# Pricing Paris Hotel Rooms: A Hedonic Pricing Approach

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## Abstract[*]

This paper uses a hedonic pricing model to estimate the implicit returns of select hotel characteristics that contribute to overnight room rates of Paris hotels. The dataset used in this paper consists of pricing information on 410 hotels and the associated general, reputational, geographical, and locational characteristics. I find that the star rating, Palace hotel rating, and Trip Advisor rating play key roles in determining standard and premium room rates. Additionally, I find that the inclusion of Wi-Fi in the room rate, the number of rooms of in the hotel, and hotel proximity to the Eiffel Tower to be added determinants in the price of premium rooms only. A price-sensitivity analysis, using prices collected on three separate dates, shows that hotel prices do not tend to fluctuate significantly between the dates of price collection.

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# I. Introduction

In 2014, the Greater Paris hotel industry offered a total 82,227 rooms from 1588 hotels (Office du Tourisme et des Congrès de Paris (2014)).[1] Additionally, Paris recorded an astonishing 36 million overnight stays in 2014. As a result, €4.4 billion in tax revenue was generated by Parisian hotels in the same year. For tourists and business travellers, hotels make up a large portion of travel expenditures. The average price for a Paris hotel room in 2014 was €177 per night.[2] With this in mind, consumers must carefully examine all of the options on the market. Hotel amenities, location, reputation, and star rating are all extremely important factors taken into consideration by both consumers and the companies selling hotel rooms.

The price of a consumer good or service can be broken down into the prices of the individual characteristics that make up the product. That is, the implicit prices of individual attributes and the specific quantity of each attribute are said to determine the price of any good or service. Using Rosen's (1974) hedonic pricing technique, one can determine the implicit prices of select attributes associated with a good or service. By summing these prices, one can derive the price of the complete good. There exists a growing literature of hedonic models applied to a number of consumer goods including early applications in the automobile and agriculture industries (e.g., Court (1939), Griliches (1958)). These models have also been extended to applications in the housing and hospitality industries (e.g., Mok *et al.* (1995), Thrane (2005)). Furthermore, they are now commonly applied in the global hotel industry (e.g., Thrane (2007), Chen and Rothschild (2010)). This paper uses a hedonic pricing model in order to determine the

[1] This statistics refers to the total number of hotel rooms contained in all hotels in the city of Paris in 2014. It does not refer to the total number of hotel bookings in Paris for the year.
[2] All statistics provided by the Office du Tourisme et des Congrès de Paris (2014).

hotel attributes that contribute to overnight room rates in Paris. It also provides the implicit returns of the select hotel characteristics.

Using data on 410 hotels obtained through individual hotel websites, Google Maps, and Trip Advisor*,* I estimate the implicit returns of general, reputational, geographical, and locational characteristics on the price of overnight stays in Paris. This model is estimated for two types of prices: the lowest available price (*low price)* and the highest available price (*high price*) in euros for a regular one-night stay for two people on Thursday, October 29th, 2015.[3] For both *low price* and *high price* regressions, I add controls sequentially. The first regression contains only the basic controls for general hotel attributes, distance to tourist sites, and star rating. I then include controls for Trip Advisor ratings and for Palace-rated hotels.[4] Lastly, I introduce geographical controls in order to test for any effects resulting from the 20 arrondissements of Paris.

This paper finds that the official star rating is an economically (and statistically) significant contributor to price for both standard and premium rooms. This result holds in different specifications of the model when controls are added sequentially. For example, relative to 3-star hotels, 4-star hotels tend to be priced 32.8% higher for standard rooms and 52.7% higher for premium rooms, holding all else equal. Moreover, there exists a large increase in price when moving from a 4-star to a 5-star hotel. Secondly, both the Trip Advisor Rating and Palace hotel rating are found to be statistically and economically significant contributors to price for both room types. Thirdly, I find that select arrondissements located on the outer circle of Paris to be associated with lower prices for both room types. Finally, my results show that chain hotels brands, proximity to the Arc de Triomphe, and proximity to the nearest metro station do not

[3] Throughout this paper, I commonly refer to *low price* rooms as standard rooms and *high price* rooms as premium rooms.
[4] In section III, I discuss the differences between the star rating, Palace rating, and Trip Advisor rating.

influence room rates. This paper also shows that there exist a few key differences between standard and premium room rates. Specifically, the inclusion of Wi-Fi in the room rate, the number of rooms in the hotel proximity to the Eiffel Tower are statistically and economically significant contributors to the price of premium rooms only.[5]

The final contribution of this paper examines the issue of hotel price sensitivity. To be exact, I find that room rates do not tend to vary significantly based on the time and date of booking.[6] I show that prices drop slightly for "last-minute" bookings of both the *low price* and *high price* rates. The gap between these two price types, however, remains relatively constant. Furthermore, the results of the hedonic regression in my sensitivity analysis point towards the same set of explanatory attributes for both room-types.

This paper is structured as follows: Section II explores the literature on the roots of the hedonic pricing technique with a focus on the hotel industry. Section III presents the data used in this analysis, including summary statistics. Section IV outlines the hedonic model used in this paper. Section V presents the results of this paper with a discussion on the important findings. Section VI provides a robustness check of the hedonic pricing model. Finally, concluding remarks are provided in Section VII.

## II. Literature Review

This section begins with a review of the literature surrounding the roots of hedonic pricing models. I then provide an overview of early applications of hedonic pricing models before extending the review to the housing and hospitality industries. The focus of this section is

[5] 95.1% of hotels in my sample offer free Wi-Fi. However, this variable has been left in due to its statistical and economic significance in the case of premium room rates.

[6] I collect and analyze hotel prices for 81 hotels on three separate dates: Friday, September 11th, 2015, Tuesday, September 29th, 2015, and Tuesday, October 27th, 2015. Please see Section VI for more details.

hedonic pricing models and their use estimating hotel room rates. This review concludes with an examination of more recent applications of hedonic pricing of consumer goods.

### *Hedonic Regression*

Rosen (1974) is widely believed to have pioneered the idea of hedonic pricing (e.g., Mok *et al.* (1995), Monty and Skidmore (2003), Lee (2014), Carew and Florkowski (2010)). He defines hedonic prices as the implicit prices of attributes or characteristics belonging to a set of differentiated products. Essentially, Rosen states that a class of differentiated products can be described as a vector of objectively measured characteristics that belong to that product. A function, describing the supply and demand side of these attributes, can be seen in the following equation:

$$P(x) = P(x_1, x_2, \ldots, x_n) \tag{1}$$

where P(x) is the hedonic price function and $x_n$ is a set of product characteristics. Taking the partial derivative of the above function with respect to any $x_n$, reflects the implicit price of that attribute, holding all else equal. The prices of these traits can be determined using econometric technique and by observing the prices of the differentiated products along with the quantity of these traits belonging to each product.

Although Rosen (1974) is often cited as the seminal work of hedonic pricing models, researchers such as Goodman (1998), trace the origins of hedonic pricing back to the work of Court (1939). Andrew Court presented this technique in the case of automobiles where he discusses the weighted relative importance of different automobile traits. In examining characteristics such as wheelbase, weight, and horsepower, he develops what is known as a hedonic price index for automobiles and applies it to 1935 data. Goodman (1998) replicates the work of Court (1939) using more recent data and concludes that Court's main results still hold up today. Furthermore, Griliches (1958) extends the literature on this technique to the agriculture industry with an analysis of fertilizer demand using hedonic regression. As such, there is evidence to suggest the existence of the hedonic technique before the introduction of Rosen's paper from 1974.

***Hedonic Pricing in the Housing and Hospitality Industries***

Mok *et al.* (1995) look to analyze the implicit prices of select attributes of private condominiums in Hong Kong. More specifically, the authors examine the return of locational, structural and neighborhood attributes to the price structure of private residential condominiums in the city. Using information on 1,027 properties, the authors examine the effects of age, distance to the central business district, a sea view, story level, floor area, school zones, and presence of entertainment or sport facilities to the selling price of these properties. Among the locational attributes, the distance to the central business district, story, and sea view are all found to have significant effects, with the latter two qualities increasing the price of the property. The two structural attributes, the gross floor area, and age of the building both have negative and significant impacts on selling price. Finally, big estates and entertainment or sport facilities are determined to be neighbourhood attributes associated with higher selling prices. Moreover, the authors add that the valuation of private condominiums in Hong Kong is sensitive to location, structural and neighbourhood attributes as shown in the elasticity of such attributes. Specifically, buyers will pay high premiums for desirable qualities such as large floor area or new buildings. However, buyers are unwilling to pay for qualities less desirable such condominiums located great distances from the central business district.

Juaneda *et al.* (2011) estimate a hedonic pricing model for Pyreneean-Mediterranean and Mediterranean costal hotels and apartments. Their data includes prices, as well as the associated general and locational characteristics for hotels and apartments for the May to October 2007 period. A primary goal of their study is to estimate prices for select locations and the time a booking is made. Relative to the 1-star rating, the authors show that the 4-star rating (124.52%) presents a greater return to price than that of a 5-star rating (79.80%).[7] As expected, hotels offering board below "all-inclusive' are all associated with lower prices. Also, gardens, number of rooms, pools, and car parking are all attributes raising the price of rooms. Single rooms reflect lower prices than the case of double rooms, while the opposite is true in the case if junior suites. Finally, select resort destinations on the Mediterranean are associated with higher prices. Similar results are found for apartments. In the case of the star rating, however, the highest possible achievement for apartments in this location is four stars. Relative to the 1-star rating, the authors find that the returns to price for this category of variables are of a lesser magnitude than those of the star ratings for hotels. Additionally, increasing the number of rooms decreases apartment prices.

The authors conclude with two main findings, focusing on time of booking factors and locational factors. Firstly, both accommodation types show signs of seasonality. More specifically, during the peak week of their time period (first full week of August), rooms prices are double that of the price in October. Seasonality is also found in the case of apartment bookings. However, this effect is slightly more pronounced for this accommodation throughout the entire period. Additionally, seasonality is highest for Spanish resorts for both accommodation types. Secondly, the authors state that the prices of select locations show evidence of the

[7] The authors believe that this result is due to the extremely low number (less than 3% of sample) of 5-star hotels in their sample.

locations overall quality. They also mention that their results show that tourists staying in hotels will sense a greater difference in destination quality then that of tourists staying in apartments.

