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Reviews and price on online platforms: Evidence from sentiment analysis of Airbnb reviews in Boston

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ABSTRACT

There is a growing interest in deriving value from user-generated comments and reviews online. For businesses and consumers using online platforms, the reviews serve as quality metrics and influence consumers purchasing decision. This study examines the relationship between guests' reviews, used as a proxy for quality, and the price set by hosts on the Airbnb platform in Boston. Using sentiment analysis to derive the quality from the reviews and a hedonic spatial autoregressive model applied to rental room prices on Airbnb, we find that prices are strategic complements and are influenced by the review score, the characteristics of the room, and the features of the neighborhood. The marketing implication is that consumers respond to the contents of online reviews, in addition to customer ratings. Policies that improve the quality of the room for one host will have a spillover effect on the price of rooms offered by other hosts.

1. Introduction

In the hospitality literature, reputation-based quality signals are commonly used to rate hotels and support a premium pricing strategy (Abrate et al., 2011; Thrane, 2005). Reputation-based quality signals, such as chain affiliation, star rating, and third-party evaluation, help the seller reduce information asymmetries by conveying the quality information to prospective buyers before consumption. With the growth of the internet, information asymmetries can be further reduced with online reputation mechanisms such as online reviews, comments, and ratings. Product quality unobservable to consumers can be accessed through the remarks and reviews posted by previous consumers online. Reviews are becoming even more important for experience goods such as hotel rooms and rental houses, which are purchased at distance (Viglia et al., 2016) with the quality being hard for travelers to assess before consumption (Klein, 1998).

A number of empirical studies in economics have examined the effect of reviews on price, sales and purchase probability (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Kim and Srivastava, 2007). Different schemes of rating are used on online platforms, and most of the empirical studies use reviews, scored or rated in terms of satisfaction by customers, but not the content of the reviews. The review scores or ratings commonly vary from thumbs up or thumbs down to scale from one to five stars (Sarvabhotla et al., 2010). However, a product or service has many attributes whose combination determine its quality. The use of scores or ratings oversimplifies quality measures by assuming that quality is a unidimensional measure (Archak et al., 2011). Economic theory posits quality as a multidimensional construct (Bowbrick, 2014) and the mechanism through which prospective customers use online reviews suggests that the content of the reviews plays an important role in the purchasing decisions. On online platforms, potential consumers go through multiple reviews about products or services, examine the positive and negative attributes of the products or services, and analyze the trade-off between the attributes before making their purchasing decisions. They use the opinions in the reviews to form their own opinion about the quality of the product or service they want to purchase. The contents of the reviews might be a fuller indicator of quality.

Researchers have shown increasing interest in understanding the opinions and feelings hidden in the millions of reviews left by consumers online (Liu et al., 2005; Pang and Lee, 2008). Chevalier and Mayzlin (2006) show that customers rely more on the reviews than the rating scores. According to Archak et al. (2011), numerical or bimodal ratings

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do not accurately capture the information embedded in the reviews and may not express precise information to prospective shoppers. Using predictive modeling, they show the effect of different product features in the reviews on sales, confirming the importance of the words used in the reviews to evaluate the products sale performance. Similarly, in the hotel industry literature, the presence of consumer reviews and ratings are found to drive sales (Blal and Sturman, 2014, Floyd et al., 2014, Ye et al., 2009a,b). However, most of the studies use star ratings and/or customer ratings as a proxy for the quality in the reviews but not the words in the reviews. Yet, there is no agreement on the relationship between hotel reviews and quality. For examples, Öğüt and Onur Taş (2012), using star ratings and customer ratings, find that these quality metrics increase hotels price and online sales. A recent study by Viglia et al. (2016) finds a positive association between review scores and hotel occupancy rates, but not a significant relationship between reviews and star ratings, suggesting that these two measures involve two different concepts of quality, contrary to the existing literature on reviews and quality.

Using data collected from Airbnb in Boston, the present study contributes to the online marketing literature on the relationship between guests' reviews and quality, and their impact on price. Unlike previous research that uses review score such as the number of reviews, star rating and customer rating, this study uses the contents of the written reviews to extract the sentiment hidden in the review and uses it as a quality measure. In addition, it decomposes the unidimensional construct of quality into disaggregated quality indicators that measure specific attributes such as location, value, and cleanliness of the rooms on Airbnb. The study compares the effects on the price of the unidimensional quality measure to the disaggregated quality attributes, and to the effect of the construct of quality derived from the opinions in the reviews with sentiment analysis. Sentiment analysis is a methodology, often used in computer science, to extract value, opinions or attitudes toward products or services from reviews (Bautin et al., 2008, Hu and Liu, 2004, Pang and Lee, 2008, Ye et al., 2009a,b). Analyses conducted with the spatial autoregressive hedonic model show that the price of a room on the platform depends not only on the intrinsic characteristics of the room and its location, but also on the price set by other hosts in the neighborhood, and the quality attributes. The study reveals that the quality score derived from sentiment analysis is a better indicator of price than the unidimensional rating score. However, the disaggregated quality measures better explain price than the quality score derived from sentiment analysis. The spatial nature of the estimation method implies that the quality measures have not only a direct effect on the room price but also a spillover effect on the price of rooms in its neighborhood.

The remainder of this paper is organized as follows. In section 2 we give an overview of the relevant literature. Section 3 presents the conceptual framework. Section 4 introduces the data and the spatial autoregressive estimation method, including a detailed description of the sentiment analysis methodology. Results of the spatial hedonic pricing model are presented in section 5. Finally, section 6 concludes.

2. Literature review

The importance of word-of-mouth (WOM) on consumer purchasing decision has been widely examined in the economic literature (Brooks, 1957; Kozinets et al., 2010; Liu, 2006). WOM contents are user-generated comments, reviews, ratings, and other communications and are perceived to be more credible than advertising (Mauri and Minazzi, 2013; Ogden, 2001) since they are real user experiences and not paid ads. Litvin et al. (2008) stresses the importance of the independence of the source of the message for WOM to be considered as a reliable source of information by customers. This is well illustrated by Mauri and Minazzi (2013) experimental study where hotel guests reviews are positively correlated with customers' hotel purchasing intention, but the presence of hotel managers' responses to the guest's reviews leads to a negative correlation with their purchasing intention. Zhang et al. (2010) confirm this finding. Using data collected from Dianping.com on restaurants, they compare the popularity of consumers' reviews with professional editors' reviews. Their study shows that consumers-created reviews are more popular than editors' reviews, as indicated by the number of page views.

There is a substantial number of studies in economics on the effect of reviews on sales. De Vany and Walls (1999), Dellarocas et al. (2007) and Liu (2006) show the impact of reviews on box office revenue. In the service industry, reviews are considered as a primary source of information on quality (Hu et al., 2008) as they reduce information asymmetry, and allow consumers to have better information about the attributes of the service they want to purchase (Nicolau and Sellers, 2010). Luca (2016), studying the impact of reviews and reputation on restaurant revenue in Washington, finds that a one-star increase in Yelp's rating increases a restaurant's revenue by 5–9 percent. Zhang et al. (2013), studying the determinants of camera sales, finds that the average online customer review, as well as the number of reviews, are significant predictors of digital camera sales.

In the hotel industry, reviews affect hotel room purchase intention, sales, and price. According to O'Connor (2008), increasing numbers of travelers consult feedback left by other customers while planning their trip. Gretzel and Yoo (2008) estimate that 75% of travelers use the feedback of other consumers whilst making travel arrangements. Vermeulen and Seegers (2009), through an experimental study in the Netherlands, confirm that online reviews affect consumers' choice in the hotel industry, but this effect is asymmetric. Results from their study indicate that positive and negative reviews do not have the same impact on a consumer's behavior. Positive reviews have a positive impact, but negative reviews have a smaller impact on absolute value than positive reviews. With regard to sales and price, Ye et al. (2011), exploiting data from a major travel agency in China, show that a 10 percent increase in traveler rating increases the volume of online reservations by more than 5 percent. Öğüt and Onur Taş (2012) also find that more positive online customer ratings increase hotel room prices and online sales.

