# APPLICATION OF FINANCIAL MARKET MODELS IN THE HOTEL INDUSTRY

by

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*To my husband, son, family and friends, for their support and love.*

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# ABSTRACT

In this dissertation, I investigated price dynamics in the hotel room-night market and attempted to explain pricing decisions from a market perspective. Since market dynamics of the hotel room-night market can be paralleled to those in the financial market, financial market models allowed for examination of various aspects of hotel room pricing decisions.

In the first study, advance-purchase discounts were estimated through application of an option pricing model considering property-specific attributes. Non-refundable advance-purchase discounts are a commonly used rate fence. One challenge to their implementation, however, is deciding upon the precise magnitude of the discount. Quan's (2002) study on the price of room reservations is a good starting point, but it is a conceptual model that assumes away other property-specific factors. This study thus tested the idea that advance-purchase discounts are affected by various components, including the value of the right to cancel a reservation (e.g., cancelation option value) and the room- and property-specific factors in the hotel room-night market (e.g., uncertainty, reviews, and seasonality). The analysis supported this hypothesis and additionally revealed that advance-purchase discounts are smaller for rooms with high review ratings in a high-demand period. Interestingly, the divergence between advance-purchase discounts and cancelation option value components widened in a high-demand period, which implies a tendency by hotels to adjust their room rates rather than the amount of discount for customers who book their stay well in advance. Theoretically, this study thus contributes to finance literature by extending the application of the option pricing model to real options for non-financial assets. This study also contributes to the hospitality literature by demonstrating the effects of property-specific attributes on advance-purchase discount magnitude. The results also have implications to the hospitality industry by providing an analytical framework by which hoteliers can estimate property-specific advance-purchase discounts.

The second study concentrated on rate parity agreement's effect on the hotel room-night market's efficiency at reflecting product characteristics in room rates. This study examined the impact of rate parity agreement between hotels and online travel agencies by comparing hotel rates between Europe and the United States. This study found that room rates were less sensitive to property quality attributes under rate parity clauses. The reflection of property quality on room rates were less efficient when hotels have rate parity agreement with OTAs. Furthermore, the

results supported the claim that rate parity exacerbates price increase in periods of high demand, which indicates possible collusion between suppliers (hotels) and distributors (OTAs). The findings provided theoretical implications by testing the market efficiency of the hotel room-night market and confirming the impact at the property level. This study also provided a perspective on pricing decision makers to understand how rate parity agreement influence their pricing decisions. Last, the findings provided support for recent policies in Europe that restrict rate parity agreements between hotels and OTAs.

The third study empirically examined hoteliers' response to the demand by observing the price movement of two rates with different cancelation policies—free cancelation rates and non-refundable rates. By modifying Hasbrouck's (1995) information share approach, this study examined the non-refundable rates' contribution to the price discovery process. The perceived quality of accommodation by customers, one of the primary determinants of the price discovery process, was included in analysis. The results suggested that non-refundable rates were contribute more to the information variance than free cancelation rates did. The findings also suggested that consumers' perceived quality and volatility influence non-refundable rates' contribution to the price discovery process. The results also have practical implications for market participants, as they help to build an understanding of aggregated demand and its impact on pricing. Non-refundable rates are generally regarded as just one of many kinds of discounted rates, but the results of this study suggest that hoteliers should carefully consider the role that non-refundable rates play in their pricing strategy.

# CHAPTER 1. INTRODUCTION

In the hotel room-night market, hotels differ their room rates according to details like reservation time, cancelation policy, or booking channel even for the same type of rooms (Hanks, 2002). In this market, customers can accept or reject the hotel's offer. Consequently, these interactions enable the hotel room-night market to determine the price point for each room product. Three studies in this dissertation thus focused on these dynamics in the hotel room-night market and attempted to explain these pricing decisions from the market's perspective. Since the pricing dynamics in the hotel room-night market are similar to those in the financial market, financial market models were applied in order to examine various aspects of pricing decisions. This approach fills a gap in the current hospitality and tourism management literature because most existing studies focus on the pricing decision from either the consumer's or the hotel management's perspective. The first study examined the market valuation of the cancelation option embedded in room rates. The market's efficiency at reflecting product characteristics in room rates were examined in the second study. The last study was an exploration of the price discovery process and demonstrated the information content in the room rates.

All three studies in this dissertation thus investigated the information content of room rates in the hotel room-night market through use of various financial models. These constantly changing rates are comparable to the movement of assets in the financial market. As an example, a stock price in the financial market represents an ownership share in the corporation and reflects the value of the firm (Bodie, 2009). A room rate can be defined as the value of room-night in a room on a specific date, which can be analogous to the stock price. While the movement of room rates under the dynamic pricing strategy is similar to stock price changes in the security market, the characteristics of the product market should be considered when applying financial models to the hotel room-night market. Particularly, the heterogeneity of quality in units derived from property-specific attributes should be considered as the distinctive feature of the hotel room-night market compared with the homogenous financial market. This distinctive market condition indicated that every hotel room has different qualities that can be identified by property-specific attributes. Since this is one of the key differences between the homogenous financial market and the product market, adjustments associated with property quality might be needed when applying financial models in such product market. Consequently, this study adjusted financial models to reflect unique hotel characteristics and more efficiently explore pricing dynamics in the hotel room-night market.

With these adjustments in mind, the first study in this dissertation concentrated on the amount of discount offered to early booking customers. The level of discount that should be awarded for advanced booking has been one of the primary questions faced by industry practitioners (Schwartz, 2006, 2008; Toh et al., 2011). The discounts should be large enough to entice price sensitive customers, but not too large for less-price sensitive customers to trade down. To address this issue, an option pricing model was utilized to quantify early book discount levels. The major portion of this discount derived from the customers right to cancel the reservation. Consequently, the option pricing model created by Black and Scholes (1973) was implemented to estimate the cancelation option value imbedded in advance-purchase discount (Black and Scholes, 1973; Merton, 1976; Quan, 2002). Since the heterogeneity of quality in the hotel room-night market can alter the application of an option pricing model, this study additionally considered property-specific attributes in the estimation of the advance-purchase discount.