Thrane (2005) applies the hedonic regression technique in the hospitality industry where he examines sun and beach package tours in Norway using tour operator catalogues from the 2003 to 2004 period. The author's data consists of information on 2-room apartment type hotels. Examining a total of 252 package tours, Thrane (2005) finds the availability of a free breakfast to be a major contributor to price, increasing the average tour by 13%. Other characteristics found to increase the price of a package tour include the presence of a restaurant at the hotel, a TV in the room, extra kitchen equipment (e.g., coffee machine), and if the hotel is a resort owned by the tour operators. Additionally, the further the hotel is located from the beach, the lower the cost of the room. Packages associated with certain tour operators are also associated with lower prices. The author also finds that the addition of a third room in the apartment tends to reduce the price of the package by about 10% per person, relative to a 2-room apartment. In a secondary model, the author includes the official star rating of the hotels using the 2-star category as the reference group. The results show the star rating to be a statistically significant contributor to price. A one-star increase in the star rating tends to lead to an 11% room rate increase, holding all else equal. This additional control is found to eliminate the statistical significance of the presence of a restaurant, the presence of a TV in the room, and the effects of resort type hotels.

Rosselló and Riera (2012) examine the advancement of marketing technologies in the European package tours market. More specifically, the authors analyze the differences in implicit prices of package tour attributes for online and offline markets. For instance, low-cost carriers and Internet-based travel sites may set considerably different prices than those of in-person travel agencies. Looking at the segmented markets, the authors find a number of notable results.

Firstly, the 4-star and 5-star hotels are associated with higher prices, relative to 1-star hotels. Furthermore, these controls are both statically significant. In contrast, the 2-star and 3-star controls are found to be statistically insignificant, relative to the 1-star rating. Secondly, their results show that select geographical factors, bed and breakfasts, half board tours, full board tours, and all inclusive tours are all associated with higher prices for both segments. Thirdly, they find that trips with the same motivation during the year, tourist packages and low-cost carriers, are all associated with lower prices for both market samples.[8] Moreover, the tourist packages show lower rates for the online market segment (e.g., Internet purchases). Finally, Rosselló and Riera (2012) note that the cost of transportation and accommodations (e.g., half board, full board and all-inclusive) are lower via online agents. This is evidence of technology lowering the cost for tour operators and consumers.

***Hedonic Pricing of Hotel Rooms***

Thrane (2007) extends his research in the hospitality industry with an application of hedonic pricing on hotels located nears Oslo, the Norwegian capital. His work looks to examine consumer prices for single and double room hotel prices. The author's final dataset consists of prices and facility attributes for 74 hotels for a March 2005 stay. Data is collected from an Internet search engine. The author's research finds that two amenities, namely hair dryers and mini bars, tend to have the greatest impact on price. Surprisingly, the presence of a hair dryer and minibar in the room increase the price of the room by 44% and 39% respectively in single rooms. Similar results are also found in the case of double rooms. Chain hotels, free parking, and the number of rooms in the hotel are also associated with higher premiums. Moreover, the

[8] The motivation factor takes into account tourists' past experiences and capability of finding more competitive prices.

further is located the hotel from Oslo Central Station, the lower the hotel premium. Surprisingly, Thrane (2007) finds that hotels offering room service tend to have lower prices by about 12%. When comparing the two types of rooms, the variable for chain hotels is only significant in the case of single rooms while the distance to central station and number of beds in the hotel is only significant for double rooms. He explains that this could be a result of differences in room type offerings in the sample. Unlike Thrane (2005), the author does not include star rating in his pricing model, as the capital does not have an official star rating system. He explains that this may in fact be an advantage as the star rating could be seen as a function of hotel attributes.

Tung *et al.* (2011) develop a hedonic pricing model for international hotels in Taiwan. This paper emphasizes the difference between the price consumers are willing to pay (e.g., willingness-to-pay) and the market price for international hotels in Taiwan. Their study examines a total of 59 hotels for the year 2009, using information published by the Taiwan Tourism Bureau. The empirical results show that the effects of the number of guest rooms, availability of leisure facilities, the ratio of employees to rooms, surrounding special tourist sites and the distance to train stations, are statistically significant. In terms of the market price for hotel rooms, a larger number of available guest rooms translate into a higher market price of hotels. From a consumer standpoint, hotel leisure facilities, nearby special tourists sites and the ratio of employees to guest rooms have positive effects on willingness-to-pay. A one employee increase in the employee to guest room ratio increases accommodation prices by 55.0%, suggesting that consumers believe they receive a higher level of service when more staff is available. Additionally, gyms and leisure facilities can increase accommodation prices by 25.4%. To note, star rating is found to have no statistically significant effect on accommodation prices. Their results differ significantly then those of Espinet *et al.* (2003).[9]

Chen and Rothschild (2010) use data from 73 hotels in July of 2007 from an Internet travel agent to develop a hedonic pricing model for hotels in Taipei. The authors look to compare hotel attributes influencing both weekend and weekday rates. As these types of rates differ due to reasons such leisure versus business stays, this should imply that the return of specific attributes differs between weekday and weekend stays. As such they estimate three models using weekday, weekend, and full week samples. The authors' empirical results show that the availability of an LED TV, location, and availability of conference rooms have significant effects on both weekend and weekday rates. Other notable results show that room size has only a significant effect on weekend rates, which would seem counterintuitive given that weekend visitors usually prefer to explore the city. Also, internet access and fitness centres have a significant effect on weekday rates only, which seems more intuitive given that weekday stays are often for business travellers. The authors also find a negative correlation between distance to city center and room rates. This could be explained by the fact that many hotels in Taipei are resort type hotels located near the ocean.

Espinet *et al.* (2003) develop a hedonic pricing model for tourist resorts in the southern Costa Brava area. Data is collected from the tour operator Travelmar for the 1991 to 1998 period. Prices are based on monthly average of daily prices for a full-board arrangement per person per day. Among the key attributes, the authors find the star rating to have a significant positive impact on the price of an accommodation. They go on to state that there is a significant increase in revenue from 3-star to 4-star hotels, but not from 1-star to 2-star hotels. Espinet *et al.*

[9] I discuss the work of Espinet *et al.* (2003) later in this section.

(2003) also find a negative relationship between hotel capacity and hotel price. However, they find positive relationships between the proximity to the sea as well as with the presence of a parking place to the price of a hotel room. Other characteristics, such as the presence of a garden, swimming pool and sports facility, are found to have insignificant effects on the price of hotel rooms in this area. Other notable results show that hotels located in certain towns tend to have higher premiums, upwards of 17%.

Andersson (2010) extends the literature on hedonic hotel pricing to analyze hotel room prices in Singapore using internet-based transactions. Using data collected from an internet-based hotel-booking agent, the author examines 563 hotel rooms from the period of January 2006 to March 2007. The author finds 4-star and 5-star hotels are associated with higher premiums. Other structural attributes associated with higher prices include in-room safes, premium rooms, and standard rooms. Micro-neighbourhood attributes associated with higher premiums include fitness centres, architectural interest, hotel facilities, and food and beverage options. Furthermore, hotels located on a popular road also see increases in price. In contrast, the authors find that the value for money (e.g., the attractiveness of price given hotel attributes) is associated with lower prices, as is distance to the city centre.

### ***Hedonic Regression: Extensions to Other Consumer Goods***

The hedonic regression technique has been applied to a number of different markets over the past years. Notably, the wine industry has been a primary focus for authors such as Carew and Florkowski (2010), Golan and Shalit (1993) and Roberto Luppe *et al.* (2009), and Kwong *et al.* (2011). In the Canadian context, Carew and Florkowski (2010) extend the technique of hedonic regression to the wine industry in British Columbia (B.C.). More specifically, the authors look to examine the importance of geographic wine appellations in the B.C. Burgundy wine market. The authors want to examine the effects of select French wine characteristics on the buying trends of wine consumers. Carew and Florkowski (2010) estimate the implicit prices of various wine attributes across appellations including select vintage, colour, alcohol content, and the price available to the buyer during purchase. Kwong *et al.* (2011) extend the Canadian analysis and also use hedonic pricing to analyze key characteristics Ontario wines. Golan and Shalit (1993) looks to apply a hedonic pricing model to the case of grapes, while Roberto Luppe *et al.* (2009) utilize a similar approach for wines originating from Brazil, Argentina, and Chile. Moreover, the hedonic pricing technique has been applied to the food industry. Such is the case for Lee (2014) who focuses his research on Atlantic Cod in Northeast US. The author estimates the implicit returns of size category, gear type, storage days, select fixed effects (e.g., buyer, seller, date, year and week of year), and other characteristics to the price of Cod.

Hedonic models have also been extended to the sporting industry. Gerrard *et al.* (2007) examine the value of stadium naming rights for the facilities of both major and non-major North American sport teams. The authors include in their model, among others, stadium age, capacity, term of the naming right team, the type of use (e.g., Live events, concerts, etc.), and host sports league (e.g., NFL, NHL, MLB, and NBA). Limehouse *et al.* (2010) examine the implicit prices of golf courses in the United States. The authors estimate the prices of grass type on the greens, availability of alcohol service, restaurants, dress codes, training facilities, and the numerous other features associated with golf courses.

The hedonic pricing technique brought to fruition by Rosen (1974) continues to grow. It has been extended to many areas including the hotel industry. My paper fits the literature of hedonic pricing models in a number of ways. Following the approach of past papers (e.g., Andersonn (2010), Chen and Rothschild (2010)), I examine internet-based hotel prices. The choice of controls for my paper is also guided by the literature. I include hotel evaluation variables including star rating (e.g., Rosselló and Riera (2012), Andersson (2010), Espinet *et al.* (2003)). I also include locational attributes such as hotel distances to tourist sites and transportation terminals (e.g., Mok *et al.* (1995), Thrane (2007), Tung *et al.* (2011)). Moreover, I choose to include general hotel attributes such as the inclusion of breakfast in the room rate (e.g., Thrane (2005)), the number of rooms in the hotel (e.g., Juaneda *et al.* (2011), Thrane (2007)), and the availability of Internet (e.g., Chen and Rothschild (2010)). Furthermore, included in the analysis are variables pertaining to geographical location (e.g., Espinet *et al.* (2003)).