Customer ratings play an essential role in evaluating customer satisfaction on online platforms such as Airbnb, which shares many common characteristics with hotels and residential properties. Airbnb is part of the growing sharing economy where individuals offer their home for rent for a short term period (Edelman et al., 2017; Ert et al., 2016; Fang et al., 2016; Schor, 2016). Gutiérrez et al. (2017) study the distributions of Airbnb in Barcelona and show that they cover the same geographic location as hotels except in the central residential areas where hotels are absent. Airbnb stays serve as substitutes for hotel stays and are shown to decrease hotel revenues (Zervas et al., 2017). Variables related to the room characteristics such as the number of room, the number of bedrooms, the distance to amenities and chain affiliation affect hotel room price (Yang et al., 2016, Zhang et al., 2011a,b). Those variables are also expected to explain room price in the accommodation sharing economy. For example, Gutiérrez et al. (2017) show evidence of a positive relationship between Airbnb locations and sightseeing sites and Wang and Nicolau (2017) identify ten site and property attributes and five amenities and services variables that affect room price on Airbnb.

Attributes such as house characteristics, distance to amenities also affect home prices (Ebru and Eban, 2011; Sunding and Swoboda, 2010). In addition, school quality (Cellini et al., 2010; Neilson and Zimmerman, 2014) and crime rate (Frischtak and Mandel, 2012; Ihlanfeldt and Mayock, 2010) impact consumers preferences and house prices. These are intrinsic house quality characteristics that consumers are willing to pay for when purchasing a house. However, school quality is not likely to impact room price on the accommodation sharing platforms, but hosts might be willing to avoid areas with higher crime rates. Some quality variables identified in the hotel industry and the housing market literature might be important in determining room price in the accommodation sharing economy while others might not. The presence of consumers reviews and ratings on the online platforms such as Airbnb can help capture attributes related to the quality of the room (Nowak and Smith,

2017) that are of importance to customers on the platform.

Quality has many dimensions and measures and customer ratings might only capture a small part of it. During the rating process, customers may refer not only to the quality of the product or service but also to its price, or both. Even when referring to the quality, some features of the product or service are considered more important than others, depending on the taste of the customer. Zhang et al. (2011a,b) show a heterogeneous impact of rating on hotel room prices. They found the impact to be only noticeable for the economy and midscale hotels and not for luxury hotels where location and the quality of services are the most important factors that determine consumers' willingness to pay. They use different ratings such as cleanliness, quality of room, location, and service and found different impacts of these ratings on price. The findings of Li and Hitt (2010) confirms the results of Zhang et al. (2011a,b). According to Li and Hitt (2010) both quality and price influence purchase decision. Their empirical analysis on digital cameras shows that ratings, being in general unidimensional, are biased by prices and are more closely correlated with the product value than its quality. More recently, Viglia et al. (2016) find a positive association between review score and hotel occupancy rate. They use diverse categories of hotels and various online review platforms and find that a one point increase in the review score increases the hotel occupancy rate by 7.5 percentage points. However, they did not find any association between review score and star rating. For Viglia et al. (2016) review score, and star rating might reflect different measures of quality.

There is a need to clarify the relationship between reviews and price. Most of the studies on the impact of reviews on price and sales in the hotel industry literature use rating or single review scores that might not represent the complexity of the customer opinion or sentiment about a good or service accurately. Allowing for a methodology, such as sentiment analysis, that mines the client's opinion in the reviews is more likely to depict correctly the quality of the good or service he/she receives. Using sentiment analysis, this study examines the role of opinions derived from reviews in consumer valuation and prices. It uses data collected in the short-term apartment rental market on Airbnb in Boston. The sentiment expressed by the reviews on the platform serves as an intrinsic indicator of the quality of the service offered by the hosts. The indicator is then used to empirically test if reviews affect price and if multidimensional ratings have identical effects on price. Our contribution is threefold. First, we use sentiment analysis to examine how the contents of online reviews could affect prices, rather than relying on customer ratings. Second, with a unique dataset, we compare the effect of the sentiment analysis of the reviews on price with the unidimensional rating score and the disaggregated quality measures. Third, we test whether rental rooms' prices are spatially correlated, and if so, whether rental prices are strategic complements or substitutes.

3. Conceptual framework

An interesting feature of online platforms, such as Airbnb, is the possibility for both hosts and guests to learn about each other before accepting the transaction. By facilitating direct interaction between participants on two sides, these platforms offer participants the possibility to control the terms of their interaction; the intermediary does not take control of these terms (Hagiu and Wright, 2015). On the Airbnb platform, hosts decide on the bundle of services they will offer (bed, couch or sofa, shared bed, Wi-Fi, etc.) and the price of their service. Guests have the possibility to define the nature and quality of the services they desire. For hosts, this has direct implications for their competitiveness. The quality of reviews left by guests can impact their business positively (if the review is positive) or negatively (if the review is negative). Hosts can also learn from their competitors and adjust their price and quality accordingly. This type of interaction where participants on one side of the network compete is referred to as inside competition or a same-side negative effect (Eisenmann et al., 2006).

Unlike studies that rely on a platform economics framework to analyze same-side network effects, this study uses the vertical product differentiation model to describe competition in the quality and price space on the Airbnb platform. The product differentiation literature has benefited from the early work of Hotelling (1929) who sets up the foundation for product and price competition in oligopolistic industries.

Building on the model of horizontal differentiation, many authors have considered the case where even though the two products are offered at the same price, one captures the whole demand because of its better quality. This case is referred to as vertical differentiation and has been examined by Mussa and Rosen (1978), Gabszewicz and Thisse (1979), Shaked and Sutton (1983), and Motta (1993). The conceptual framework used in this study builds on the vertical product differentiation models of Wauthy (1996) and Motta (1993). Although there are a number of hosts on Airbnb in a city, most of them compete with a set of competitors within a range, e.g., one, two, or three miles (for example, Zervas et al.'s Airbnb competition study [2017] uses small and large radiuses of one and five miles). We, therefore, consider the following two-stage game based on duopolistic competition. Hosts choose the quality of their room in the first stage, and in the second stage, they compete for the price given these qualities. We suppose costs are fixed $c(s_i) = \frac{s_i^2}{2}$ and are incurred during the first stage of the game. At the second stage, as in Motta (1993), firms incur a constant production cost. The cost for quality development in the first stage is considered as a sunk cost in the second stage. One caveat of modeling Airbnb using the traditional profit-maximization framework is that owners, especially part-time ones, might pursue utilization maximization rather than profit utilization, as argued by Horn and Merante (2017). Edelman et al. (2017) show that a subset of hosts discriminate against guests with African-American names violating the civil rights acts of 1964 (Todisco, 2014). This suggests that a subset of hosts might be maximizing utility instead of profits. This discrimination is likely to occur with units professionally managed or rented on a full time basis. Due to data unavailability, we are not able to tell part-time rentals from full-time rentals or professionally managed rentals, so we proceed with the traditional profit-maximization framework.

Guests have an identical indirect utility function with the following preferences:

$$u = \begin{cases} \theta s - p & \text{if the guest rents the apartment of quality } s \text{ at price } p \\ 0 & \text{if he does not rent} \end{cases} \tag{1}$$

where $\theta \in \left[\underline{\theta}, \overline{\theta}\right]$ is a taste parameter uniformly distributed with unit density. The mass of guests is $\int_0^1 dz = 1 - 0 = 1$ and the cumulative distribution $F(\theta) = \int_0^\theta dz$ is the fraction of guests with a taste parameter lower than θ. Guests with higher taste parameters are willing to rent (pay for) a room of higher quality. The s term represents the quality and the higher the quality of the room, the higher the utility reached by the guest. We have a high-quality host s_2 and a low-quality one s_1 with $s_2 > s_1$ and quality differential

$$\Delta s = s_2 - s_1 > 0 \tag{2}$$

There is a lower bound to the level of quality since hosts need to meet a minimum quality standard before posting their room on the platform. Using backward induction, we will solve for the sub-game perfect Nash equilibrium.