The second study examined the effect of the hotel room-night market's efficient reflection of property-specific attributes in room rates. When obtaining room rates with different rate fences in various destinations, it was discovered that rate parity clauses were restricted in certain regions in order to prevent possible anti-competitive behavior (Trivago Business Blog, 2019). In the hospitality literature, there have been debates around the need for and effect of rate parity agreements between suppliers (e.g., hotels) and distribution channels (e.g., OTAs) (Demirciftci et al., 2010; Haynes & Egan, 2015; Scott, 2015). Prior studies have investigated regulations on rate parity in European nations, specifically the terms of stock price responses of hotels and OTAs (Sharma & Nicolau, 2019), and price comparison between various distribution channels (Hunold et al., 2018). However, there has been little research related to how the existence of rate parity alters room rates at the property level. Based on the theory of efficient market hypothesis (Fama, 1991, 1998), the second study thus investigated rate parity's impact on market efficiency by testing rate parity's impact on the room rates through property-specific attributes.

The third study in this dissertation focused on the information content of price dynamics for room rates under different cancelation policies. Dynamic pricing strategy is one of the most frequently discussed topics in the hotel revenue management field. While evidence has been given that hotel managers actually implemented dynamic pricing strategy (Abrate et al., 2012), there has been a lack of investigation regarding how property-specific conditions might be reflected in room rate adjustments with different cancelation policies. To understand the price movement of two similar assets based on the same room types but for different customer groups, there was a need to study price discovery across free cancelation rates and non-refundable rates. Price discovery refers to the dynamic process reflected new information in the market (Baillie et al., 2002; Chakravarty et al., 2004; Chu et al., 1999; Dimpfl et al., 2017; O'Hara, 2003; Yan & Zivot, 2010). In the hotel industry, non-refundable rates are frequently displayed as rates discounted from free cancelation rates. However, when comparing two rates to assets in the financial markets, non-refundable rates were comparable to underlying assets, and free cancelation rates were interpreted as derivatives that could be categorized as combinations of non-refundable rates and a cancelation option. Thus, the contribution of non-refundable rates to the price discovery process was examined through application of the information share approach suggested by Hasbrouck (1995). Furthermore, consumers' perceived quality of accommodation was considered as one of the determinants of the price discovery process.

To summarize, three studies in this dissertation applied financial models and theories to explain price dynamics in the hotel room-night market. These studies were independently organized yet interrelated. The topics discussed in this dissertation were based on the room rates with different cancelation policies and explored information content of the hotel room-night market. The first study concentrated on estimating the level of discount for early booking by incorporating an option pricing model in order to measure cancelation option value. Then the total discount offered by hotels was categorized as a cancelation option value and discount-adjustment component through property-specific attributes. The second study identified market inefficiencies derived from the rate parity agreement between hotels and distribution channels by comparing room rates in Europe and the United States. Applying the price discovery process to market microstructure theory, the third study revealed how hotel managers allowed demand to reflect pricing decision and the factors that affected such a process. To apply financial models in the hotel room-night market, all three studies considered property-specific attributes. This consideration was necessary to application of financial models to the product market, as the property-specific attributes can control the heterogeneity of assets in the hotel room-night market.

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# CHAPTER 2. ADVANCE-PURCHASE DISCOUNT: WHAT IS IN AN ADVANCE-PURCHASE DISCOUNT? A HEDONIC PRICING MODEL BASED ON CANCELATION OPTIONS AND PROPERTY-SPECIFIC FACTORS

## 2.1. Introduction

Non-refundable advance-purchase discounts used frequently as rate fence to segregate price-sensitive consumers with flexible schedules from those who are willing to pay for convenience (Guillet et al., 2014; Hanks et al., 2002). Thus, despite lowering room rates, advance-purchase discounts provide hotels with a number of benefits. First, advance-purchase discounts allow hotels to capture additional demand from price-sensitive travelers without diluting revenue from those who pay the full rate. Second, advance-purchase discounts can help travelers to reduce their search-and-switch behavior (Chen & Xie, 2013). Finally, by providing free cancelations to full-rate customers, advance-purchase discounts can aid hotels in mitigating perceived unfairness (Kimes & Wirtz, 2003).

When implementing advance-purchase discounts, one of the primary questions faced by industry practitioners is how much of a discount should be given for advance purchases. The discount should be large enough to attract new price-sensitive travelers; however, it should not be so large as to entice full rate-paying travelers to trade down. Quan (2002) provided a starting point to quantitatively answer this question, arguing that a hotel room gives the guest a right to buy the room night at a fixed rate in the future, similar to how a European option gives investors the right to buy a stock at a fixed price at a future date. Thus, the room reservation has a value, and this value could be quantified using the Black–Scholes option pricing model.

However, Quan's (2002) study featured a significant limitation: it did not consider property-specific attributes that may also affect room pricing in a competitive market. When travelers reserve a room with a non-refundable rate, they generally consider various aspects, such as an uncertainty in their travel plans, possible room rate drops in a set of competing hotels, their preference in hotel attributes. Hence, the advance-purchase discounts can be diverged from the theoretical value of cancelation from the option pricing model. Therefore, the current study aimed to analyze advance-purchase discounts by considering both the value of the right to cancel the reservation (option value component) and the effect from property-specific attributes (discount-adjustment component) in a hedonic pricing model.

## 2.2. Theoretical Background

Advance-purchase discounts have been frequently used for pricing products/services, such as hotel rooms, airline tickets, travel packages, and car rental services. In the literature on intertemporal pricing, advance-purchase discounts have been examined as the optimal pricing policy under uncertain demands and scarce capacity. Dana (1998) demonstrated the advance-purchase discounts in the airline industry as a profit maximizing practice in the market of uncertain demand and to the conditions of uncertain demand and great inventory costs. The study showed that consumers with low-valuation and more assured demand select to purchase in advance with reduced prices. Gale and Holmes (1993) also examined advance-purchase discounts as a profit maximizing strategy for airline companies that are in the monopoly market with capacity constrictions. Nocke et al. (2011) characterized advance-purchase discounts as a price discrimination device for consumers with heterogenous expected valuations, revealing that advance-purchase discounts can be ideal if consumer diversity is sufficiently large.