## III. Data

In this research, I use a dataset consisting of Paris hotel room rates and a series of general, locational, geographical, and rating characteristics of each respective hotel. The pricing information corresponds to a regular one-night stay for two people on Thursday, October 29th, 2015.[10,11] The price in euros of the cheapest available room (*low price*) and the price in euros of the most expensive available room (*high price*) are the two room rates in my data.

For each observation, select hotel characteristics are recorded. Firstly, my dataset contains the official star rating according to the Paris rating system, from 1-star to 5-star ratings.[12] An additional "Palace" rating is exists for outstanding 5-star hotels providing exceptional quality and amenities. Customer evaluations from Trip Advisor are also collected for

10 The "regular" room rate specifies a room price void of any discounts, promotional rates, specials, or price reductions of such a nature.
11 The price of an October stay is collected to avoid any effects of low or high seasonality.
12 The following resource provides a detailed description of the Paris hotel rating system: http://europeupclose.com/article/French-hotel-rating-system/.

all observations. These ratings are based on a 1-star to 5-star (or bubble) system.[13] Contrary to the official Paris hotel rating system, Trip Advisor presents its ratings on a full or half-star basis.[14] Trip Advisor ratings take into consideration several factors including the quality of the ratings, the quantity of the ratings, and the age of each rating. Trip Advisor specifies that a 1-star rating is equivalent to a “terrible” rating, whereas a 5-star rating is equivalent to an “excellent rating”.

Locational attributes reflect the distance in kilometers from the hotel to the Eiffel Tower, Arc de Triomphe, and nearest metro station. The general hotel attributes in my sample include the number of rooms belonging to the hotel, whether the price of breakfast is included in the room rate, the availability of free Wi-Fi, and whether the hotel belongs to a hotel chain (e.g., Best Western). Finally, geographical traits are included in order to identify where each hotel is located among the 20 arrondissements of Paris.[15]

Data was collected from official hotel websites during July of 2015 by undergraduate students of Carleton University and the University of Ottawa.[16,17] The pricing information is collected from the official hotel websites in order to capture the posted rate offered by the hotels. Collecting the information in this manner enables the analysis to avoid discounts or promotional rates offered by travel booking sites such as *expedia.ca* and *booking.ca*, to name a few.[18] Additionally, official hotel websites are the primary sources of information for official star

[13] Trip Advisor ratings are presented as half or full bubbles. For the purposes of this paper, I will refer to a bubble as a star.

[14] The only possible overall ratings for Trip Advisor are 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, and 5. It is viewed as an overall measure of quality.

[15] A detailed map of Paris that identifies all 20 arrondissements is presented in Appendix A.

[16] The data was collected as part of two courses taught by Marc Prud’homme: 1) ECO2147: Analysis of Social and Economic Data (University of Ottawa). 2) ECON 4700 A: Measurement Economics (Carleton University).

[17] Appendix A presents the assignment instructions for students at the University of Ottawa.

[18] I recognize that there exists a subset of individuals who receive discounted rates (e.g., Government rates, corporate rates). Unfortunately, this issue cannot be addressed in this paper.

rating, location, number of rooms, availability of free breakfast, availability of free Wi-Fi, and the hotel brand. Certain websites also provide distances to nearby landmarks. When such information is available, it is collected for distances to the Eiffel Tower, the Arc de Triomphe, and the nearest metro station.

It must be noted that necessary modifications to the original dataset are undertaken. This is in part due to the fact that certain information is not available on hotel websites. When information regarding distances to nearby tourist attractions and metro stations is not available from the primary source, it is collected using *Google Maps* in order to capture the most accurate measurement of distance.[19] Furthermore, customer evaluations are taken from *Trip Advisor*, a travel booking and review site used worldwide.[20] During the data cleaning process, some hotel data was found to be incorrect. For these observations, time independent information (e.g., star rating, location) is corrected to reflect the accurate information. Moreover, a number of hotels in my sample required pricing information to be updated. Specifically, these hotels contained pricing information for a Friday, September 25th, 2015 booking. As a result, new pricing information was collected during August of 2015 for a Thursday, October 29th, 2015 stay.[21]

The sample has been restricted to include only hotels located within the 20 arrondissements of Paris. Hotels located outside the city centre, in La Défense, and in the Disneyland Paris resort are excluded from the sample.[22] This restriction is imposed because the

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[19] The *Google Maps* tool enables users to measure the distance from two specific points. This information can be recovered in kilometers and meters. Users can determine distances by searching two distinct landmarks, or by simply viewing and selecting the locations on the map.

[20] *Trip Advisor* allows its users to rate, rank, and write reviews on their travel experiences. Users can also book vacation, and or hotel stays through this web site.

[21] The time-dependency of hotel prices is analyzed in the robustness check of this paper. Using prices collected at a later date (e.g., September and October), I find that hotel prices decrease slightly for "last-minute" booking, but largely remain stable. Furthermore, the estimates of the model remain stable across time.

[22] La Défense is the major business district of Paris.

analysis focuses only on hotels in the city centre. Hotels located outside the city centre and in the Disneyland resort are in many cases located long distances from any metro stations. Additionally, it could be said that those choosing to stay in resort-type hotels have chosen so to enjoy the benefits of the resort (e.g., theme parks) and not those of the city of Paris. Finally, duplicate hotel observations were excluded from the sample, as duplicate observations would skew the results of the research. The final sample consists of data on 410 hotels.[23]

Table 1 presents summary statistics from the hotel sample. The average hotel has 67 rooms with the smallest hotel having 5 rooms and the largest having 1025 rooms. The average price for the cheapest available rooms is €184.74. Hotel prices can reach as high as €1290 per night, with the lowest price being €35 for a one night stay. The average price for the most expensive available hotel room is €398.84, with the priciest room at €8325 and the lowest price set at €37 per night. Additionally, the price of breakfast is only included in 31.2% of the room rates.

The average star rating among hotels is 2.99. The 3-star hotel rating is the most abundant in the sample, representing nearly 41.0% of all hotels. Following behind is the 2-star rating (23.2%), the 4-star rating (20.0%), the 5-star rating (8.5%), and finally the 1-star rating (7.3%).[24] In contrast, customer evaluations from Trip Advisor reflect higher ratings with an average rating of 3.93.

Free Wi-Fi access seems to be present in almost all hotels reaching nearly 95.1% of the sample. In terms of average distance to popular tourist sites, hotels are located 4.87 km to the Eiffel Tower and 5.0 km to the Arc de Triomphe. However, the distances reach as far as 18.1 km

[23] In some cases, the exact same hotels along with the same set of characteristics were collected multiple times. This was due to the fact that many individuals contributed to the collecting of hotel information. As such, duplicate observations were collected in some instances. In these cases, only a single observation of the group was kept in the sample.

[24] Please see Table 2 for a star rating count according to arrondissements.

and 18.8 km to the Eiffel Tower and Arc de Triomphe respectively. As for transportation, the average distance from a hotel to the nearest metro station is 0.328 km with the furthest hotel located 1.7 km away from a metro station. Moreover, approximately 29.0% of hotels in the sample are chain hotels.

In terms of geographical location, the largest number of hotels is located within the 8th (37), 6th (33), and 9th (28) arrondissements. These areas are located in central Paris and contain such tourist attractions as the Champs-Elysées and Opera Garnier. It is also important to note that 5-star hotels are located in the 1st, 2nd, 3rd, 4th, 6th, 8th, 9th, 16th, and 17th arrondissements and are not present in any other areas. Finally 2.4% of hotels have received the Palace rating which are located in arrondissements 1, 2, 8, and 16.

## IV. Hedonic Pricing Model

In this section, I present the hedonic pricing model used in this paper. As suggested by Rosen (1974), economic theory does not tell us the true specification of the hedonic model. I follow an approach commonly used in the literature by using a log-linear model. My choice of controls (e.g., star rating) is also guided by the literature.

$$Ln(price)_i = \beta_0 + S_i \beta_1 + D_i \beta_2 + G_i \beta_3 + + \beta_4 E_i + A_i \beta_5 + \mu_i \qquad (2)$$

where $ln(price)_i$ is the log price in euros of (Paris) hotel *i*. The model is estimated for both the *low price* and *high price* dependent variables.[25] $S_i$ is a vector of four binary variables representing official star ratings (with the 3-star rating as the reference group). Next, $D_i$ is a vector of three locational attributes, reflecting hotel distances in kilometers to the Eiffel Tower, Arc de

[25] Recall that *low price* represents the lowest available price offered by hotel *i* for a Thursday, October 29th stay for two people. *high price* represents the highest available price offered by the same hotel *i* for an October 29th stay for two people.

Triomphe, and nearest metro station. $G_i$ represents four general hotel characteristics including: the number of rooms, two binary variables for the inclusion of breakfast and Wi-Fi in the room rate, and a binary variable for chain hotels. $E_i$ is a control for online Trip Advisor customer evaluations. Trip Advisor evaluations are represented as a continuous variable (ranging from 1 to 5 stars) and are not presented as binary variables due to the possibility of partial star ratings (e.g., 3.5 stars).[26] Finally, $A_i$ is a vector of 19 binary variables for the geographical location (arrondissement) of hotels.

Equation (2) is estimated in a sequential manner. More precisely, controls are added sequentially in order to examine any changes on the implicit returns of the independent variables after controlling for geographical, star rating, and customer evaluation effects. In the first specification, I estimate the implicit returns for the official star rating (*1-star*, *2-star*, *4-star*, and *5-star*), for locational attributes (*eiffel*, *arc,* and *metro*), and for general hotel characteristics (*rooms*, *breakfast*, *wifi*, and *chain*). In the second specification, I add in the control for customer evaluation (*tripadvisor)*. Additionally, a parameter for the Palace hotel rating (*palace*) is added to the official star rating vector, $S_i$. In the final specification, I also include the geographical controls (e.g., *a1, a2*, *a3*, etc.).