A guest is indifferent between quality 1 and quality 2 if he has a taste parameter that satisfies:

$$\tilde{\theta} s_1 - p_1 = \tilde{\theta} s_2 - p_2 \quad \Longrightarrow \quad \tilde{\theta} = \frac{p_2 - p_1}{\Delta_s} \tag{3}$$

A guest is indifferent between renting on Airbnb and not renting at all if he has a taste parameter that satisfies:

$$\widehat{\theta}s_1 - p_1 = 0 \quad \Longrightarrow \quad \widehat{\theta} = \frac{p_1}{s_1} \tag{4}$$

From (3) and (4) we derive that a guest with a taste parameter $\theta \geq \tilde{\theta}$ rents the apartment of quality 2 and the proportion of guests who rent the room of quality 2 is:

$$\int_{\tilde{\theta}}^{\overline{\theta}} f(x)dx = F\left(\overline{\theta}\right) - F\left(\tilde{\theta}\right) = \overline{\theta} - \frac{p_2 - p_1}{\Delta_s} \tag{5}$$

and guests who rent the room of quality 1 have a taste parameter $\tilde{\theta} > \theta \geq \frac{p_1}{s_1}$ and their proportion is:

$$\int_{\widehat{\theta}}^{\tilde{\theta}} f(x)dx = F\left(\tilde{\theta}\right) - F\left(\widehat{\theta}\right) = \frac{p_2 - p_1}{\Delta_s} - \frac{p_1}{s_1} \tag{6}$$

We derive the demands for high and low qualities hosts:

$$\begin{cases} q_1(p_1, p_2) = \dfrac{p_2 - p_1}{\Delta_s} - \dfrac{p_1}{s_1} \\ q_2(p_1, p_2) = \overline{\theta} - \dfrac{p_2 - p_1}{\Delta_s} \end{cases} \tag{7}$$

In Nash equilibrium, firms choose their price to maximize their profit given by:

$$\prod_i = [p_i - c)]q_i \tag{8}$$

where *c* is the constant unit production cost. We can set the constant unit cost to 0 and the first order condition gives

$$q_i + \frac{\partial q_i}{\partial p_i} p_i = 0 \tag{9}$$

Solving for prices in the first order conditions and using results from equation (7) give the following reaction functions:

$$\begin{cases} p_1^R = p_1 = \dfrac{1}{2}\dfrac{s_1}{s_2} p_2 \\ p_2^R = p_2 = \dfrac{1}{2}\left(p_1 + \overline{\theta}\Delta s\right) \end{cases} \tag{10}$$

From equation (10) we can derive the equilibrium prices set by the high and low-quality hosts:

$$\begin{cases} p_1^* = \dfrac{s_1 \Delta s \overline{\theta}}{4s_2 - s_1} \\ p_2^* = \dfrac{2s_2 \Delta s \overline{\theta}}{4s_2 - s_1} \end{cases} \tag{11}$$

Motta (1993) shows that these are Nash equilibrium prices. We can also derive:

$$p_2^* - p_1^* = \frac{\Delta s(2s_2 - s_1)\overline{\theta}}{4s_2 - s_1} > 0 \tag{12}$$

Equation (12) implies that, in equilibrium, high-quality hosts set higher prices compared to low-quality hosts.

Substituting (12) into (7) gives the equilibrium demand:

$$\begin{cases} D_1^* = \dfrac{s_2 \overline{\theta}}{4s_2 - s_1} \\ D_2^* = \dfrac{2s_2 \overline{\theta}}{4s_2 - s_1} \end{cases} \tag{13}$$

Since we are interested in the effect of the rival's price on the host *i* price, we can derive:

$$\begin{cases} \dfrac{\partial p_1^R}{\partial p_2} = \dfrac{1}{2}\dfrac{s_1}{s_2} > 0 \\ \dfrac{\partial p_2^R}{\partial p_1} = \dfrac{1}{2} > 0 \end{cases} \tag{14}$$

This predicts that prices are strategic complements. When a host increases its price, its rival also increases his price. When the low-quality host price increases his price, the response of the high-quality host is larger than the reaction of the low-quality host following an increase in price by the high-quality host:

$$\frac{\partial p_1^R}{\partial p_2} = \frac{1}{2}\frac{s_1}{s_2} < \frac{1}{2} = \frac{\partial p_2^R}{\partial p_1} \tag{15}$$

4. Data and methods

4.1. Data and estimation procedure

The data used in this study are from the Airbnb platform for Boston and were retrieved from Inside Airbnb[1] during the month of September 2016. Airbnb is a short-term rental platform that offers lodging to travelers. It connects individuals who want to rent their apartment to temporary visitors. Airbnb charges both the host and the guest a service fee by facilitating the transaction between the two parties.

We have data for 2051 individual hosts on Airbnb in our sample, which is concatenated with data from other sources. The Airbnb data contains the characteristics of the apartment offered, its geographic coordinates, the price per night, and the reviews by previous guests. The Airbnb data is combined with economic data for the Boston area derived from the American Community Survey at the tract level. Shapefiles of the parks, transportation system and central business district are joined to the Airbnb data set using ArcGIS. Table 1 presents a detailed description and the summary statistics of the variables utilized in this study. We include several key characteristics of an apartment (that is price, number of persons a room can accommodate, number of bathrooms and bedrooms in the apartment) and some neighborhood variables including the distances to the nearest convention center, central business district, closest violent crime area, and train station. Measures of income and education level are also included.

To test the relationship between room prices and quality and examine the best measure of quality, we consider eight quality-signaling variables. First, we use a unidimensional measure of quality that measures the overall satisfaction of the guests. The unidimensional measure is similar to the single rating score used by previous studies in the hospitality literature. Second, for each room, we derive a quality measure from the contents of the reviews left by previous guests. Using sentiment analysis, the opinions in the reviews are mined, and a score is derived. The mean score of the reviews for each room is used as a proxy for the quality of the room.[2] Third, we consider six disaggregated measures of quality, which are ratings by guests of specific aspects of the services provided by their hosts. These measures are accuracy, cleanliness, check-in, communication, location and the value of the apartment. The quality measure related to the accuracy of the listing reflects how accurate the description of the apartment on the Airbnb platform is compared to the guest's experience. The quality rating cleanliness evaluates the cleanliness of the property including the rooms, bathrooms and common areas. The check-in quality relates to how welcome the guest felt when he/she first arrived. Communications with the hosts as a quality measure provides an evaluation of how long it takes the host to respond and the accuracy and

[1] Inside Airbnb is an independent, non-commercial set of tools that collects and facilitates the access to publicly available information about a city's Airbnb listings.

[2] Details on the opinion mining using sentiment analysis are presented in the next section.

Table 1
Description and Summary Statistics of the variables.