From the perspective of the information acquisition literature, advance-purchase discounts (e.g., the price difference between free cancelation rate and the non-refundable rate) can be inferred as the information acquisition cost (Bar-Isaac et al., 2010; Crémer & Khalil, 1992; Lewis & Sappington, 1994; Nocke et al., 2011). For example, consumers with free cancelation rates can adjust their reservations during the period between their initial purchase (e.g., reservation date) and the last cancellable date (e.g., 2–3 days prior to check-in) whenever they acquire new information (e.g., finding a lower rate in competing hotels). Therefore, hotels intend to charge higher rates for consumers who choose free cancelation rates, and the difference can be interpreted as the information acquisition cost.

In the hotel industry, advance-purchase discounts, classified as a transaction-based rate fence by Kimes (2009), are commonly used to target customers who require lower rates but allow for inflexibility in their reservation. Budget travelers who have high certainty regarding the details of their travel can accordingly be incentivized to reserve rooms early at non-refundable rates. Thus, the existence of customers who fix their travel plans motivate hotels to offer advance-purchase discounts to increase their occupancy rates. Advance-purchase discounts also signal the suppliers' intention to manage customers' book-and-search behaviors (Chen et al., 2011). In other words, the prevalence of advance-purchase discounts reflects hoteliers' willingness to pay for taking away customers' free cancelation option.

### 2.2.1. Option Value Component

A hotel room reservation with free cancelation gives the traveler the right to buy a room night at a given room rate at a specific point in the future. This is conceptually equivalent to European call options (Quan, 2002). A call option permits the option holder the right, but not the obligation, to buy an underlying asset at a given price at a specific expiration date in the future. Following Quan's (2002) logic, free cancelation rates include the cost of the room night and the option to cancel the reservation. At the same time, hotels also offer discounted non-refundable rates that are neither cancellable nor refundable. The co-existence of these two rates provides an opportunity to empirically measure the value of cancelation as the difference between the free cancelation rate and the non-refundable rate for the same room nights reserved at the same time. Thus, similar to option contracts, advance-purchase discounts have a positive value for a limited time period, with the value diminishing as time passes (Finch et al., 1998; Quan, 2002).

The advance-purchase discounts in room reservation can be measured by real option analysis, which is a technique implemented to measure low-price guarantee options in the hospitality industry. Marcus and Anderson (2006) estimated costs associated with low-price guarantees in the vehicle rental service by using the geometric Brownian motion of option valuation in a monopoly situation. Similarly, the value of the low-price guarantee was calculated from the real option payoffs and exotic option approach (Carvell & Quan, 2008). While it can be one of the ideal approaches to measure the value of advance-purchase discounts, it is difficult to apply in the real world, because future minimum room rates from competing hotels should also be estimated. Moreover, hoteliers may face difficulties in estimating future room rates even for their own hotel rooms. It also would be hard to set exact competing rooms from nearby hotels, as hotel rooms are heterogenous in many attributes. For these reasons, the current study selected the Black–Scholes formula to measure the cancelation option value and additionally consider various hotel specific attributes to estimate total advance-purchase discounts.

While this study claimed that the advance-purchase discounts in room reservation is similar to the European call option, the application of the Black–Scholes formula to the cancelation option pricing must consider the different characteristics of the underlying assets. The Black–Scholes option pricing model estimates the value of option contracts by considering several factors, including time to maturity, underlying asset price and asset price volatility, exercise price, and risk-free rates (Black & Scholes, 1973; Merton, 1973). Some of the important assumptions underlying the formula are as follows, no dividends payment after the option expiration date, constant interest rate and the volatility, and continuous underlying asset prices (Bodie, 2009).

The first consideration for the application is the perishability of the underlying room night for the cancelation option value. Once the reservation date expires, the opportunity to sell the room night for that date is lost forever. Thus, the value of the service becomes zero if not sold at some point in time. Therefore, it is not appropriate to compare room rates for different reservation dates even for the same types of rooms. To control this issue, specific room reservation dates were fixed before calculating the cancelation option value.

Second, the underlying asset is less liquid in the hotel room cancelation option than the option on stocks. Trading in stocks is not limited in quantity, therefore, the price changes are observed all the time. In comparison, room nights are limited in quantity. The room rate changes can no longer be seen once the rooms are sold out. Furthermore, the room rates are stable for a certain period and frequently changes if the date approaches to check-in. To minimize the effect from illiquidity, this study collected room reservation rates at hotels in popular travel destinations for last two months before the check-in. Given that hotels tend to actively manage their room rates when the date approaches to check-in, this study acquired relatively constant variance of room rates in the data collection period. Considering the two months of short-term price data helps to alleviate the illiquid transaction problem in option pricing for room reservation without losing many data points, because 70% of booking activities are observed in 0 to 60 days prior to their arrival (SOJERN, 2019).

Third, the Black–Scholes formula assumes a continuous stock price, as the stock price constantly follows a geometric Brownian motion, thus producing a log-normal distribution for stock price between any moment in time (Black & Scholes, 1973; Merton, 1976). In comparison, hotel room rates have discontinuous prices and possible price jumps. To overcome this limitation, this study focused on room rates from big chain-hotel companies for a high-demand period. Such big chain-hotel companies actively manage their room inventories using dynamic pricing models. Particularly for high-demand periods (e.g., summer vacation, Christmas holiday, New Year's Day, etc.), they tend to change room rates frequently in response to the changing demands from travelers. Accordingly, the following hypothesis is proposed:

*Hypothesis 1: The advance-purchase discounts are positively related to the value of cancelation.*

### 2.2.2. Discount-Adjustment Component

#### *2.2.2.1. Room Rate Volatility and Advance-Purchase Discounts*

The finance literature has provided compelling theories and strong empirical evidence to show that the reduction of cash flow volatility can create value for a firm (Giambona et al., 2018). A firm can employ either financial hedging or operational hedging to address cash flow volatility (Allayannis et al., 2001). However, in the case of demand uncertainty-induced cash flow volatility, financial hedging is not feasible, because there are no financial markets and derivatives for hotel room rates.