The customer evaluation variable was initially excluded from my model as it may be seen as a duplication of the official star rating. However, it has been added on the justification that customer ratings are not subject to a set of conditions or rules as are official star ratings. For instance, a consumer may rate a 3-star hotel with a 5-star rating if he or she has a fantastic stay.

[26] I am therefore assuming that, for the Trip Advisor star rating, the effect of moving up one star is the same throughout the rating system. A priori this may seem like a strong assumption. However, including Trip Advisor ratings as a binary variable has no real effect on my results. In Section VI, I present a robustness check where I include the Trip Advisor ratings as a set of binary variables. I show that the main results of this paper do not change. Moreover, the return to price for each one star increase in the rating is of similar magnitude.

The reverse scenario could occur for a 5-star hotel, receiving a 1-star customer rating based on a poor experience. The addition of the Palace hotel rating has been done to examine the further effects of the special rating for 5-star hotels.[27] It was initially withheld due to its direct relation to the 5-rating. The final sets of binary variables for arrondissement are included to test for geographical effects on hotels within the city centre limits.

## V. Empirical Results and Discussion

Hedonic regression analysis is undertaken for both the *low price* and *high price* dependent variables. Although the $\hat{\beta}$ coefficients for continuous variables can be interpreted in the standard method for a log-linear model, the estimated dummy coefficients must be exponentially transformed. Specifically, $\hat{\beta}$ coefficients are transformed using $(e^{\hat{\beta}} - 1)$, where *e* is the base of the natural logarithm and $\hat{\beta}$ is the estimated coefficient of the variable (e.g., Espinet *et al.* (2003), Chen and Rothschild (2010)). The coefficients for continuous variables and the transformed coefficients of dummy variables can be interpreted as the percentage return of the independent variable to the dependent variable, holding all else equal.

### *Low Price Sample*

In Table 3, I present the OLS regression results of my hedonic model for the *low price* dependent variable. Column (1) of Table (3) presents the results for the case where only the base controls are included. The set of star rating variables reflect the expected signs. That is, I find negative returns associated with the *1-star* and *2-star* ratings relative to the 3-star rating and positive

[27] Recall that the Palace hotel rating refers to select 5-star hotels, which receive the prestigious rating due to their exceptional quality and amenities (e.g., on-site spa).

returns associated with the *4-star* and *5-star* ratings relative to the 3-star rating. All star ratings are found to be economically and statistically significant at the 1% level. For example, relative to the 3-star rating, *1-star* and *2-star* ratings tend to be associated with 82.4% and 42.3% lower rates respectively. In contrast, relative to the 3-star rating, the *4-star* and *5-star* ratings tend to be associated with 39.1% and 219.3% higher rates respectively. These results are not surprising since hotel vendors tend to charge higher rates for high-rated hotels, which tend to offer more services and amenities. Also, the results show a significant increase from the 4-star to 5-star categories, holding all other variables equal. This may be in part due to the fact that some 5-star rated hotels are also classified as Palace hotels. I do not find any marginal increases of such a magnitude between other of rating groups.

In addition, Column (1) of Table (3) shows the *breakfast* control to be a statistically significant at the 10% level, with positive returns associated with this amenity estimated at 7.0%. This implies that holding all else equal, a €150 room would tend increase to €160.50 if it began including breakfast in the room rate. I consider this result to be economically significant given that consumers would be paying an additional €10.50 fee. As for the other general hotel attributes such as *wifi*, *rooms*, and *chain*, I find these variable to be non-significant statistically.[28] The result of *wifi* could be explained by the fact that almost all hotels in the sample offer free Wi-Fi. The result for the *rooms* control suggests that the size of the hotel has no impact on room rates for vendors. Finally, the non-significance of the *chain* variable implies that hotels cannot necessarily collect premium room rates for being a chain brand. It also implies that with so many hotels in the market, chain brand hotels would lose customers to their competition by setting higher rates.

[28] Despite the little variation in the availability of free Wi-Fi, this control is not withheld from the model due its statistical significance for high price rooms.

The distance to the Eiffel Tower is found to be the only statistically significant locational variable. The results show that for every kilometer increase in the distance from the Eiffel Tower, room rates decrease by 3.3% on average. Holding all else equal, this result would suggest that a hotel located 20 km from the site would be 62.7% cheaper than the exact same hotel located 1 kilometer away from the site. I believe this to be an economically significant result. The fact that the distance to the metro station is not found to be statistically significant could be due to the high number of metro stations in Paris. Additionally, the Arc de Triomphe may not have the same appeal to consumers as the Eiffel Tower.[29] Also, it may not be a primary reason for visiting Paris for business people or tourists.

Column (2) of Table 3 includes the controls for customer evaluations and the Palace hotel rating. The results show that the *tripadvisor* and *palace* controls are both statistically significant at the 1% level. In addition, these controls are economically significant. A one-star increase in a Trip Advisor rating tends to increase room rates by 22.5%. The sign of this result is expected, as a positive customer perception of the hotel would in most cases increase the willingness-to-pay of consumers. Furthermore, a Palace hotel rating tends to lead to a 90.0% higher price. The sign of this result is as expected given that this rating would identify extremely luxurious hotels which usually come at a high premium.

With the addition of the *tripadvisor* and *palace* controls, all of the star rating variables is once again found to be statistically and economically significant with the expected signs. However, the return of *5-star* variable diminishes, now estimated at a 134.2% price increase,

[29] Other tourist sites located near the Eiffel Tower and Arc de Triomphe include the Place de la Concorde and the Louvre. For a list of other tourists attractions located in Paris, please refer to the map of Paris located in Appendix A.

relative to 3-star hotels.[30] This result is intuitive given that I have added additional rating controls (e.g., Palace rating and Trip Advisor Rating). Here, the statistical significance of the *breakfast* and *eiffel* attributes is eliminated. This would suggest that vendors place a greater importance on the customer evaluations and star ratings when pricing a room. No other controls in the model show statistical significance with the added controls.

Finally, in Column (3) of Table 3, I present the results for the full specification containing the geographical controls. More specifically, I test the effects of the arrondissements of Paris. The results show that a number of districts located on the outside limits of Paris are statistically and economically significant. The results show negative returns to *a10* (20.7%), *a13* (27.4%), *a14* (34.6%), *a15* (30.7%), *a17* (19.2%), *a18* (25.5%), and *a19* (26.3%) relative to arrondissement 8.[31] For the other arrondissements, I find these districts to be non-significant contributors to room rates. The inner core of Paris (e.g., arrondissements 1 to 9) is concentrated within a small geographical location. Hotels located in these areas are all of a similar distance to nearby popular attractions. Customers seem to prefer to be located within these districts. Another possible explanation is that districts in the outer boundary of Paris are not located nearby any major shopping centres or venues of such a nature. Furthermore, these districts may not be considered desirable areas of the city for reasons such as a poor visual appeal, lack of popularity, isolation, etc. Holding all else equal, a €200 room located in arrondissement 1 would sell for €148.59 if it were located in arrondissements 14.

Adding in the geographical controls has no large effect on the star ratings. In fact, all star ratings are found to be economically and statistically significant at the 1% level. The magnitudes

[30] In the first specification of the model the 4-star ratings tends to increase room rates by 219.3% relative to 3-star hotels.
[31] Arrondissement 8 is chosen as the reference group since this district contains the largest number (37) of hotels in my sample.

of these variables are very similar to those of Column (2). The *tripadvisor* control remains a statistically and economically significant contributor. However, the implicit return of this variable has decreased slightly. Similarly, the *palace* control remains statistically and economically significant. Moreover, I do not find any of the general hotel attributes to be significant contributors to room prices. This result indicates that for a standard room, geographical, hotel rating, and customer evaluation are the only factors taken into consideration when pricing a room. Again, locational attributes do not reflect statistically significant returns.

### *High Price Sample*

Table 4 presents the OLS regression results for the *high price* dependent variable. Column (1) of Table 4 presents the results when only the base controls are included. As in the case for *low price*, the star rating variables have once again the predicted signs. All four star ratings are found to be economically significant and statistically significant at the 1% level. Relative to the 3-star rating and holding all else equal, I find negative returns of 96.8% and 53.3% associated with *1-star* and *2-star* ratings respectively.[32] As for the *4-star* and *5-star* ratings, my results show large positive returns of 64.4% and 464.6% relative to the 3-star rating respectively. The magnitude of these returns is much larger than in the case of the standard room rates. Furthermore, I find an extreme jump in the returns from a 4-star to a 5-star rating. This could be explained by the fact that some 5-star hotels have also achieved the Palace rating. It could also suggest that 5-star hotels charge a very high premium for luxury rooms, whereas many 1-star to 4-star hotels may not have high-luxury type rooms.

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[32] Recall that dummy coefficients are transformed using $(e^{\hat{\hat{\beta}}} - 1)$ in order to express the variables as a percentage return to price, holding all else equal.

Column (1) of Table 4 also presents the results for locational attributes. In this group, the distance to the Eiffel Tower is once again a significant contributor to price, decreasing room rates by 5.7% for every additional kilometer away from the site. As for the *arc* and *metro* controls, these variables are not statistically significant. A similar argument to the one provided in the *low price* group can be applied. That is, with the large number of metro stations in Paris, this may not be a significant factor in setting room rates. Additionally, as the Arc de Triomphe may not be a primary reason for visiting Paris, the distance to the landmark would be largely irrelevant. The final vector of attributes analyzed in Column (1) of Table 4 is the general hotel attributes. Surprisingly, I find none of these attributes to be statistically significant. This result is identical to those produced for standard low priced rooms.

In Column (2) of Table 4, I add in the *tripadvisor* and *palace* controls. The results reflect a very similar outcome to the case of *low price.* Both controls have the expected signs with slightly higher magnitudes than for the *low price* rooms. Also, a one star increase in a hotel's Trip Advisor rating tends to lead to a 31.5% higher price. Additionally, the Palace-rated hotels tend to on average to be associated with 124.1% higher room rates relative to 3-star hotels. These added controls are both statistically and economically significant. That being said, it would seem that hotel vendors see customer evaluations and star rating to have a stronger influence on room rates in the case of premium rooms.