Variable	Description	Size	Mean	Std Dev	Minimum	Maximum
Structural Variables						
Price	Apartment rental price (dependent variable)	2051	165.19	114.49	20	1300
Accommodate	Number of persons the room can accommodate	2051	3.11	1.86	1.00	16.00
Bathroom	Number of bathrooms in the apartment	2051	1.18	0.49	0.00	6.00
Bedrooms	Number of bedrooms in the apartment	2051	1.26	0.79	0.00	5.00
Neighborhood variables						
Convention	Euclidian distance (in feet) to the closest convention center	2051	8247.94	7716.91	73.97	41,733.11
MBTA	Euclidian distance (in feet) to the closest train station	2051	1782.66	2128.51	35.07	17,950.10
CBD	Euclidian distance (in feet) to the central business district	2051	4056.16	5867.97	0.00	35,574.53
Crime	Euclidian distance (in feet) to the closest violent crime area	2051	58.54	318.37	0.00	7342.16
Income	Per capita income at the closest census tract	2051	51,282.59	29,310.81	7011.00	120,813.00
Graduate	Percentage of the tract median family with at least a bachelor degree	2051	60.43	23.98	5.40	88.90
Quality-signaling variables						
Sentiment_score	The score derived from sentiment analysis of the reviews	2051	10.81	4.75	−8.00	47.00
Unidimensional_rating	Unidimensional rating of guests' overall satisfaction	2051	92.75	8.35	20.00	100.00
Accuracy	Rating of the accuracy of the description of the apartment on the Airbnb platform	2051	9.50	0.89	0.00	10.00
Cleanliness	Rating of the cleanliness of the property	2051	9.38	1.00	2.00	10.00
Checking	Rating of how welcome the guest felt when he/she first arrived	2051	9.71	0.68	2.00	10.00
Communication	Rating by the guest of an evaluation of how long it takes the host to respond and the accuracy and usefulness of the host's responses	2051	9.69	0.71	0.00	10.00
Location	Rating by the guest of how satisfied he/she is about the location of the property in the neighborhood and its proximity to amenities	2051	9.44	0.86	0.00	10.00
Value	Rating of guest satisfaction with paying the room rate for the service received	2051	9.25	0.89	2.00	10.00
Number of reviews	Number of reviews per rooms rented on Airbnb	2051	10.96	12.74	1.00	82.00

usefulness of the host's responses. A quality variable for the satisfaction of the guest about the location of the apartment in the neighborhood and its proximity to amenities is also considered. The last quality measure used, the sensitivity check, is related to the value of the listing, which evaluates the guest satisfaction with paying the room rate for the service received.

4.2. Derivation of quality scores with sentiment analysis of the reviews

Natural language processing and linguistic techniques provide the foundation for sentiment analysis, which has been used in recent years to derive opinions from texts (Hu and Liu, 2004, Popescu and Etzioni, 2007, Ye et al., 2009a,b). This approach is used here to mine the opinions in the reviews left by guests on Airbnb and derive a quality score from those reviews. AFINN's general purpose lexicon helps extract the sentiments from the words used by the reviewers. AFINN was developed by Nielsen (2011) and is a lexicon based on unigrams (single words). The lexicon contains English words where each unigram is assigned a score that varies between minus five (−5) and plus five (+5). The negative scores indicate negative sentiments and positive scores indicate positive sentiments. The newest version of the lexicon, AFINN-111, which contains 2477 words and phrases, is used in this study. To perform the analysis on sentiment, the words used in each review are assigned an opinion score, and the total score of a review is given by the sum of the scores of the words in that review. Specifically, the following procedure is followed:

- The reviews are cleaned of punctuation, numbers, extra spaces and non-textual contents.
- Irrelevant words are removed using "stopwords" with English as the language of reference. Stopwords are words such as "I," "the," "a," "and" that do not add value to a review.
- Each word is replaced by its stem (the root of the word).
- Each stem is then matched with a word or unigram in the list of sentiment words in the AFINN lexicon. If a match is found in the lexicon, the stem is attributed the score of the match.
- The final score of a review is the sum of the scores of positive and negative matches.

Airbnb estimates that 70% of the guests provide a review on their experience. Only the reviews written in 2016 were used for our analysis since customers on online platforms focus on more recent comments (Pavlou and Dimoka, 2006). Our algorithm is built to detect sentiment in reviews written in English, we use Cavnar and Trenkle (1994) N-gram-based approach for text categorization to retrieve the reviews written in English. The N-gram-based approach has been shown to achieve a 99.8% correct classification rate when used to classify articles written in different languages on the Usernet newsgroup (Cavnar and Trenkle, 1994). We use the texcat package (Feinerer et al., 2013) for the review categorization. This package replicates and reduces redundancy in the Cavnar and Trenkle (1994) approach. Fig. 1 presents the frequency of the languages that appeared in the reviews; notice that almost all of the reviews are written in English. On Airbnb, an automatic review in the form of *"Host cancelled this reservation … This is an automated posting"* is generated when hosts cancel the booking prior to arrival. Those reviews are dropped from the dataset. In total, 22,651 reviews were mined and the average of the review score per room is used as a proxy for the room quality.

To illustrate the sentiment analysis methodology used, let us consider the following review: "*the apartment is beautiful, we have access to a cozy big room, Alan the host was courteous however, the neighborhood was very boring*". The words that indicate an emotional state are associated with their corresponding match in the AFINN dictionary. These words are "beautiful", "cozy," "big," "courteous," "boring" and their corresponding scores are, respectively, +3, +2, +1, +2, and −3. This review has 5 as a sentiment score which corresponds to the sum of the scores for the words that denote an emotional state. Fig. 2 shows a text cloud of the most frequent 1000 words where the size of each word is proportional to its frequency in the reviews and Table 2 presents a sample of the reviews and the scores associated with them.

4.3. Empirical estimation procedure: the spatial autoregressive model

The Moran's I statistic and the Lagrange multiplier are used to test for the presence of spatial effects in the price data. Results of the tests in Tables 3 and 4 indicate the presence of spatial dependence through the spatial lagged price. Ordinary Least Squares is known to produce biased, non-consistent and inefficient estimates in the presence of spatial association in the form of spatial dependence or spatial autocorrelation (Anselin, 1988; Anselin and Bera, 1998), so a spatial hedonic price model is used for estimation.

The spatial autoregressive model (SAR) accounts for the presence of a spatial lag dependent variable. The model is specified as follows:

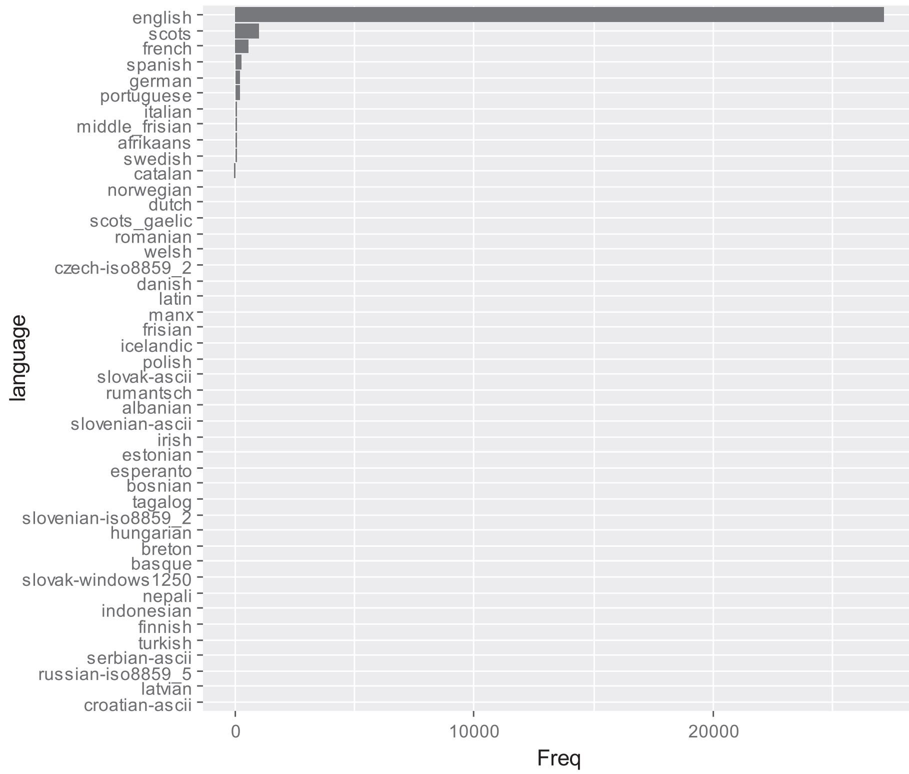

Fig. 1. Frequency of the languages used to write the reviews on Airbnb in Boston.