Chang (2009) demonstrated that, in terms of operational hedging, revenue management can mitigate the effects of exchange-rate risk on average daily rate (ADR) and revenue per available room (RevPAR). When hotels update their room rates in response to demand uncertainty, their RevPAR and subsequent cash flows can generally be maintained at relatively stable rates, because price and demand quantity move in reverse directions. However, frequent changes in room rates may lead to consumer confusion and perceived price unfairness (Kimes, 2002).

Locking down demand early by providing advance-booking discounts represents an alternative approach to addressing demand volatility. This method can aid hotels in realizing revenues before unexpected demand shocks hit the market, thus avoiding uncertainties in future demand and room-rate changes (Quan, 2002). From a risk management perspective, locking down demand provides incentives for hotels facing high demand and room-rate volatility to employ advance-booking discounts to ensure potential revenues. Based on such information, the following hypothesis is proposed:

*Hypothesis 2: The advance-purchase discount is higher in hotels with high price volatility than in hotels with low price volatility.*

Seasonality in the hospitality industry has been one of the major concerns for hospitality practitioners, because it can bring difficulties in maintaining all areas of operations, such as marketing, human resources management, finance, and stakeholder management (Baum & Lundtorp, 2001). Hotel room rates fluctuate greatly during peak periods, such as holidays and large events. Espinet et al. (2012) concluded that more hotel services and higher hotel scales are associated with fewer seasonal variations in hotels' room rates. Herrmann and Herrmann (2014) also demonstrated that hotel room rates are highly influenced by major events such as Oktoberfest. Similar to the previous studies' examination on how hotel room rates are influenced by seasonal demands, the advance-purchase discounts, which reduce non-refundable rates, can be narrowed down for peak seasons, because of the high-demand and limited room supply. Hence, the following hypothesis is proposed:

*Hypothesis 3: The advance-purchase discount is smaller in a high-demand period than in a low-demand period.*

#### *2.2.2.2. Room and Property-specific Attributes*

While the Black–Scholes model provides a good estimate of the value of advance-purchase discounts, the actual discounts observed on the market can diverge from such theoretical values. Due to the competitive landscape of the hotel industry, this gap may come from property-specific factors, such as location, consumer reviews, complimentary services, brand affiliation, and other hedonic and utilitarian motivations (Carroll & Sileo, 2014). Such factors must be taken into consideration to effectively compete with other hotels that offer non-refundable rates.

Given that potential customers can compare non-refundable rates to stay in multiple hotels, such hotels have incentives to offer additional discounts beyond the level of discount offered by their competitors (McCardle et al., 2004). However, consumer-favorable attributes could influence travelers' booking choices and decrease the advance-purchase discount magnitude that is needed. Travelers searching within a set price range are more likely to choose rooms from hotels that have better consumer reviews, convenient locations, higher brand recognition, and additional complimentary services (O'Neill & Xiao, 2016; Öğüt & Onur Taş, 2012; Xie et al., 2014). According to the 2012 US Consumer Travel Report, the most influential factor in a traveler's decision to stay at a hotel is the price, followed by its location (Gasdia & Rheem, 2013). Additional factors related to service, including hotel brand affiliation, amenities, reviews, and hotel scales, can also influence this decision (Carroll & Sileo, 2014). Such favorable factors enhance consumers' preference for a hotel and reduce their price sensitivity (Kamakura & Russell, 1989). The higher the demand inelasticity, the smaller the discount needed to stay competitive. Hence, the above-mentioned property-specific attributes can affect advance-purchase discounts within a competitive market. For the purposes of the present study, the factors related to consumers' evaluation, such as number of reviews and review ratings, were explored.

According to the consideration set theory of brand choice, hotel awareness is a key predictor of hotel consideration (Nedungadi, 1990; Vermeulen & Seegers, 2009). Further, it has been proven that both positive and negative reviews can increase consumers' awareness of specific hotels. Therefore, the number of reviews (including both positive and negative) can serve as an indirect indicator of hotel awareness, with the likelihood of consumer booking being positively correlated to hotel review exposure (i.e., number of reviews available). Accordingly, hotels that have small number of reviews have more incentive to give additional advance-purchase discounts than those with sufficient reviews. Thus, the following hypothesis is proposed:

*Hypothesis 4a: Hotels that have low number of reviews are more likely to offer advance-purchase discounts than hotels with high number of reviews.*

Review ratings can affect both room rates and advance-purchase discounts, as travelers prefer hotels with high review ratings, perceiving them to be of higher quality. Positive reviews increase booking intention and consumer trust (Sparks & Browning, 2011). Drawing on this assumption, Öğüt and Onur Taş (2012) found that higher customer ratings significantly increased room sales. This indicates that hotels with higher review ratings have little incentive to offer a higher advance-purchase discount, as they already have high demand for rooms. Hence, the following hypothesis is suggested:

*Hypothesis 4b: The advance-purchase discounts are smaller in hotels with high review ratings than hotels with low review ratings.*

## 2.3. Methodology

### 2.3.1. Sample and Data Collection

Daily hotel room rate information from three major hotel companies in six travel destinations was collected between October 21, 2019 and January 1, 2020 for high- and low demand periods. The data collection period was based on the travelers' reservation behavior research (Table 1). According to the North America Travel Trends in 2018, 72% of travelers booked their stay between 0–59 days prior to their arrival (SOJERN, 2019). Hence the two-month data collection period can cover the room rate changes for the majority of travelers. Data were also collected from major hotel companies' direct booking channels (e.g., hotel websites) to measure the pure price changes by revenue managers. New York, Los Angeles, Orlando, Paris, Rome, and Venice were chosen in order to observe changes in hotel rooms' advance-purchase discounts from popular business and leisure travel destinations. This study examined various aspects, such as the size of the travel destination, leisure/business travel purposes, popularity of the destination according to the World Travel & Tourism Council, TripAdvisor's Travelers' Choice Awards 2019, and the tourism authority in each city. The selected cities were categorized into two groups: large cities with mixed travel purposes (New York, Los Angeles, Rome, and Paris) and leisure destinations (Orlando and Venice) (Table 2).