Again, all star ratings are found to be economically significant and statistically significant at the 1% level. These values are slightly lower than in the case of Column (1) as one would expect with the addition of a $6^{th}$ star rating. This result follows a similar pattern to that of the *low price* group. The *eiffel* control remains statistically significant in Column (2). Holding all else equal, room rates tend to decrease by 3.0% for every kilometer away from the landmark. I find this result to be economically significant as is the case for the standard rooms. In contrast to Column (1), *wifi* and *rooms* are now significant contributors to the room price. The *wifi* control reflects lower prices in the magnitude of 23.7%, holding all other variables equal. This result could be explained by the fact that some luxury hotels do not offer free Wi-Fi services. Instead, they may prefer to offer a reduced room rate and charge for this type of amenity upon the customers' arrival. Furthermore, I find that for every increase in the number of rooms in the hotel, *high price* rooms increase by 0.1%. This would imply that a room with an overnight rate of €400 would be priced at €440 if it had 100 extra rooms. Given that the hotel with the lowest number of room is 5 and the highest contains 1025, this attribute could have economically significant impacts.

Once again, *eiffel* is the only locational variable statistically significant in this case. This is not the case for standard hotel rooms, which do not take into account this distance. Again, *arc* and *metro* are found to be statistically insignificant contributors to price. This mirrors the results of the *low price* group.

In Column (3) of Table 4, I examine the effects of adding in the geographical controls. As is the case for *low price*, a number of arrondissements are found to be associated with lower prices relative to arrondissements 8. I find that *a10* (25.3), *a13* (44.3%), *a14* (46.0%), *a15* (51.7%), *a17* (23.2%), *a18* (35.9%), and *a19* (52.7%) tend to reflect lower room rates relative to arrondissements 8. These are the exact same districts found to be statistically significant in the *low price* group. As expected, hotel located on the outer limits of the Paris, for the most part, charge lower overnight rates.

Adding the geographical controls has no effect in terms of the statistical significance and the magnitude of the implicit return of variables. However, it appears as though the star ratings have a higher importance for premium rooms. The general hotel characteristics in Column (3) of Table 4 are of similar magnitude to those of Column (2). Once again, I find the *wifi* and *rooms* controls to be economically and statistically significant. In terms of locational attributes, I find the *eiffel* control to be significant at the 10% level. Again, the implicit return for this control is higher for premium rooms than for standard rooms. As expected, *arc* and *metro* are not found to be statistically significant contributors to price. The explanation for this would follow in a similar manner to that of the *low price* group.

In sum, I find the star rating, Palace hotel rating, Trip Advisor rating, and geographical factors to be economically and statistically significant contributors to standard and premium room rates. Furthermore, the inclusion of Wi-Fi in the room rate, the number of rooms in the hotel, and hotel proximity to the Eiffel Tower are important determinants in the case of premium rooms only. Overall, I find my results are stable. Potential issues of hotel room price sensitivity are addressed in Section VI.

### *Hotel Subsample*

Later in the paper, I address the issue of price sensitivity. Using a subsample of 81 hotels taken from the 1$^{st}$, 5$^{th}$, 6$^{th}$, 8$^{th}$, and 9$^{th}$ arrondissements, I analyze the stability of hotel prices over time and examine the robustness of my coefficients over time.[33],[34] In order to show the representativeness of the random sample, I estimate the full model for both room types for the 81 hotels.[35]

[33] These arrondissements are the districts that hold the greatest number of hotels in my sample.
[34] New pricing information is collected from Expedia.fr.
[35] The subsample was created by scanning through the data and arbitrarily selecting hotels. I attempted to create a subsample with an even distribution of 1-sar to 5-star hotels.

In Column (1) of Table 5, I present the results of the *low price* subsample. Excluding the 1-star rating, all star rating variables and the Palace hotel rating are found to be economically and statistically significant. The lack of significance of the *1-star* rating is believed to be due to the small number of 1-star rated hotels in the sample. Furthermore, I show that the *Trip Advisor* and *arrondissement* controls to be both statistically (and economically) significant. In this subsample, I also find the *rooms, chain*, and *eiffel* to be statistically significant at the 5%, 10%, and 10% levels respectively. However, it is important to note that the same set of hotel characteristics (e.g., star rating, Palace rating, Trip Advisor rating, and arrondissement) are all once again statistically and economically significant in this subsample. Furthermore, the returns to price of these controls are all of a similar magnitude to those of the full sample.

Column (2) of Table 5 presents the results for the *high price* subsample. Again, all star ratings (with the exception of *1-star*) are found to be economically and statistically significant at the 1% level. These controls also have a comparable return to price to those of the full sample. The *Trip Advisor* and *Palace* variables are again determinants of room rates, both economically and statistically significant. As in the case of the *low price* subsample, I find the controls for the number of rooms, hotel chains, and the distance to the Eiffel Tower to factor into hotel room rates.[36] Finally, these results show a statistical insignificance for the arrondissement controls. I believe this to be due to the fact that the arrondissements used in this subsample are all located within a smaller geographical area, all of which are located near primary tourists attractions.

This section is intended to show the representativeness of my subsample. I believe that the results of this section show exactly that. Although I do find few differences regarding the statistical significance of certain variables, the goal of the price sensitivity analysis is to show

[36] The *eiffel* and *rooms* controls are also both economically and statistically significant for the full sample.

that my results are robust irrespective of the date of price collection. This robustness check is presented in Section VI.

## VI. Robustness Check

This section presents a series of robustness checks. Firstly, I discuss the issue of endogeneity related to the potential concerns of measurement error and omitted variable bias. Secondly, I examine the validity of using the Trip Advisor ratings as a continuous variable. Precisely, I estimate the full model for both price groups using the Trip Advisor ratings as a set of binary variables. Finally, I address the issue of price sensitivity. Using a sample of 81 hotels, with prices that were collected on three separate dates, I analyze the robustness of my results over time.

### *Issue of Endogeneity*

*i. Measurement Error*

In order to minimize the issue of measurement error, a data scanning process is undertaken. Upon receiving the initial raw data, errors related to certain variables including star rating, arrondissement, and hotel proximity to the Eiffel Tower, Arc de Triomphe, and nearest metro station were observed. These characteristics are, for the most part, time-independent. As such, I verify all entries for arrondissements using individual hotel websites. Moreover, each value collected for my three distance controls (*eiffel*, *arc*, and *metro*) was checked using Google Maps. When these distances appeared inaccurate, the correct distances were collected from Google Maps in order to replace the incorrect values.

All star ratings were checked in order to ensure complete accuracy. It must be noted that it is possible that some hotels in my sample have either gained or lost stars since the date of collection. However, in order to achieve a designated star level, hotels must meet a number of criteria pertaining to service, spoken languages of staff, and room size, among others. Given these guidelines, it is highly unlikely that the ratings of the hotels in my sample have changed since the date of collection.

In a first test, I drop the 41 observations for which either the star rating or arrondissements has been changed.[37] This is done as a precaution in order to eliminate any potentially inaccurate observations. The full model for both price groups is then estimated. In doing so, I find nearly identical results to the full sample. For the *low price* group, the results hold with the exception of *chain,* which is now statistically significant at the 10% level. As for the *high price* group, all of my results hold with all variables showing similar implicit returns to that of the full sample.

In a second test, I drop all 52 observations collected from Carleton University students. This is done because these observations contain price data collected in a month other than that of the observations collected by students of the University of Ottawa.[38] The full model is then estimated for both price groups. Overall, the results remain largely unchanged. Later in this section, a price-sensitivity analysis is conducted in order to show that my results are robust regardless of the date and time the prices are collected.

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[37] During the data scanning process, some observations were found to have incorrect information pertaining to star rating and arrondissement. In these cases, I adjusted the information to reflect the correct star rating and arrondissement.

[38] Prices for the Carleton University observations were collected in August of 2015. This is due to the fact that original prices were collected for a booking on Friday, September 25$^{th}$, 2015. It was verified that the prices reflected the same set of collected hotel attributes.

*ii. Omitted Variable Bias*

The second issue of endogeneity is related to omitted variable bias. It is possible that some hotel characteristics, which have been left out of the model, are correlated with both the dependent variable and one or more independent variables. The hedonic model could potentially include other hotel characteristics such as the availability of fitness centres (e.g., Andersson (2010)), room size (e.g., Chen and Rothschild (2010)), minibar (e.g., Thrane (2007)), etc. Although information on these additional attributes has not been collected, certain reasons can be provided to justify their omissions. Firstly, as Paris is a popular destination for tourists, the availability of a fitness centre may not factor in to the decisions of consumers. Instead, they may prefer to discover the sites of Paris. The same type of argument follows for room size and in-room amenities. Furthermore, as this paper focuses on the city centre of Paris, proximity of hotel to the airport would be relatively similar for all hotels.

Although I cannot directly address the issue of omitted variable bias, I am fairly confident that I have included a good range of variables. I estimate four supplementary variations of my model in order to examine its stability. Columns (1), (2), and (3) of Table 6 present the results of three alternate specifications of the model for the *low price* dependent variable. Column (1) of Table 6 presents the results after removing the vector of general attributes. Column (2) of Table 6, gives the results upon removing the vector of locational attributes. Lastly, in Column (3) of Table 6, I present the results after removing both the general and locational vectors. My results point to the same set of explanatory variables as those of Table 3. Moreover, the implicit returns of these controls are of very similar magnitude. In Columns (1), (2), and (3) of Table 7, I complete the same process for the *high price* dependent variable. These results also show the stability of my model. Comparing Table 7 to Table 4, I find the same sets of variables are economically and statistically significant.

The issue of omitted variable bias is a challenge faced by all researchers. It is possible that I could include other hotel characteristics into the model. However, this section provides comforting outcomes in that the results are not sensitive to the exact specification of the model. My results are robust irrespective of the set of variables that are excluded. In the end, I am confident that I would find the same results if I included other variables.