Fig. 2. World clouds of reviews on Airbnb in Boston.

Table 2
Sample of reviews and their score.

Reviews[a]	Score
Check-in/check-out was easy and it waa easy to get to the house from the metro station which took me only 5 mins or even less. The house was clean but only problem was that there was only one bathroom but other than, the house is a perfect place to stay.	5
We stayed at Alex place for 2 nights and are totally happy that we have chosen it. The bed was comfy, the room was very nice and the host and her husband are super friendly.	11
This place was a great little place to stay and call you own for how ever long you need. only a few minute walk to the Boston Commons and public transportation. A lot of great little shops just around the corner. I highly recommend this place if you just need a little get away for a few days!!! Thanks again Paige	10
The apartment was perfect for our family. Check in and check out was easy, the apartment was clean and quiet, decent sized kitchen. Location is awesome. We had a great time.	14

[a] The reviews are presented as written on Airbnb; we did not correct the typos.

Table 3
Moran I test on prices on Airbnb in Boston.

Weights matrix threshold	Moran I	p-value
1 miles	0.19	0.000
3 miles	0.07	0.000
5 miles	0.007	0.000

$$P = \rho WP + X\beta + \varepsilon \tag{16}$$

where the dependent variable P is the n by 1 vector of the renting prices. The Box-Cox transformation suggests a log transformation of the price variable as the functional form that best fits the data. W is an n by n spatial distance matrix. We use 1 mile as the distance threshold. X is an n by k matrix of exogenous explanatory variables with a constant term vector. It includes the structural characteristics of the apartment such as the number of bathrooms, the number of people it can accommodate, the type of room, the cancellation policy, the number of reviews, and the neighborhood characteristics such as the distance to the nearest convention center, distance to the nearest bus or train stop, distance to the CBD, distance to the closest violent crime area, the area's unemployment rate, and level of education. It also includes the quality-signaling variable.

The β term is a k by 1 vector of coefficients of the explanatory vari-

Table 4
OLS regression diagnostic test for spatial dependence of prices on Airbnb in Boston.

Test	Value and significance per weigh matrix		
	1 mile	3 miles	5 miles
Lagrange Multiplier (SARMA)	58.49***	7.24**	0.09
Lagrange Multiplier (error)	19.708***	3.12*	0.36
Lagrange Multiplier (lag)	53.227***	3.28*	5.46**
Robust LM (error)	5.26**	3.95*	0.00
Robust LM (lag)	38.78**	4.11*	5.38**

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level.

ables; ε is the independent error term which follows a normal distribution with zero mean ($0_{n\ x\ 1}$) and a constant variance (σ^2); ρ is the price spatial lag (WP) coefficient. Mobley et al. (2009) and Mobley (2003) show that the coefficient ρ on the spatial lag price variable identifies strategic response of hosts to price changes. Price complementarity corresponds to a positive spatial lag coefficient while substitutability corresponds to a negative spatial lag coefficient. If the prices are strategic complements, the expectation is that the sign of ρ is positive.

According to Anselin (1988), estimating equation (16) with maximum likelihood will produce consistent and efficient estimates. Contrary to the OLS model, the coefficients on the regressors in equation (16) are not the marginal impacts of a one unit increase in their value on the dependent variable (Gravelle et al., 2014; Le Gallo et al., 2003; Lesage, 2008). The reduced form of the equation (16) gives the intuition behind this result:

$$(I - \rho W)P = X\beta + \varepsilon \tag{17}$$

Which can be rearranged as

$$P = (I_n - \rho W)^{-1}X\beta + (I_n - \rho W)^{-1}\varepsilon \tag{18}$$

This is useful in examining the partial derivative of P_i with respect to change in the j,rth variable x_{jr}:

$$\frac{\partial P_i}{\partial x_{jr}} = (I_n - \rho W)^{-1}(I_n\beta_r)_{ij} \tag{19}$$

The partial derivative here is different from the usual OLS scalar derivative expression β_r. Instead, the partial derivative is an n-by-n matrix. The partial derivative on off-diagonal elements ($j \neq i$) are different from zero (which would be the case with OLS). This shows that changes in the explanatory variable of any host on Airbnb can affect the price of all the hosts on the platform. The own partial derivative is referred to as the direct effect and is captured by the diagonal element of $(I_n - \rho W)^{-1}(I_n\beta_r)_{ii}$. The indirect or spillover effect corresponds to the off-diagonal elements of the matrix (when $j \neq i$). Averaged over all observations, these measures give the average direct effect, the average indirect effect and the average total effect (Lesage, 2008). Changes in the quality variable are used to illustrate each of these effects. If a host i improves the quality of his room, the average direct effect measures the average impact on price for host i (averaged other all observations). The impact of the change in room quality by all the other hosts on host i's price (averaged over all observations) is given by the average indirect effect. Finally, the total average effect measures the impact on price of changes in all hosts quality. It is equal to the average direct effect plus average indirect effect.

5. Econometric results and discussion

Ten models were estimated: Model 1 uses Ordinary Least Squared; Model 2 uses the Spatial Autoregressive (SAR) model with 1 mile as the distance threshold weight matrix and the spatial lag as the only explanatory variable; Models 3-10 add the rest of the explanatory variables to the SAR with different specifications of the quality-signaling variables which are, respectively, the unidimensional measure of quality, the quality derived from the sentiment analysis, and the six disaggregated alternative measures of quality (accuracy, cleanliness, checking, communication, location, and value). We use the package spdep (Bivand et al., 2013; Bivand and Piras, 2015) for estimations. We also conduct a series of sensitivity tests. First, we perform a linear mixed effects analysis by including a random effect at the census tract level. Second, we vary the spatial weight matrix by increasing it to 3 and 5 miles. Third, we estimate the model with spatial fixed effect at the zip code level.

Results of the OLS regression and maximum likelihood estimation of the Spatial Autoregressive (SAR) models are presented in Table 5. The sign and significance level of the estimates are consistent across the ten models. The AIC is lower in four of the SAR models compared to the OLS model, indicating a better fit. The Lagrange Multiplier test on spatial error dependence in the SAR models does not reveal a spatial dependence in the residual errors and we use robust standard errors for our estimates. Only the results of the SAR models are presented to answer the questions of this study.

Results of the theoretical model predict that hosts will compete for prices in the short-term rental market; prices are expected to be strategic complements. The spatial autoregressive coefficient is positive and highly significant (e.g., a parameter of 0.30 in the SAR specifications). This indicates that room prices are strategic complements on Airbnb in Boston. A price increase by one host leads to a price increase by its neighbors.

The SAR estimates are not the partial derivatives as shown by equation (19); Table 6 decomposes the total effect for variables into its direct and indirect components with the unidimensional and sentiment scores as the quality measures. The results of the estimation confirm the consistency of the sign, significance level, and size of the estimates across the models. Structural variables such as the number of persons the room can accommodate, the number of bathrooms, and the number of bedrooms are positive and statistically significant. Listings with more bedrooms, more bathrooms and that can accommodate more persons tend to set higher prices. This is consistent with the previous literature on the hotel industry (Cirer Costa, 2013; de Oliveira Santos, 2016; Espinet et al., 2003). When a quadratic term for the number of persons a room can accommodate is included, this variable exhibits a diminishing marginal effect on price. Changes that increase the number of persons a room can accommodate has a larger impact on price for hosts whose rooms accommodate fewer persons than for hosts whose room accommodate larger number of guests up to the turning point of 10 (0.18/(-2*-0.009)) persons. The number of bedrooms in the apartment has a larger impact on price (24 percent) than the number of bathrooms (12 percent).