Table 1. Length of Time between the Time of Booking and the Subsequent Arrival

| Days before the date of stay | Proportion | Cum. Proportion | Rank |
|---|---|---|---|
| 0-7 | 21% | 21% | 2 |
| 8-14 | 11% | 32% | 4 |
| 15-21 | 9% | 41% | 5 |
| 22-29 | 9% | 50% | 5 |
| 30-59 | 21% | 71% | 2 |
| More than 60 days | 28% | 100% | 1 |

*Note. Source- Reprinted from North America Travel Trends in 4Q 2018, SOJERN (2019)*

Table 2. Selected Travel Destinations

| | City Categories | Description |
|---|---|---|
| Paris, France | Largest City, Capital City | Direct travel & tourism GDP was $28.0B in 2017. 48.7% of hotel overnights related to business travel in 2018 |
| Rome, Italy | Largest City, Capital City | Direct travel & tourism GDP was $9.5B (5.3% of total GDP) in 2017. Visitors for business accounted for 17% in 2018 |
| Venice, Italy | Leisure City, Port City | Direct travel & tourism GDP was $3.5B (11.4% of total GDP) in 2017. |
| New York, NY, USA | Largest City, Port City | Direct travel & tourism GDP was $24.8B (3.5% of total GDP) in 2017. Total visitors were 62.8M, and business travelers were 13M (21%) in 2017 |
| Los Angeles, CA, USA | Secondary City, Port City | Total visitors were 50M, and business travelers accounted for 21% of total travel spend in 2018 |
| Orlando, FL, USA | Leisure City | Direct travel & tourism GDP was $24.8B (18.7% of total GDP) in 2017. |

*Note. City categories are based on City Travel & Tourism Impact 2018 by World Travel Tourism Council. Capital city includes 33 cities, which are the capital of their respective country. Largest cities include 38 cities, which are defined as the largest city within their respective country, according to population. Port city includes 32 cities, which are defined as those with a large seaport within its boundaries. Secondary city includes ten sub-national cities that hold important economic and functional roles within their respective country. Leisure city includes ten cities, where leisure travel is the dominant segment. Descriptions were from City Travel & Tourism Impact 2018 and the statistics from the tourism authority in each city.*

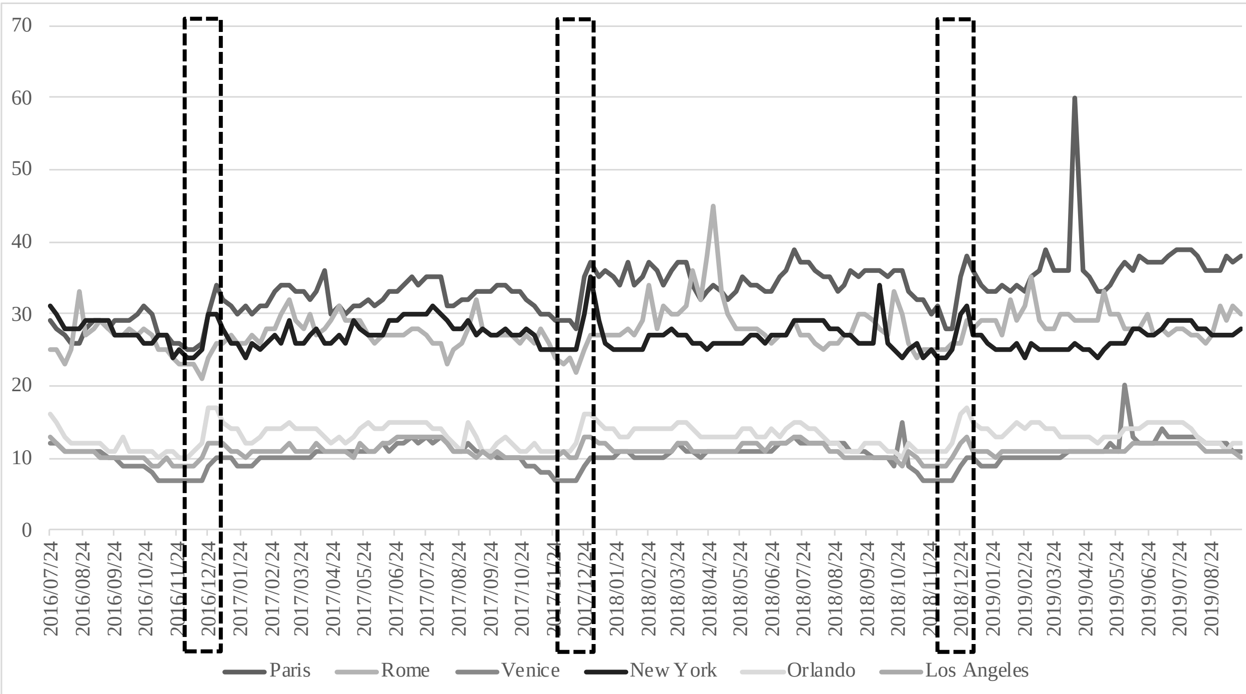
In the individual hotel level, many room rates were observable. For the data collection purpose, the current study categorized the sample (i.e., destinations) into subgroups (i.e., major hotel companies in a destination) and collected data from each subsample. Therefore, room rates were collected within the target sample. To accumulate sufficient sample, three major hotel companies operating in the US and Europe were chosen. Then, the room rates were saved every day during the data collection period.

All rates were recorded based on a night stay in a standard or a standard-equivalent room in six different cities in the US and Europe. Two hypothetical reservation periods represented the high- and low-demand periods, respectively. Google Trends search results, which can provide a normalized weekly search request for a given query on Google, were used as a demand proxy

(Farronato & Fradkin, 2018). In the hospitality and tourism management literature, Google Trends has been used as a demand proxy for forecasting demands (Önder & Gunter, 2016; Park et al., 2017; Sun et al., 2019). The query of interest was the name of each city in the travel category from the worldwide trends for the last five years. Although this study considered the summer season as the peak season of the year for most of the destinations, December was chosen as a hypothetical check-in date in the current study. This is because the demand proxy from Google Trends in December has a distinct difference in demand between the second week (i.e., a week before Christmas) and the last week (i.e., New Year's holiday) in all destinations (Figure 1). Therefore, the period between December 30, 2019 to January 1, 2020 (i.e., New Year's holiday) was selected as a high-demand period, and the two weeks preceding this period (December 16 to 18, 2019) comprised the low-demand period.