***Trip Advisor Ratings: A Binary Variable Approach***

This section addresses my earlier assumption on the Trip Advisor ratings. Specifically, I state that it is justifiable to include these ratings as a continuous variable. I assume that the return to price between each rating group is of similar magnitude. In a robustness check, I create binary variables for the Trip Advisor ratings. Specifically, these binary variables are presented in the following format: *tripadvisor-1* (e.g., 1 and 1.5 stars), *tripadvisor-2* (e.g., 2 and 2.5 stars), *tripadvisor-3* (e.g., 3 and 3.5 stars), and *tripadvisor-5* (5 stars). The reference group for these variables is *tripadvisor-4* (e.g., 4 and 4.5 stars).[39]

In Table 8, I present the results of this alternate full model for both *low price* and *high price* samples. For the *low price* group in Column (1) of Table 8, the increase in the return to price for every one star increase in the Trip Advisor rating is of very similar magnitude. Furthermore, the main results are consistent with the original full model presented in Table 3. That is, the same sets of variables are statistically and economically significant. The *high price* group in Column (2) of Table 8 shows similar results to those of Column (1) for the *tripadvisor* dummy variables. I do not find many significant changes in magnitude when moving from the

[39] Recall that I refer to the Trip Advisor rating "bubbles" as stars.

lowest rating through to the top rating.[40] However, relative to the other *tripadvisor* variables, I do find a smaller increase in the return to price when moving from 2-star to 3-stars. The same sets of explanatory variables are found to be statistically and economically significant for this room type. It can therefore be justified to present the Trip Advisor rating as a continuous variable in the original model.

***Price Sensitivity Analysis***

In order to examine the volatility of hotel prices and the sensitivity of prices to the date of collection (e.g., Month before versus last-minute), a sensitivity analysis is undertaken. It also provides an indication of the sensitivity of the estimated coefficients. Three additional series of price data are collected from the French Expedia online travel-booking site.[41] As I show, the average prices for each date of collection do not vary much. Additionally, the ratios of *low price* to *high price* move proportionally for each collection date.

My sample consists of 81 observations from hotels of arrondissements 1, 5, 6, 8, and 9.[42] These arrondissements represent the geographical areas containing the most hotels in my original sample. Hotels are chosen at random with the greatest attempt to collect a variety of 1-star to 5-star hotels.[43] The lowest offered rate and the highest offered rate for a Thursday, October 29th stay for two people is collected from the travel site on Friday, September 11th, Tuesday,

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[40] In a separate test, I create more specific binary variables for each full star and half star overall rating. The results of this test remain largely the same to those of the main binary variable approach.
[41] I use Expedia.fr as prices are listed in euros as opposed to Canadian dollars. The original pricing data is collected in euros from the respective hotel websites (e.g., www.shangri-la.com/Paris).
[42] The first collection contained 100 hotels. However, hotels were eliminated from the sample if they were unavailable (e.g., fully booked) on a subsequent collection date. The final sample consists of 81 observations.
[43] Hotels were chosen by scrolling through the data and arbitrarily selecting observations. An attempt was made to create a subsample with an even distribution of 1-sar to 5-star hotels.

September 29th, and Tuesday, October 27th.[44] The lowest available price reflects the lowest offered rate in euros, void of any early cancellation premiums or other surcharges of that type. The highest possible price reflects the highest offered room rate (in euros) for two people. In the event that a two-person capacity room is not offered, the prices for a three-person capacity room are collected. Moreover, the collected prices reflect the same hotel attributes of the original data. For example, if the original price collected in the main sample indicated a breakfast included in the price, the prices collected from Expedia also include a breakfast charge. Any inconsistencies between the original sample and the robustness sample regarding breakfast or the availability of free Wi-Fi were recorded.[45]

Table 9 presents the summary statistics of my robustness sample. For the lowest offered rates, the average room rates vary between €222.69 and €238.37 for the three dates of collection. Similarly, for the high price sample, the average room rates for the first, second, and third dates range from €365.91 and €386.28. Additionally, the price difference between *low price* and *high price* are €147.57, €148.63, and €143.22 for all three dates respectively. These price statistics show that hotel prices do not tend to fluctuate significantly. The decline in prices from the second to third collection dates can be attributed to the fact that the latter of these dates represents a last-minute price. As hotels still have unsold rooms two days prior to the booking date, these rates have most likely been lowered in an attempt to complete a last-minute sale. In terms of the ratio of low to high priced rates, my results also show that price ratios move in a similar fashion.[46] Furthermore, Table 10 shows the number of hotels according to

[44] All dates are for the year of 2015.
[45] Such is the case for 8 observations.
[46] The decrease from the second to third date of collection may be attributable to the fact that premium rooms are less abundant relative to regular rooms. As such, some hotels may have sold out of premiums rooms, leaving only the regular room rate available to customers.

arrondissement and star rating. Again, 3-star (37) rated hotels are the most prominent within the group with 1-star (2) rated hotels the least represented in the sample.

Table 11 presents the estimated results of the full model for the *low price* dependent variable for the three dates of collections. Not surprisingly, all star variables are found to be economically and statistically significant with the exception of the 1-star rating. Here, the 1-star rating is no longer statistically significant. This result may be in part due to the fact the number of 1-star hotels in this sample is very small. With the exception of the *wifi* control, the same set of independent variables is found to be statistically significant in all three regressions. In Table 12, I present the regression results of the full model estimated for the *high price* dependent variable. Once again, all star ratings, the Palace rating, Trip Advisor rating, and geographical controls are found to be statistically and economically significant. For both dependent variables, I get results which are very robust across time and that are inline with the other Tables of this paper.

## VII. Conclusion

In the paper, I develop a hedonic pricing model in order to estimate the implicit returns of select hotel attributes towards the price for a one-night stay. Collecting pricing data from 410 hotels along with the accompanying general, reputational, geographical, and locational characteristics associated with the booking allows me to derive a number of important results.

First, I show that the star rating is an important determinant in the pricing of hotels rooms. These variables are economically and statistically significant for both regular and premium rooms, even after controlling for all hotel attributes. I also find that hotels with the 5-star rating charge significantly higher prices relative to the other ratings. Second, I show that

Trip Advisor customer evaluations and the Palace hotel rating are significant contributors to room rates, both statistically and economically. This result holds for both *low price* and *high price* rooms, yet it carries a heavier weight for *high price* rooms. Finally, I show that hotel prices can in some cases be affected by geographical factors. More specifically, a number of arrondissements in the outer circle of Paris are associated with lower prices. I conclude that this result is derived from the fact that they are located much further from tourist attractions other than the Eiffel Tower and the Arc de Triomphe.

When examining the differences between the two types of room rates, my results show a few key differences in terms of pricing determinants. The number of rooms, availability of Wi-Fi, and distance to the Eiffel Tower is only statistically and economically significant in the case of premium rooms. Also, controlling for Trip Advisor ratings and Palace hotel ratings renders the distance to the Eiffel Tower statistically insignificant for low priced rooms. Finally, the implicit returns for all statistically significant variables are, for the most part, larger for *high price* rooms. In this analysis, a number of unexpected results are derived. Locational attributes relating to distance to nearby tourist sites and metro stations are all found to be not statistically and economically significant once all controls have been added. Secondly, I find that free Wi-Fi is associated with lower prices in the case of premium rooms.

The price sensitivity analysis of this paper shows that prices gathered at three intervals do not tend to fluctuate significantly between dates of collection. Although I find a slight decline in both the *low price* and *high price* subsamples as we move closer to the booking date, the *low price* to *high price* gap remains relatively constant.  Overall, the model provides robust estimates across time.

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## Appendix A: University of Ottawa Assignment Data Collection Instructions

uOttawa

Faculté des sciences sociales | Faculty of Social Sciences

**Département de science économique**
**Department of Economics**

# Analysis of Economic and Social Data
# Summer 2015

### Data collection guidelines for hotel rates in Paris


Instructor: Marc Prud'Homme
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**Guidelines**

1. **Deadline**
   The deadline for submitting your version of the Excel files is Friday July 1st at midnight. No late returns will be accepted.

2. Objective: To complete a database of Paris hotel prices that will then be used to measure the contributions of the various features of the hotel to its price. This is going to be a hedonic model. Read more about that technique here:
   https://en.wikipedia.org/wiki/Hedonic_regression

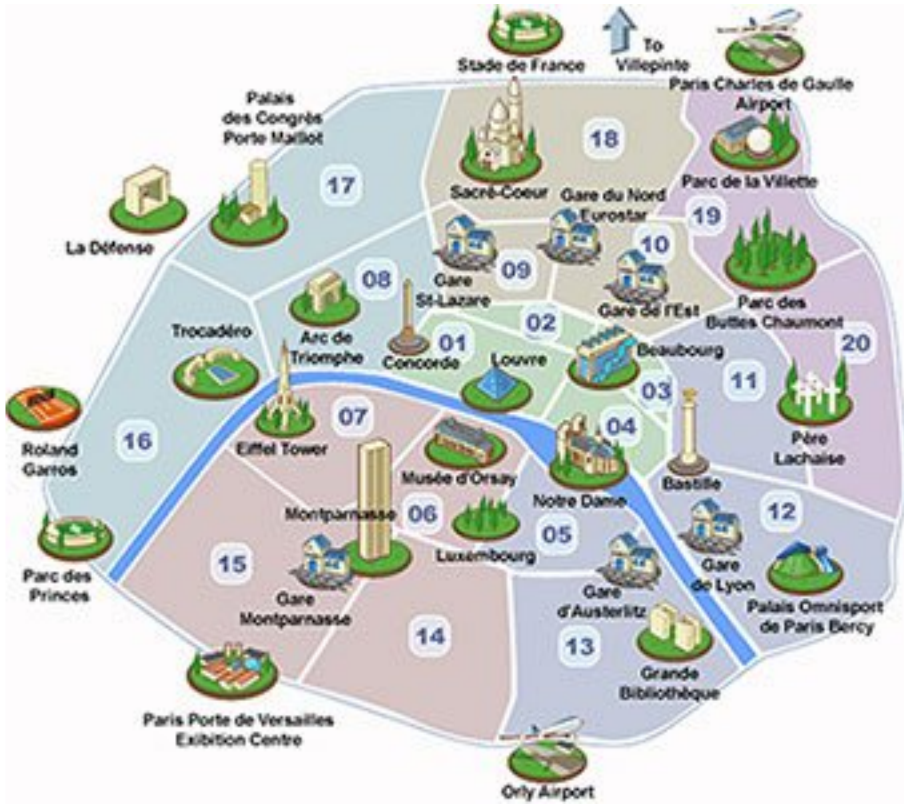
   No worries, I will be doing the regressions.