The theoretical model predicts that hosts with high-quality rooms will set a higher price compared to hosts with low-quality rooms. The coefficient of the quality variable allows us to test if price is affected by room quality. As in the hotel marketing literature, our estimation result confirms expectation. Quality variables have a highly significant and positive coefficient across all the regression models implying that quality is positively associated with room price. Based on Table 6, the result suggests that a one point increase in review score will increase room price by 0.9 percent if the unidimensional rating quality score is used and by 1.4 percent when the sentiment quality measure is used. This result implies that the sentiment quality measure is a better proxy for quality than the unidimensional rating score. The result also confirms Archak et al. (2011) and Chevalier and Mayzlin (2006) on the importance of the content of the reviews compared to the unidimensional rating such as review score. The sentiment analysis approach helps extract the opinion hidden in the reviews proxying more features related to the room quality than the unidimensional rating score. The unidimensional measure of quality measures the overall satisfaction of the guests while the sentiment score measures indirectly important features quality.

This result also suggests that the one size fits all approach using the unidimensional rating might not perform as well as an approach that

Table 5
Estimates of the spatial lag regressions with 1 mile as weight matrix on Airbnb in Boston.

Variables Dependent variable: lnPrice		OLS	SAR								
		I	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
W_LnPrice			0.92***	0.29***	0.30***	0.29***	0.30***	0.30***	0.30***	0.30***	0.30***
			(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Intercept		3.77***	0.35***	2.14***	2.64***	2.67***	2.73***	2.67***	2.61***	2.67***	2.66***
		(0.21)	(0.11)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Unidimensional_rating		0.05***		0.006***							
		(0.00)		(0.00)							
Sentiment_score					0.01***						
					(0.001)						
Accuracy						0.04***					
						(0.006)					
Cleanliness							0.06***				
							(0.006)				
Checking								0.03***			
								(0.007)			
Communication									0.03***		
									(0.007)		
Location										0.03***	
										(0.007)	
Value											0.02***
											(0.007)
Number of reviews		−0.002***		−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
		(0.00)		(-.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accommodate		0.13***		0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodate^2		−0.006***		−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***	−0.006***
		(0.001)		(0.001)	(0.001)	(0/001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bathroom		0.08***		0.08***	0.08***	0.08***	0.08***	0.08***	0.08***	0.07***	0.08***
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bedroom		0.17***		0.16***	0.17***	0.17***	0.16***	0.17***	0.17***	0.17***	0.16***
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Room_type	Private Room	−0.42***		−0.41***	−0.41***	−0.41***	−0.40***	−0.41***	−0.41***	−0.41***	−0.41***
		(0.02)		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	Shared Room	−0.68***		−0.67***	−0.68***	−0.68***	−0.66***	−0.68***	−0.68***	−0.68***	−0.68***
		(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Cancellation Policy	Moderate	0.05***		0.06***	0.06***	0.06***	0.05***	0.06***	0.06***	0.06***	0.06***
		(0.02)		(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	Strict	0.02		0.02	0.02	0.02	0.01	0.02	0.02	0.03	0.03
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Super-strict	0.23***		0.25***	0.26***	0.25***	0.21***	0.23***	0.22***	0.23***	0.24***
		(0.06)		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Log Distance	Convention	−0.11***		−0.06***	−0.06***	−0.06***	−0.06***	−0.06***	−0.06***	−0.06***	−0.06***
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	MBTA	−0.004		−0.008	−0.004	−0.007	−0.011	−0.005	−0.005	−0.004	−0.005
		(0.009)		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
	CBD	−0.01***		−0.007***	−0.006**	−0.007**	−0.007***	−0.007***	−0.007***	−0.006*	−0.007***
		(0.00)		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	Crime	0.00		0.004	0.004	0.005	0.004	0.005	0.005	0.004	0.005
		(0.00)		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log Education		0.06**		0.04**	0.05***	0.04***	0.04**	0.04**	0.04**	0.03*	0.04**
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log Income		0.07***		0.06***	0.05***	0.07***	0.06***	0.06***	0.06***	0.06***	0.06***
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AIC		1088.2	3097.2	1049.2	1069.1	1073.2	1017.3	1095.8	1094.2	1100.7	1097.7
LM test for residual autocorrelation		0.77***	0.21	0.01	4.49	0.05	0.04	0.01	0.001	0.02	0.02

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level. Robust standard errors are in parenthesis.

disaggregates the quality measure into its different components. To test this hypothesis, we consider six disaggregated measures of quality, which are evaluation by guests of specific features of the services provided by their hosts. The disaggregated measures are accuracy, cleanliness, check-in, communication, location and the value of the apartment. Results of the coefficients of these variables presented in Table 5 show consistent, positive and significant coefficients providing substantial evidence to support the theoretical hypothesis that hosts with high quality rooms set a higher price compared to hosts with low quality rooms. The results of the decomposition of the impacts of the quality variables on price are presented in Table 7 where the total impact of each quality variable is decomposed into its direct and indirect component. The size of the unidimensional measure of quality is significantly lower compared to the other measures. Among the disaggregated measures of quality, cleanliness has the highest impact on price (9.8 percent) followed by accuracy (6.4 percent). Value has the lowest impact (4.2 percent). The impact of the unidimensional measure of quality on price is less than one-fourth of the impact of value, the lowest disaggregated measure of quality. This confirms Li and Hitt (2010) results where the unidimensional measure of quality has been shown to be more associated with the product value than to its quality. All the impacts (direct, indirect, and total) of the review score generated through sentiment analysis are closer to the impacts of the disaggregated measures of quality compared to the unidimensional measure. This result suggests that sentiment analysis of the reviews will better approximate quality than the unidimensional measure of quality, and using the unidimensional measure of quality will create a downward

Table 6
Direct, indirect and total effects of the impact of the regressors on room price with 1 mile as weight matrix on Airbnb in Boston.

Variables Dependent variable: lnPrice		Impacts with unidimensional measure			Impacts with sentiment score		
		Direct	Indirect	Total	Direct	Indirect	Total
Accommodate		0.129***	0.054***	0.183***	0.126***	0.054***	0.181***
Accommodate2		−0.006***	−0.003***	−0.009***	−0.006***	−0.003***	−0.009***
Bathroom		0.085***	0.035***	0.120***	0.084***	0.036***	0.121***
Bedroom		0.168***	0.071***	0.239***	0.172***	0.074***	0.246***
Quality measure		0.006***	0.003***	0.009***	0.010***	0.004***	0.014***
Number of reviews		−0.002***	−0.001***	−0.003***	−0.002***	−0.001***	−0.003***
Room_type	*Private Room*	−0.412***	−0.174***	−0.586***	−0.416***	−0.180***	−0.596***
	Shared Room	−0.680***	−0.286***	−0.966	−0.680***	−0.294***	−0.975***
Cancellation Policy	*Moderate*	0.061***	0.025***	0.086***	0.064***	0.027***	0.091***
	Strict	0.029	0.012	0.041	0.029	0.013	0.042
	Super-strict	0.251***	0.106***	0.357***	0.270***	0.116***	0.387***
Log Distance	*Convention*	−0.065***	−0.027***	−0.093***	−0.066***	−0.028***	−0.094***
	MBTA	−0.008	−0.003	−0.011	−0.005	−0.002	−0.007
	CBD	−0.007***	−0.003***	−0.010***	−0.006***	−0.003***	−0.009***
	Crime	0.004	0.002	0.006	0.005	0.002	0.007
Education		0.044***	0.019***	0.063***	0.053***	0.023***	0.075***
Income		0.063***	0.026***	0.089***	0.052***	0.023***	0.075***

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level.

Table 7
Decomposition estimates of the direct and indirect effects of quality variables on rooms' prices on Airbnb in Boston.