Individual hotels' characteristics were also obtained, including hotel scale and the number of restaurants. Such information as the number of restaurants in each hotel was obtained from TripAdvisor and the hotels' respective websites. Hotels' hotel scales of 1–5 were recorded based on the chain scale segmentation from Smith Travel Research (STR) to control for room-rate differences between hotels. The hotel scales were as follows: luxury (5), upper upscale and upscale (4), upper midscale (3), midscale (2), and economy (1). The number of restaurants in a location was graded on a scale of 0 to 100 according to TripAdvisor. The higher the grade, the easier it is for travelers to find restaurants and things to do within walking distance.

Additional factors related to the consumers' evaluation of hotels were also obtained, such as average review rating and number of reviews. The average review rating was based on the 1 to 5 rating system. The hotels were categorized as excellent (4.5–5.0), very good (3.5–4.0), average (3.0), poor (2.0), and terrible (1.0). Both average review rating and number of reviews were based on reviews posted on TripAdvisor as of March 1, 2020. The destinations variable was a categorical variable consisting of six destinations defined in this study (i.e., New York, Los Angeles, Orlando, Rome, Paris, and Venice). The final sample included 12,944 observations from 399 hotels operated by three worldwide hotel chains.




*Note. Search keywords are Paris, Rome, Venice, New York, Los Angeles, and Orlando within a travel category at Google Trends.*

Figure 1. Goggle Trends Search Results

### 2.3.2. Variables

#### *2.3.2.1. Advance-Purchase Discounts*

An advance-purchase discount is the total amount of the discount given in a non-refundable rate compared to the free cancelation rate for the same type of room. All non-refundable rates this study collected were non-refundable after reservation and presented as prepay and save rates, early bird saving rates, early booking rates, or advance-purchase rates on hotels' direct channels. Free cancelation rates were displayed as standard rates, or flexible rates in hotels' websites. In the present study, the advance-purchase discount was calculated as the difference between the free cancelation rate and the non-refundable rate of each observation, as shown in Eq. (1) below:

*Advance-purchase Discount (APD) = Free cancelation rate (FC) – Non-refundable rate (NF)* (1)

#### *2.3.2.2. Cancelation Option Discounts*

A cancelation option discount was calculated via the Black–Scholes option pricing model. However, as the model was developed to analyze stock prices rather than room rates, some adjustments were made (Black & Scholes, 1973; Hull, 2017). The cancelation option discount was thus calculated using the following equation (Eq. 2):

$$V = PN(d_1) - e^{-r(T-t)}XN(d_2), \tag{2}$$

where $d_1 = \frac{ln\left(\frac{P}{X}\right)+(r+\frac{\sigma^2}{2})(T-t)}{\sigma\sqrt{T-t}}$ and $d_2 = d_1 - \sigma\sqrt{T-t}$.

In this equation, *V* represents the value of cancelation in the advance-purchase discount (i.e., cancelation option discount), *N(·)* represents the normal cumulative probability distribution function, *P* represents a free cancelation rate on the reservation day (i.e., current price), *X* represents the exercise price that pared with a non-refundable rate on the reservation day, *r* represents a risk-free rate, $\sigma$ represents the price volatility of the free cancelation rate, and *T-t* represents the last available free cancelation date minus the reservation (observation) date (i.e., time to maturity).

While the market price of a stock at any given time is used as the current price for stock options, it would be incorrect to use room rate on the reservation day as the current price for room reservations. This is because underlying assets are time invariant for stocks, but room nights are perishable. That is, the room rate booked for a future stay is different from the room rate on the reservation date, even for the same room. Likewise, exercise price was set as a non-refundable rate on the reservation day, because it represented the true market price of the room night at the time of booking (i.e., the implied strike price). Further, in keeping with previous studies, the three-month T-bill rate was used to denote the risk-free rate (Hull, 2017). The annualized volatility of free cancelation rates with observed daily room rate changes were used for the price volatility of the free cancelation rate. The current study also assumed that the time to maturity for each room was the period between the reservation date and the last available free cancelation date, because money cannot be refunded to guests after this pre-arranged date. Since this pre-arranged date is ranged between one day prior to check-in to one week prior to check-in, this study applied the midpoint of three days prior to check-in as the last available free cancelation date.

#### *2.3.2.3. Room- and Property-specific Attributes*

To reflect room rate-related attributes to the model, this study included room rate, room rate volatility, and demand variables. The free cancelation rate for each room type in the sample data were included in the hedonic pricing model. Price volatility was derived from the observed free cancelation rates. Price volatility was calculated by the standard deviation of free cancelation rates, which were obtained daily for an observation period. This study indirectly accommodated room demand by collecting reservation information for both low- and high-demand periods. The High Demand Period variable was given a value of 1 if the room was reserved for a high-demand period of New Years' holiday (Dec. 30, 2019 to Jan. 1, 2020) and 0 for room rates for reservations during the Dec. 16 to 18, 2019 period. Property-specific attributes were considered through hotel scales, number of reviews, review ratings, and a measurement for the number of nearby restaurants and attractions. Hotel scales are given on a scale of 1 to 5 from luxury to economy hotels. The number of reviews, which represented hotels' awareness, and review ratings reflected customers' evaluations of the hotel. The number of restaurants was included as a measurement for convenience of using restaurants and attractions. These variables were extracted from TripAdvisor's hotel review page.

#### *2.3.2.4. Control Variables*

Given that there are many factors influencing advance-purchase discounts in room reservation, Google Trends search results, destinations categorical variable, and observation week dummies were controlled for in the model. Google Trends search results in the travel category for each destination show the magnitude of searches done over a certain period. In the current study, this variable was included as a travel demand proxy for selected destinations. Dummy variables for the selected destinations were additionally included to control location-specific variations.