3. Fill in the required fields in the Excel file. Read carefully what is required in terms of data in the Excel file.

4. Save the Excel file using a name that includes your full name and send me that file by email.

5. Collect 10 hotel prices as if you were booking the hotel for two people for one night on October 29th (2015). The price is the **Euro price**.

6. Make sure to spread out your hotels across Paris (not all in the same arrondissement - The Excel file explains what an arrondissement is). I include an image here.




7. Distribute the number of collected prices according to the following patterns of star ratings: 2 one-star hotels, 2 two-star hotels, 4 three-star hotels, 1 four-star hotel, and 1 five-star hotel.

TABLE 1
Summary statistics

| | Mean | | Minimum | Maximum |
|---|---|---|---|---|
| *Price (euros)* | | | | |
| *low price* | 184.74 | (156.46) | 35 | 1290 |
| *high price* | 398.84 | (828.50) | 37 | 8325 |
| *Official Star Rating* | | | | |
| *1-star* | 0.073 | (0.261) | - | - |
| *2-star* | 0.232 | (0.422) | - | - |
| *3-star* | 0.410 | (0.492) | - | - |
| *4-star* | 0.200 | (0.401) | - | - |
| *5-star* | 0.085 | (0.280) | - | - |
| *palace* | 0.024 | (0.155) | - | - |
| *General Attributes* | | | | |
| *rooms* | 66.612 | (101.17) | 5 | 1025 |
| *breakfast* | 0.312 | (0.464) | - | - |
| *wifi* | 0.951 | (0.216) | - | - |
| *chain* | 0.290 | (0.454) | - | - |
| *Customer Evaluation* | | | | |
| *tripadvisor* | 3.926 | (0.636) | 1 | 5 |
| *Distance (km)* | | | | |
| *eiffel* | 4.869 | (4.631) | 0.3 | 18.1 |
| *arc* | 5.003 | (2.949) | 0.13 | 18.8 |
| *metro* | 0.328 | (0.228) | 0.12 | 1.70 |
| Observations | 410 | | | |

NOTE: Standard deviations in brackets.

TABLE 2
Hotels by official star rating and arrondissement

| | *1-star* | *2-star* | *3-star* | *4-star* | *5-star* | Total |
|---|---|---|---|---|---|---|
| *Arrondissement* | | | | | | |
| 1st | 0 | 5 | 5 | 7 | 8 | 25 |
| 2nd | 3 | 4 | 1 | 4 | 1 | 13 |
| 3rd | 1 | 3 | 5 | 1 | 1 | 11 |
| 4th | 0 | 2 | 8 | 2 | 1 | 13 |
| 5th | 1 | 7 | 10 | 3 | 0 | 21 |
| 6th | 2 | 6 | 16 | 8 | 1 | 33 |
| 7th | 0 | 7 | 12 | 7 | 0 | 26 |
| 8th | 0 | 5 | 11 | 7 | 14 | 37 |
| 9th | 0 | 9 | 11 | 5 | 3 | 28 |
| 10th | 6 | 5 | 9 | 1 | 0 | 21 |
| 11th | 2 | 3 | 7 | 3 | 0 | 15 |
| 12th | 4 | 5 | 8 | 1 | 0 | 18 |
| 13th | 3 | 3 | 4 | 1 | 0 | 11 |
| 14th | 2 | 8 | 13 | 1 | 0 | 24 |
| 15th | 0 | 8 | 8 | 9 | 0 | 25 |
| 16th | 0 | 3 | 9 | 6 | 5 | 23 |
| 17th | 1 | 2 | 13 | 9 | 1 | 26 |
| 18th | 4 | 2 | 4 | 4 | 0 | 14 |
| 19th | 1 | 4 | 10 | 1 | 0 | 16 |
| 20th | 0 | 4 | 4 | 2 | 0 | 10 |
| Observations | 30 | 95 | 168 | 82 | 35 | 410 |

TABLE 3
Regression results: *low price*

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| *Star Rating* | | | | | | |
| *1-star* | -.601*** | (.071) | -.408*** | (.070) | -.387*** | (.070) |
| *2-star* | -.353*** | (.044) | -.254*** | (.042) | -.259*** | (.041) |
| *4-star* | .330*** | (.047) | .284*** | (.043) | .284*** | (.042) |
| *5-star* | 1.161*** | (.066) | .851*** | (.069) | .796*** | (.070) |
| *General Attributes* | | | | | | |
| *rooms* | .000 | (.000) | .000 | (0.000) | .000 | (.000) |
| *breakfast* | .068* | (.037) | .036 | (.033) | .033 | (.033) |
| *wifi* | -.028 | (.082) | -.104 | (.074) | -.086 | (.073) |
| *chain* | .039 | (.040) | .053 | (.037) | .055 | (.036) |
| *Distance (km)* | | | | | | |
| *eiffel* | -.033*** | (.011) | -.014 | (.010) | -.016 | (.016) |
| *arc* | .001 | (.010) | -.013 | (.009) | -.003 | (.013) |
| *metro* | -.013 | (.074) | .002 | (.067) | -.015 | (.067) |
| *Customer evaluation* | | | | | | |
| *tripadvisor* | - | | .225*** | (.031) | .194*** | (.031) |
| *Palace Rating* | | | | | | |
| *palace* | - | | .642*** | (.115) | .644*** | (.112) |
| *Geographical* | | | | | | |
| *arrondissements* | - | | - | | Yes | |
| Observations | 410 | | 410 | | 410 | |
| R-squared | .671 | | .735 | | .767 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 4
Regression results: *high price*

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| *Star Rating* | | | | | | |
| *1-star* | -.677*** | (.100) | -.407*** | (.099) | -.387*** | (.101) |
| *2-star* | -.427*** | (.062) | -.289*** | (.059) | -.303*** | (.060) |
| *4-star* | .497*** | (.066) | .433*** | (.060) | .423*** | (.061) |
| *5-star* | 1.731*** | (.093) | 1.303*** | (.097) | 1.215*** | (.101) |
| *General Attributes* | | | | | | |
| *rooms* | .000 | (.000) | .001** | (.000) | .001*** | (.000) |
| *breakfast* | .060 | (.051) | .016 | (.047) | .012 | (.047) |
| *wifi* | -.106 | (.115) | -.213** | (.104) | -.205* | (.105) |
| *chain* | .022 | (.057) | .040 | (.052) | .048 | (.052) |
| *Distance (km)* | | | | | | |
| *eiffel* | -.057*** | (.015) | -.030** | (.014) | -.042* | (.023) |
| *arc* | .012 | (.014) | -.007 | (.013) | .018 | (.019) |
| *metro* | -.024 | (.104) | -.003 | (.094) | -.007 | (.096) |
| *Customer evaluation* | | | | | | |
| *tripadvisor* | - | | .315*** | (.044) | .279*** | (.045) |
| *Palace Rating* | | | | | | |
| *palace* | - | | .876*** | (.162) | .877*** | (.161) |
| *Geographical* | | | | | | |
| *arrondissements* | - | | - | | Yes | |
| Observations | 410 | | 410 | | 410 | |
| R-squared | .671 | | .733 | | .755 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 5
Regression results: *price sensitivity analysis subsample*

| | (1) *Low price* | | (2) *High price* | |
|---|---|---|---|---|
| *Star Rating* | | | | |
| *1-star* | .187 | (.167) | -.100 | (.296) |
| *2-star* | -.349*** | (.088) | -.506*** | (.155) |
| *4-star* | .291*** | (.069) | .340*** | (.122) |
| *5-star* | .668*** | (.099) | .998*** | (.174) |
| *General Attributes* | | | | |
| *rooms* | .001* | (.000) | .003*** | (.001) |
| *breakfast* | .064 | (.058) | -.077 | (.102) |
| *wifi* | .224 | (.167) | -.374 | (.295) |
| *chain* | -.134** | (.066) | -.321*** | (.117) |
| *Distance (km)* | | | | |
| *eiffel* | -.072** | (.016) | -.165*** | (.060) |
| *arc* | .032 | (.023) | .059 | (.041) |
| *metro* | -.178 | (.109) | .005 | (.192) |
| *Customer evaluation* | | | | |
| *tripadvisor* | .122* | (.069) | .212* | (.122) |
| *Palace Rating* | | | | |
| *palace* | .742*** | (.149) | .785*** | (.262) |
| *Geographical* | | | | |
| *arrondissements* | Yes | | No | |
| Observations | 81 | | 81 | |
| R-squared | .845 | | .793 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 6
Regression results: remove select attributes for *low price*

| | (1) *Remove General Attributes* | | (2) *Remove Locational Attributes* | | (3) *Remove Locational and General Attributes* | |
|---|---|---|---|---|---|---|
| *Star Rating* | | | | | | |
| *1-star* | -.394*** | (.067) | -.379*** | (.070) | -.388*** | (.067) |
| *2-star* | -.274*** | (.041) | -.256*** | (.041) | -.273*** | (.040) |
| *4-star* | .305*** | (.041) | .289*** | (.042) | .308*** | (.041) |
| *5-star* | .826*** | (.068) | .780*** | (.070) | .829*** | (.068) |
| *General Attributes* | | | | | | |
| *rooms* | - | - | .000 | (.000) | - | - |
| *breakfast* | - | - | .031 | (.033) | - | - |
| *wifi* | - | - | -.078 | (.072) | - | - |
| *chain* | - | - | .061* | (.037) | - | - |
| *Distance (km)* | | | | | - | - |
| *eiffel* | -.014 | (.016) | - | - | - | - |
| *arc* | -.004 | (.013) | - | - | - | - |
| *metro* | -.022 | (.066) | - | - | - | - |
| *Customer evaluation* | | | | | | |
| *tripadvisor* | .180*** | (.030) | .196*** | (.031) | .182*** | (.030) |
| *Palace Rating* | | | | | | |
| *palace* | .679*** | (.110) | .658*** | (.111) | .692*** | (.110) |
| *Geographical* | | | | | | |
| *arrondissements* | Yes | | Yes | | Yes | |
| Observations | 410 | | 410 | | 410 | |
| R-squared | .764 | | .765 | | .761 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 7
Regression results: remove select attributes for *high price*