Quality Variables	Direct	Indirect	Total
Unidimensional rating	0.006***	0.003***	0.009***
Sentiment score	0.010***	0.004***	0.014***
Accuracy	0.045***	0.019***	0.064***
Cleanliness	0.069***	0.029***	0.098***
Check-in	0.031***	0.013***	0.044***
Communication	0.032***	0.014***	0.046***
Location	0.030***	0.013***	0.043***
Value	0.029***	0.013***	0.042***

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level.

bias for the estimate of the impact of quality on price.

Among the quality variables, cleanliness better explains room price, followed by accuracy. Cleanliness seems to be the most important quality variable associated with price. This result is consistent with de Oliveira Santos (2016) who study more than 8000 hostels worldwide and identify cleanliness, location, and facilities as the main characteristics that explain accommodation prices. With the growth of online platforms, where reviews can inform prospective guests, Airbnb hosts should improve these quality variables since they can affect the demand for their rooms.

For all the quality variables the average direct effect on room price is higher than the indirect effect. On average, one-third of the impact of the quality variable on price comes from the indirect impact from hosts located nearby (as they increase their prices in response). This confirms the existence of a spillover effect. Policies that provide an incentive for hosts to improve the quality of their room have a direct positive impact on the price of their room on Airbnb but also an indirect positive impact on the other hosts in their neighborhood.

The number of reviews also is relevant in explaining price. Airbnb

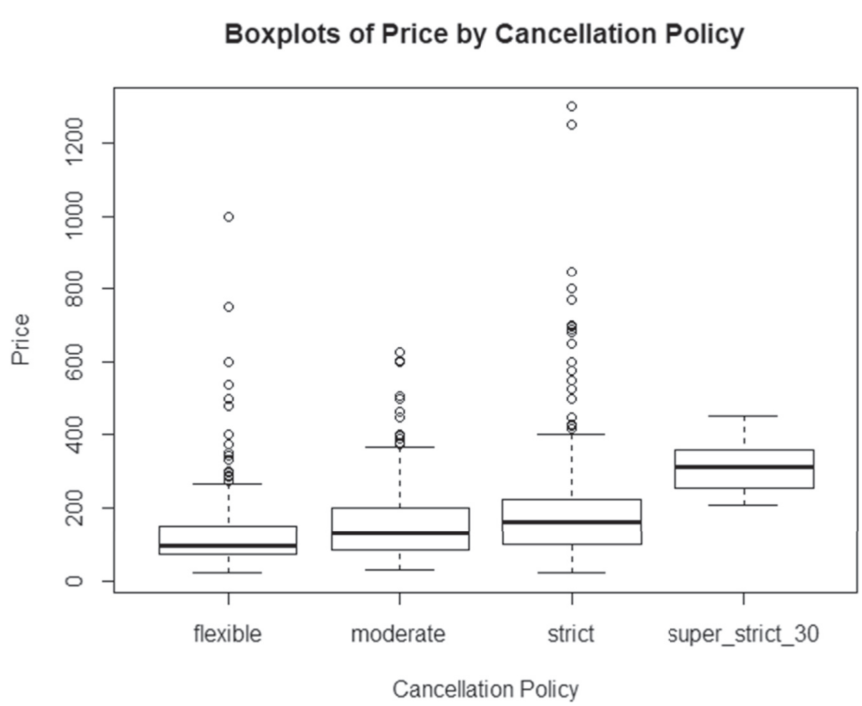

Fig. 3. Boxplot of price by cancellation policy on Airbnb in Boston.

estimates that 70% of guests provide a review on their host. The number of reviews is used to approximate the demand for rooms. The negative sign for the coefficients largely reflects the law of demand; the demand for higher price rooms is smaller.

Estimates of the impact of the room type on price show that shared rooms and private rooms, compared to entire homes, are cheaper. A shared room is the cheapest among all three. The coefficients for the dummy variables associated with these variables are significant and negative. Shared rooms are 97 percent cheaper than entire homes while private room are only 59 percent cheaper.

The coefficients on the dummies for cancellation policies show that, compared to a flexible cancellation policy, hosts who use moderate, strict and super-strict cancellation policies set higher prices. The cancellation policy can be seen as a segment differentiation strategy by hosts. As Fig. 3 shows, average price increases with stricter cancellation policies. To test if the impact of review varies by lodging segment, the SAR model was run for each segment using the unidimensional rating and sentiment score as quality measure. Results in Table 8 indicate that, except for moderate cancellation policy in the sentiment score case, the impact of quality on room price decreases as we move from flexible to super-strict cancellation policy. The impact of quality on price for super-strict cancellation policy segment is not significant at 5% confidence level. Zhang et al. (2011a,b) found similar results when studying the determinants of hotel room prices. When considering lodging segments, they found a positive impact of quality on room price for economy and midscale hotels. However, in their study, for luxury hotels, quality does not affect room price. They conclude that for the higher lodging segment, quality is no longer a differentiation factor. On Airbnb in Boston, all the hosts who use a super-strict cancellation policy offer an entire home or apartment for rent on the lodging platform. For these hosts, the quality of their room is already embedded in the type of room they offer thus the insignificance of the quality variable.

Proximity to amenities has been shown to affect the price in hedonic price models in previous studies. Our results indicate that the distance to the nearest convention center and closeness to the CBD have the sign and significance level as expected. Participation in conferences for a short-term period is among the reasons guests book rooms on Airbnb. The results of our estimation support why hosts that are located closer to convention centers set higher prices compared to hosts that are located further away from them. A one percent decrease in the distance that separates a room from the nearest convention center leads to a 0.09 percent increase in price. The positive and significant coefficient on the CBD variable indicates that a one percent decrease in the distance that separates the host from the CBD contributes to a room rate premium of 0.01 percent. Most of the amenities being located in the CBD, hosts closer to the CBD set a higher price compared to host located further from it. The distance to the closest train station does not affect price, as evidenced by the non-significance of their coefficients. This provides little evidence to support a probable relationship between the availability of public transport system and the price set by hosts on Airbnb. Contrary to our expectation, location away from area with violent crime does not command a room price premium either.

Among the socioeconomic variables, the coefficients for education and income per capita are positive and significant. We attribute the result to the theory of demand for housing (Green and Hendershott, 1996). Neighborhoods with higher education and income levels are more desirable, increasing the demand for houses in those neighborhoods. High demand leads to high rental prices and might explain the high prices for the rooms rented on Airbnb. A one percent increase in the percentage of families with at least a bachelor degree in the census tract where the room is located leads to a 0.07 (0.06 with the unididensional rating score) percent increase in the room price. A similar change in income leads to a 0.08 percent increase in price.

6. Sensitivity analysis

A series of alternative specifications are estimated for robustness checks. The estimation procedure is replicated with a linear mixed effects model. The same controls are used as fixed effects variables. A random effect at the census tract level is added to characterize idiosyncratic variation that is due to census tract differences. The census tract might be a source of non-independence that needs to be considered within the model. We test for the significance of the spatial lag price and review score variables using likelihood ratio tests. P-values are obtained, and a likelihood ratio test is performed on the full model with respect to the spatial lag price and with respect to the review score against the model without these variables. The lme4 package (Bates et al., 2015) is used in the estimation of the linear mixed model estimation. Table 9 presents the log-likelihood ratio test results. The results of the linear mixed effects models confirm the spatial autoregressive model results. The coefficients for both review score and lag prices are consistent with our assumption. Prices are strategic complements, and hosts with rooms of high-quality

Table 8
Decomposition of the impact of review score for flexible, moderate, strict and super strict cancellation policies on Airbnb in Boston.

Segments	Unidimensional score			Sentiment score		
	Direct	Indirect	Total	Direct	Indirect	Total
Flexible	0.008***	0.001***	0.009***	0.015***	0.001***	0.016***
Moderate	0.006***	0.002***	0.008***	0.003***	0.002***	0.005***
Strict	0.006***	0.001***	0.007***	0.010***	0.001***	0.012***
Super strict	0.006*	0.000*	0.006*	0.007*	0.000*	0.007*

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level.