### 2.3.3. Hedonic Pricing Model

The hedonic pricing model assumes that goods possess a collection of attributes that combine to form bundles of characteristics considered valuable by the consumers (Lancaster, 1966; Rosen, 1974). In the hospitality literature, a hedonic price approach has been applied to pricing a room rate, which can be interpreted as a combination of observed attributes. Previous studies have incorporated hotel scale, location, hotel age, and size of hotels as major attributes for pricing hotel rooms. For instance, such attributes as hotel scale, hotel age, distance and transportation were investigated to price a hotel's location (Bull, 1994). Espinet et al. (2003) applied the hedonic price approach and revealed that hotel scale, location, hotel size, and distance from major attractions are the main factors of holiday hotels. Monty and Skidmore (2003) also used the hedonic pricing model by evaluating willingness to pay for various aspects of bed and breakfast accommodations in Southeast Wisconsin, revealing that hotel amenities, such as a hot tub, a private bath, and a larger room, are statistically significant factors affecting room price. Chen and Rothschild (2010) employed the hedonic pricing model to investigate hotel room prices in Taipei. The results indicated that location, LED TV, and conference facilities were significant service attributes for hotels in Taipei on both weekday and weekend room rates. Hung et al. (2010) investigate the major factors of hotel room pricing strategies by applying the quantile regression approach. The study found that hotel age and market conditions are the two major determinants in upscale hotels. Zhang et al. (2011) modified the hedonic pricing model by incorporating geographically weighted regression to capture heterogeneity for local hotels.

Based on the general ideas embedded in hedonic price approach and its application in the hospitality literature, the current study aimed to determine the pricing of the value of advance-purchase discount by using the hedonic price approach. The determinants of advance-purchase discount (APD) is a function of cancelation option discount (O), characteristics of room rates (R) (e.g., room rates, room rate volatility, and room demand), property-specific attributes (A) (e.g., hotel scale, review rating, number of reviews, number of restaurants and attractions), and control variables (C). Robust standard errors and time-fixed effect were applied to control for heteroskedasticity and different demand conditions over time, respectively. Accordingly, the regression model demonstrated the relationship between various attributes and advance-purchase discount. An ordinary least squares regression model can be written, as shown in Eq. (3):

$$APD_i = f(O_i, R_i, A_i, C_i), \qquad (3)$$

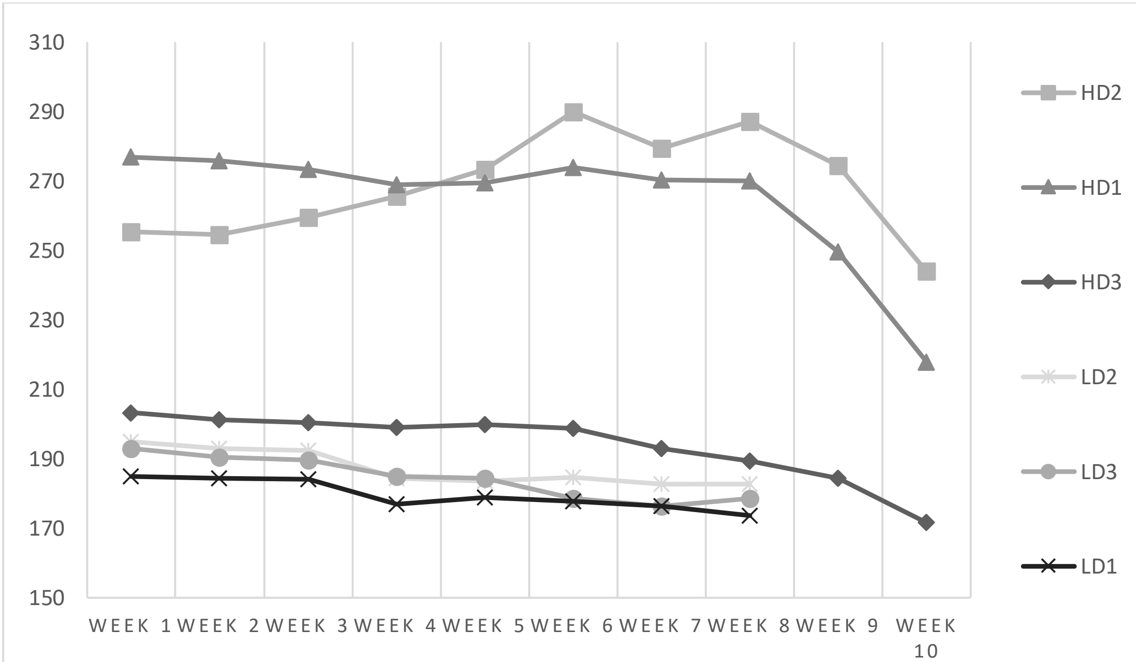
where $O_i$ represents the cancelation option discounts, $R_i$ is a vector of room rate characteristics, $A_i$ denotes hotel specific attributes, and $C_i$ indicates control variables.

## 2.4. Results and Discussion

Room rate movements showed different patterns by room demands. While room rates were relatively stable in the low-demand period, they changed more dynamically in the high-demand period (Figure 2). For the hypothetical reservation at December 31 (HD2 in Figure 2), for example, room rate peaked at US$289.96 for a month before check-in and dramatically decreased to US$243.93 in the last week.

The mean values of advance-purchase discounts for a low-demand period ranged between US$21.47 and US$28.47 (Table 4). Discounts diminished as time approached the check-in date in a low-demand period, but these stagnated in the last two weeks (Figure 2.2), indicating last-minute deep discounts existing from hotels that had excess inventory in the last week. For the high-demand period, different patterns in advance-purchase discounts were observed. First, the discounts showed greater fluctuation between US$21.04 and US$34.22. Second, they showed a stiff decreasing curve in the last three weeks prior to check-in. This finding supports the assumption that there are less available rooms for last-minute reservations in the high-demand than in the low-demand periods.

