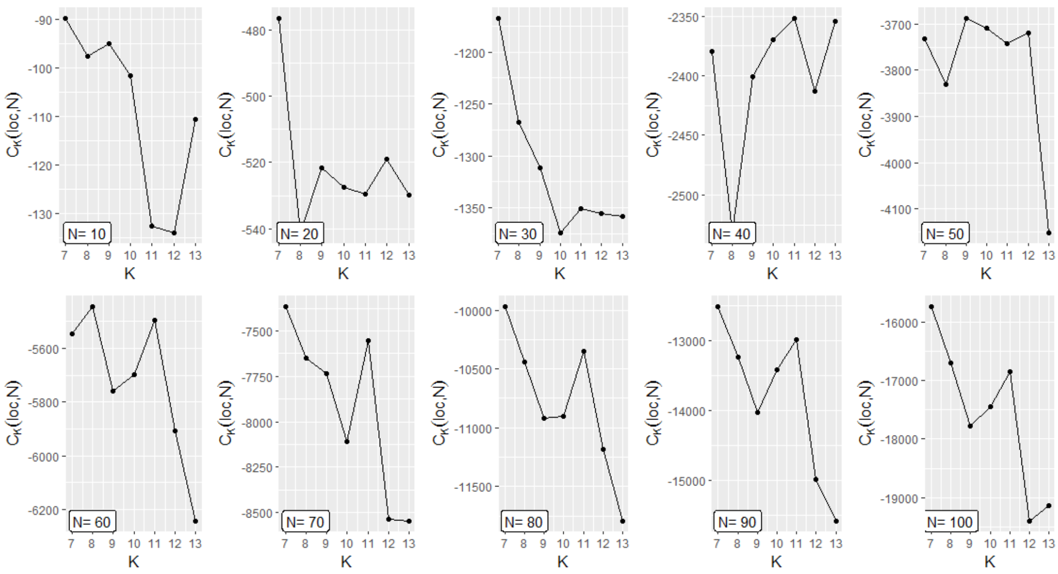
C.2. Choosing the Optimal Number of Topics

Mimno et al. (2011) devise an evaluation metric, *coherence score*, which stands for how often the keywords in the same topic occur together throughout all reviews. The coherence score can be used to evaluate the semantic coherency among the keywords in each topic of an estimated model. Following the recommendation by Mimno et al. (2011), we choose the number of topics based on the coherence score for the location topic, which we calculate as follows:

1. We choose the number of the top keywords ($= N$) among $\{10,20,30, \ldots ,100\}$.
2. We list the top N keywords. Let $w_i^{(loc)}$ be the top ith keyword for the location topic.
3. We measure $D\left(w_i^{(loc)}\right)$ for $i = 1, \ldots, N$, denoting how many reviews contain the ith location keyword and $D\left(w_i^{(loc)}, w_j^{(loc)}\right)$, representing how many reviews contain both the i and jth location keywords for $\forall i < j \; and \; \forall j \leq N$. Using these measures, we calculate normalized cooccurrence scores of two different keywords denoted by $score\left(w_i^{(loc)}, w_j^{(loc)}\right) = log\left(\frac{D\left(w_i^{(loc)}, w_j^{(loc)}\right)+1}{D\left(w_i^{(loc)}\right)}\right)$ for $\forall i < j \; and \; \forall j \leq N$.
4. For $\forall \; K \in \{7,8,9, \ldots ,13\}$, we calculate the coherence score of the location topic for K topics and the top N keywords, $C_K(loc, N)$, by calculating $C_K(loc, N) = \sum_{j=2}^{N} \sum_{i=1}^{j-1} score\left(w_i^{(loc)}, w_j^{(loc)}\right)$.
5. We repeat steps 1 to 4 for $\forall \; N \in \{10,20, \ldots ,100\}$.

Figure C1 shows how for each number of the top keywords (N), the coherence scores of the location topic change as the number of topics (K) increases. The model with seven topics has the highest coherence scores for seven values of N (i.e., $N = 10, 20, 30, 70, 80, 90, 100$). Therefore, we adopt seven as the optimal number of topics. We use the location topic scores from the corresponding LDA model to investigate the information spillovers of online reviews.

Figure C13. Coherence Scores



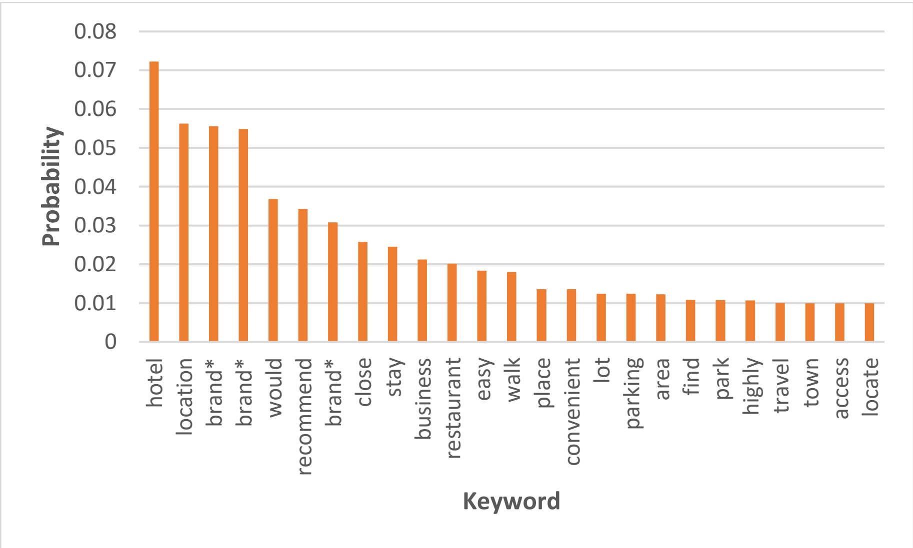
C.3. Results

Table C1 shows the keywords of each topic except for the location topic (see Section 7.1. for location keywords). We observe that the keywords under each topic are associated with one theme. Figure C2 displays the conditional word probabilities of the top 25 location topic keywords. The conditional word probabilities of the 25 location topic keywords add up to 60.5%, which implies that a reviewer is likely to use one of the top 25 keywords with more than 60% probability when discussing the location topic.

Table C1. Topic Keywords

Topic: Staff									
Staff	Great	Clean	Friendly	Room	Comfortable	Helpful	Stay	Well	Quiet
Definitely	Pleasant	Accommodate	Extremely	Wonderful	Place	Courteous	Professional	Awesome	Attentive
Topic: Service									
Desk	Front	Check	Get	Us	Go	Day	Room	take	Say
would	Ask	Call	Give	Tell	Back	Member	Leave	Could	Night
Topic: Room quality									
Room	Night	Work	Could	One	Bathroom	Floor	Sleep	Get	Door
Use	Like	Would	Water	Shower	Need	Bad	Seem	Old	Noise
Topic: Amenities									
Hotel	Good	Nice	Area	Service	Excellent	Pool	Enjoy	Overall	Food
Really	Price	Facility	Place	Bar	Value	Experience	Restaurant	Need	Kid
Topic: Food									
Breakfast	Bed	Room	Everything	Hot	Suite	Would	Free	Comfortable	Pillow
Choice	Coffee	Love	Large	Well	Also	Internet	Like	Offer	Food
Topic: Memorable experience									
Stay	Time	Make	Always	Hotel	Visit	Family	Year	Best	Property
Every	Experience	One	Home	Like	Feel	Way	Travel	Back	Thank

Figure C24. Conditional Word Probability Distribution of the Location Topic Keywords



Note. Brand* is a masked keyword related to the brand identity.