Table 9
Likelihood ratio tests for the statistical significance of price lag and quality variables in the linear mixed effects models.

			Estimates	AIC	BIC	LogLik	Deviance	Chisq Chi
Unidimensional quality measure	Test for lag price	Model without price lag		1040	1152	−500	1000	
		Model with price lag	0.29	1018	1136	−488	976	23.83***
	Test for quality	Model without quality		1082	1194	−521	1042	
		Model with quality	0.006	1018	1136	−488	976	65.5***
Sentiment score quality measure	Test for lag price	Model without price lag		1061	1174	−510	1021	
		Model with price lag	0.30	1038	1156	−498	996	25.01***
	Test for quality	Model without quality		1082	1194	−521	1042	
		Model with quality	0.01	1038	1156	−498	996	45.56***

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level.

set higher prices compared to hosts of low-quality rooms.

The full SAR specification regression is also estimated with 3 and 5 miles as weight matrices. Increasing the threshold of the weight matrix allows the hosts to have a larger number of competitors. The results of the estimates are presented in Table 10. The sign of the estimates for both the review score and the spatial lag price is consistent with the results obtained using 1 mile as a weight matrix.

We also run the regressions with a location fixed effect at the zip code level. The estimates presented in Table 11 are consistent with our results.

7. Conclusion

Online reviews and ratings are largely recognized to impact consumers' purchase decisions especially on online platforms where they serve as a proxy for quality of products and services. Many studies in the hotel industry literature use rating or single review scores to examine the relationship between quality and price. However, evidence from the existing literature suggests that single rating measure can lead to biased conclusions on the relationship between reviews rating and price since the single measure might not represent the complexity of the customer opinion or sentiment about a good or service accurately.

This article contributes to the literature on the impact of quality on price in the hospitality industry. Contrary to the existing literature, where unilateral rating review as scored by the guest is used as a proxy for quality, this study relies on a novel approach to derive the score in the reviews. With sentiment analysis, the opinions in the reviews are extracted and scored to derive the total score of the review. This study also uses a spatial hedonic price model to account for the spatial correlation of price data. Using data from Airbnb platform, the results of the empirical analysis suggests that scores derived from the sentiment analysis of the reviews are better indicators of quality than single rating scores.

Although disaggregated multidimensional components of quality such as cleanliness, accuracy, communication, location, are better predictors of the listing price than the reviews, the latter is still a better proxy for quality than unidimensional rating scores. Reviews reveal information about the intrinsic quality of the hosts and these reviews affect the demand on the Airbnb platform. The reviews affect not only the host price but also the price of other neighboring hosts. The policy implication for Airbnb is to create incentives or policies for hosts to improve the quality of their listings. This will have spillover effects on the price set by other hosts. Cleanliness of the property and accuracy of the listing are the two most important quality measures that affect price and the policies should be directed towards improving those qualities.

The theoretical model suggests that when a host increases its price, its rivals also increase their price, making them strategic price complements. The results of the empirical analysis support the theoretical framework. Other factors, such as the number of bedrooms and bathrooms, as well as the number of people a room can accommodate, also have a positive effect on the price set by the owners. Distance to the convention center

Table 10
Estimates of the spatial lag regression with 3 and 5 miles as weight matrix on Airbnb in Boston.

Variables Dependent variable: lnPrice		Unidimensional score		Sentiment score	
		3 miles	5 miles	3 miles	5 miles
W_LnPrice		0.08*	0.22**	0.09*	0.21**
		(0.05)	(0.10)	(0.05)	(0.10)
Intercept		3.26***	2.60***	3.74***	3.18***
		(0.37)	(0.56)	(0.37)	(0.56)
Quality		0.007***	0.007***	0.01***	0.01***
		(0.000)	(0.000)	(0.001)	(0.001)
Number of reviews		−0.002***	−0.002***	−0.002***	−0.002***
		(0.000)	(0.000)	(-.000)	(0.000)
Accommodate		0.13***	0.12***	0.12***	0.12***
		(0.01)	(0.01)	(0.01)	(0.01)
Accommodate2		−0.006***	−0.006***	−0.006***	−0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
Bathroom		0.08***	0.08***	0.08***	0.08***
		(0.01)	(0.01)	(0.01)	(0.01)
Bedroom		0.17***	0.17***	0.17***	0.17***
		(0.01)	(0.01)	(0.01)	(0.01)
Room_type	*Private Room*	−0.42***	−0.42***	−0.42***	−0.42***
		(0.01)	(0.01)	(0.02)	(0.02)
	Shared Room	−0.68***	−0.68***	−0.68***	−0.68***
		(0.05)	(0.05)	(0.05)	(0.05)
Cancellation Policy	*Moderate*	0.05***	0.05***	0.06***	0.05***
		(0.02)	(0.02)	(0.02)	(0.02)
	Strict	0.02	0.02	0.02	0.02
		(0.01)	(0.01)	(0.01)	(0.01)
	Super-strict	0.23***	0.23***	0.25***	0.25***
		(0.06)	(0.06)	(0.06)	(0.06)
Log Distance	*Convention*	−0.10***	−0.11***	−0.10***	−0.11***
		(0.01)	(0.01)	(0.01)	(0.01)
	MBTA	−0.003	−0.003	−0.000	−0.006
		(0.009)	(0.012)	(0.009)	(0.010)
	CBD	−0.01***	−0.01***	−0.012***	−0.01**
		(0.00)	(0.00)	(0.003)	(0.003)
	Crime	0.004	0.005	0.005	0.005
		(0.003)	(0.003)	(0.003)	(0.003)
Log Education		0.06**	0.06**	0.07**	0.07***
		(0.01)	(0.01)	(0.01)	(0.01)
Log Income		0.07***	0.07***	0.07***	0.07***
		(0.01)	(0.01)	(0.01)	(0.01)
AIC		1087.2	1085.2	1107.5	1106.5
LM test for residual autocorrelation		10.301***	0.42	9.09***	0.49

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level. Robust standard errors are in parenthesis.

Table 11
Estimates of the regression of the effect of review score on price on Airbnb in Boston with spatial fixed effect at the Zip Code level.

Variables Dependent variable: lnPrice		Model with zip code fixed effect and unidimensional score as quality measure	Model with zip code fixed effect and sentiment score as quality measure
Intercept		3.53***	4.06***
		(0.26)	(0.25)
Unidimensional_rating		0.006***	
		(0.000)	
Sentiment_score			0.01***
			(0.001)
Number of reviews		−0.002***	−0.001***
		(-.000)	(0.000)
Accommodate		0.12***	0.12***
		(0.01)	(0.01)
Accommodate2		−0.006***	−0.006***
		(0.001)	(0.001)
Bathroom		0.08***	0.07***
		(0.01)	(0.01)
Bedroom		0.16***	0.17***
		(0.01)	(0.01)
Room_type	Private Room	−0.40***	−0.41***
		(0.02)	(0.02)
	Shared Room	−0.66***	−0.66***
		(0.05)	(0.05)
Cancellation Policy	Moderate	0.05***	0.06**
		(0.02)	(0.02)
	Strict	0.02	0.02
		(0.01)	(0.01)
	Super-strict	0.28***	0.30***
		(0.06)	(0.06)
Log Distance	Convention	−0.08***	−0.07***
		(0.01)	(0.01)
	MBTA	0.002	0.003
		(0.01)	(0.01)
	CBD	−0.01*	−0.01
		(0.007)	(0.007)
	Crime	0.006	0.006
		(0.003)	(0.003)
Log Education		0.01	0.01
		(0.03)	(0.03)
Log Income		0.09***	0.08***
		(0.02)	(0.02)

Note: * denotes that the estimates are significant at 10% and ** and *** denote that they are significant at 5% and 1% level.

and the CBD also impact room price. However, distance to the closest transportation facility and violent crime area does not command a price premium on Airbnb in Boston.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2018.11.003.

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