| | (1) *Remove General Attributes* | | (2) *Remove Locational Attributes* | | (3) *Remove Locational and General Attributes* | |
|---|---|---|---|---|---|---|
| *Star Rating* | | | | | | |
| *1-star* | -.394*** | (.098) | -.377*** | (.101) | -.387*** | (.098) |
| *2-star* | -.335*** | (.059) | -.290*** | (.059) | -.322*** | (.058) |
| *4-star* | .486*** | (.060) | .432*** | (.061) | .493*** | (.059) |
| *5-star* | 1.303*** | (.099) | 1.222*** | (.101) | 1.31*** | (.099) |
| *General Attributes* | | | | | | |
| *rooms* | - | - | .001*** | (.000) | - | - |
| *breakfast* | - | - | .006 | (.033) | - | - |
| *wifi* | - | - | -.194* | (.104) | - | - |
| *chain* | - | - | .054 | (.052) | - | - |
| *Distance (km)* | | | | | - | - |
| *eiffel* | -.038 | (.023) | - | - | - | - |
| *arc* | .017 | (.019) | - | - | - | - |
| *metro* | .011 | (.096) | - | - | - | - |
| *Customer evaluation* | | | | | | |
| *tripadvisor* | .232*** | (.044) | .288*** | (.045) | .240*** | (.044) |
| *Palace Rating* | | | | | | |
| *palace* | .943*** | (.161) | .903*** | (.160) | .964*** | (.161) |
| *Geographical arrondissements* | Yes | | Yes | | Yes | |
| Observations | 410 | | 410 | | 410 | |
| R-squared | .744 | | .752 | | .742 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 8
Regression results: *Trip Advisor rating as a binary variable*

| | (1) *Low price* | | (2) *High price* | |
|---|---|---|---|---|
| *Star Rating* | | | | |
| *1-star* | -.430*** | (.071) | -.449*** | (.101) |
| *2-star* | -.287*** | (.041) | -.330*** | (.059) |
| *4-star* | .295*** | (.043) | .433*** | (.061) |
| *5-star* | .826*** | (.070) | 1.240*** | (.100) |
| *General Attributes* | | | | |
| *rooms* | .000 | (.000) | .001*** | (.000) |
| *breakfast* | .031 | (.033) | .001 | (.047) |
| *wifi* | -.076 | (.074) | -.202* | (.106) |
| *chain* | .049 | (.036) | .042 | (.052) |
| *Distance (km)* | | | | |
| *eiffel* | -.024 | (.016) | -.050** | (.023) |
| *arc* | .004 | (.013) | .027 | (.019) |
| *metro* | -.014 | (.068) | -.005 | (.097) |
| *Customer evaluation* | | | | |
| *tripadvisor-1* | -.519*** | (.190) | -.884*** | (.271) |
| *tripadvisor-2* | -.326*** | (.084) | -.351*** | (.119) |
| *tripadvisor-3* | -.129*** | (.040) | -.257*** | (.060) |
| *tripadvisor-5* | .278*** | (.093) | .461*** | (.132) |
| *Palace Rating* | | | | |
| *palace* | .578*** | (.123) | .644*** | (.112) |
| *Geographical arrondissements* | Yes | | Yes | |
| Observations | 410 | | 410 | |
| R-squared | .765 | | .757 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 9
Summary statistics: Expedia.fr

| | *Mean* | | *Minimum* | *Maximum* |
|---|---|---|---|---|
| *Price (euros)* | | | | |
| *low price Sept. 11th* | 238.37 | (181.46) | 76.51 | 1019.00 |
| *low price Sept. 29th* | 237.64 | (185.17) | 89.10 | 1019.00 |
| *low price Oct. 27th* | 222.69 | (192.54) | 66.51 | 1095.00 |
| *high price Sept. 11th* | 385.94 | (583.39) | 89.10 | 4595.00 |
| *high price Sept. 29th* | 386.28 | (628.87) | 95.00 | 4595.00 |
| *high price Oct. 27th* | 365.91 | (642.19) | 66.51 | 4695.00 |
| *Official Star Rating* | | | | |
| *1-star* | 0.025 | (0.156) | - | - |
| *2-star* | 0.124 | (0.331) | - | - |
| *3-star* | 0.457 | (0.501) | - | - |
| *4-star* | 0.235 | (0.426) | - | - |
| *5-star* | 0.160 | (0.369) | - | - |
| *palace* | 0.049 | (0.218) | - | - |
| *General Attributes* | | | | |
| *rooms* | 62.96 | (82.07) | 10 | 478 |
| *breakfast* | 0.222 | (0.418) | - | - |
| *wifi* | 0.988 | (0.111) | - | - |
| *chain* | 0.346 | (0.479) | - | - |
| *Customer Evaluation* | | | | |
| *tripadvisor* | 4.124 | (0.451) | 3 | 5 |
| *Distance (km)* | | | | |
| *eiffel* | 4.384 | (1.079) | 1.60 | 6.90 |
| *arc* | 4.181 | (1.616) | 0.60 | 8.10 |
| *metro* | 0.346 | (0.262) | 0.028 | 1.50 |
| Observations | | 81 | | |

NOTE: Standard deviations in brackets.

TABLE 10
Hotels by official star rating and arrondissement: Expedia.fr

| | *1-star* | *2-star* | *3-star* | *4-star* | *5-star* | Total |
|---|---|---|---|---|---|---|
| *Arrondissement* | | | | | | |
| 1st | 0 | 1 | 4 | 5 | 7 | 17 |
| 5th | 1 | 5 | 10 | 2 | 0 | 18 |
| 6th | 1 | 1 | 8 | 4 | 1 | 15 |
| 8th | 0 | 1 | 7 | 4 | 3 | 15 |
| 9th | 0 | 2 | 8 | 4 | 2 | 16 |
| Observations | 2 | 10 | 37 | 19 | 13 | 81 |

TABLE 11
Regression results: *low price* (Expedia.fr)

| | (1) *Friday, September 11th, 2015* | | (2) *Tuesday, September 29th, 2015* | | (3) *Tuesday, October27th, 2015* | |
|---|---|---|---|---|---|---|
| *Star Rating* | | | | | | |
| *1-star* | .175 | (.154) | .141 | (.143) | -.139 | (.173) |
| *2-star* | -.141* | (.043) | -.169** | (.076) | -.211** | (.091) |
| *4-star* | .196*** | (.065) | .261*** | (.060) | .232*** | (.073) |
| *5-star* | .434*** | (.094) | .576*** | (.087) | .632*** | (.105) |
| *General Attributes* | | | | | | |
| *rooms* | .001* | (.000) | .001** | (0.000) | .001** | (.000) |
| *breakfast* | -.008 | (.069) | -.006 | (.064) | .016 | (.077) |
| *wifi* | .404* | (.228) | .303 | (.212) | -.224 | (.256) |
| *chain* | -.096 | (.062) | -.078 | (.058) | -.056 | (.069) |
| *Distance (km)* | | | | | | |
| *eiffel* | -.110*** | (.036) | -.070** | (.034) | -.080* | (.041) |
| *arc* | .016 | (.034) | -.038 | (.032) | -.043 | (.038) |
| *metro* | .079 | (.104) | .028 | (.096) | .047 | (.116) |
| *Customer evaluation* | | | | | | |
| *tripadvisor* | .278*** | (.065) | .199*** | (.060) | .212*** | (.072) |
| *Palace Rating* | | | | | | |
| *Palace* | .904*** | (.140) | .845*** | (.130) | .785*** | (.157) |
| *Geographical* | | | | | | |
| *arrondissements* | Yes | | Yes | | Yes | |
| Observations | 81 | | 81 | | 81 | |
| R-squared | .870 | | .891 | | .876 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.

TABLE 12
Regression results: *high price* (Expedia.fr)

| | (1) *Friday, September 11th, 2015* | | (2) *Tuesday, September 29th, 2015* | | (3) *Tuesday, October27th, 2015* | |
|---|---|---|---|---|---|---|
| *Star Rating* | | | | | | |
| *1-star* | -.081 | (.240) | -.063 | (.241) | -.300 | (.254) |
| *2-star* | -.213* | (.127) | -.263** | (.127) | -.245* | (.134) |
| *4-star* | .292*** | (.101) | .361*** | (.101) | .294*** | (.107) |
| *5-star* | .684*** | (.146) | .599*** | (.146) | .643*** | (.154) |
| *General Attributes* | | | | | | |
| *rooms* | .001** | (.001) | .001** | (0.001) | .002*** | (.001) |
| *breakfast* | -.024 | (.107) | .062 | (.107) | .040 | (.113) |
| *wifi* | .463 | (.354) | .666* | (.355) | .193 | (.375) |
| *chain* | -.105 | (.097) | -.017 | (.097) | -.053 | (.103) |
| *Distance (km)* | | | | | | |
| *eiffel* | -.202*** | (.057) | -.145** | (.057) | -.137*** | (.060) |
| *arc* | .027 | (.053) | -.012 | (.053) | -.046 | (.056) |
| *metro* | .215 | (.161) | .208 | (.162) | .213 | (.171) |
| *Customer evaluation* | | | | | | |
| *tripadvisor* | .276*** | (.100) | .195* | (.101) | .242*** | (.106) |
| *Palace Rating* | | | | | | |
| *Palace* | 1.068*** | (.218) | 1.323*** | (.219) | 1.243*** | (.231) |
| *Geographical arrondissements* | Yes | | Yes | | Yes | |
| Observations | 81 | | 81 | | 81 | |
| R-squared | .835 | | .839 | | .849 | |

NOTE: Standard deviations in brackets. *p< 0.1, **p< 0.05, ***p<0.01.