The mean of cancelation option discounts ranged between US$21.77 and $30.29 and between $20.39 and $64.71 for the low- and high-demand periods, respectively. Similar to advance-purchase discounts, cancelation option discounts diminished as time approached the check-in date in the low-demand period. In comparison, the high-demand period showed a diminishing curve, demonstrating the lowest point at three weeks prior to check-in before rebounding in the last two weeks. The cancelation option discounts also diverged from the advance-purchase discounts in the high-demand period. This indicated that hoteliers did not fully reflect the value of cancelation from the option pricing model in a busy season. Pairwise correlation analysis suggested that advance-purchase discounts were positively correlated with all parameters, such as cancelation option discounts, room rate volatility, hotel scale, review rating, and Google Trends.




*Note. LD denotes low-demand period and HD indicates high-demand period. W1 is the first observed week of Oct. 21-27, 2019 and W2 - W10 are consecutive weeks following W1.*

Figure 2. Mean Free Cancelation Rate by Demand Subgroup

Table 3. Description of Variables and Summary Statistics

| Variable | Description | Mean | STD |
|---|---|---|---|
| FC Rate | Free Cancelation Rate | 218.32 | 202.78 |
| NF Rate | Non-refundable Rate | 184.76 | 145.26 |
| AP Discount | Advance Purchase Discount | 29.46 | 78.46 |
| Option Discount | Cancelation Option Discount | 32.49 | 31.43 |
| Volatility | Standard Deviation of FC Rate | 17.99 | 53.17 |
| Hotel Scale | Hotels' Scales of 1 - 5 | 3.46 | 0.77 |
| Review Rating | Traveler Review Rating from TripAdvisor | 4.22 | 0.56 |
| No. Reviews | Accumulative Number of Reviews from TripAdvisor | 1,417.10 | 1,719.66 |
| Google Trends | Trends Search Results for each destination | 24.31 | 8.47 |
| No. of Restaurants | 1-100 scale measure of nearby restaurants and attractions | 83.49 | 23.49 |

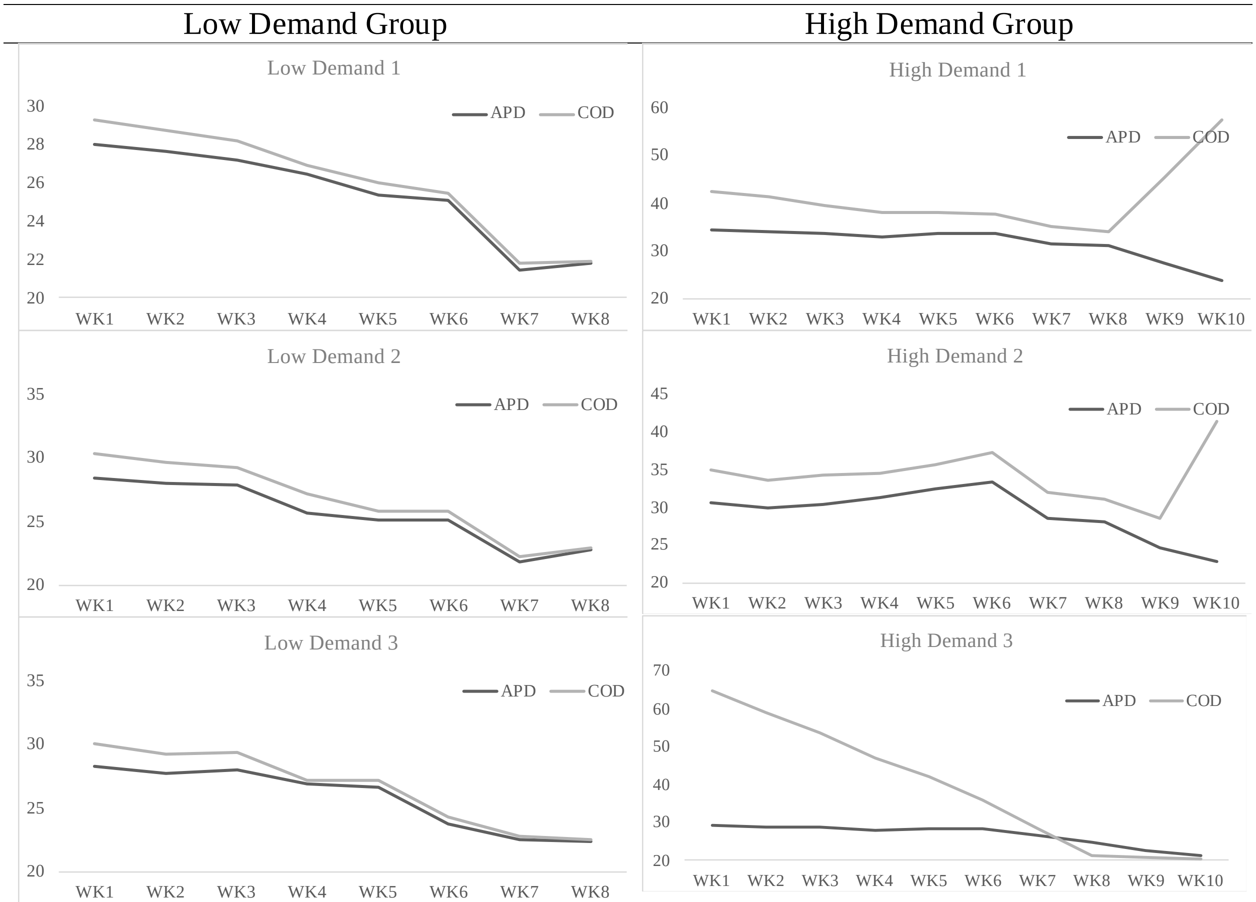



Figure 3. Mean Advance-Purchase Discounts and Cancelation Option Discounts by Demand Subgroup

Table 4. Pairwise Correlations

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) APD | 1 | | | | | | | | |
| (2) Opt. Dis. | 0.8562* | 1 | | | | | | | |
| (3) Vol. | 0.0673* | 0.4257* | 1 | | | | | | |
| (4) FC Rate | 0.8463* | 0.7667* | 0.3072* | 1 | | | | | |
| (5) Scale | 0.1493* | 0.3606* | 0.0675* | 0.2622* | 1 | | | | |
| (6) Rev. R. | 0.0606* | 0.2418* | 0.1734* | 0.2107* | 0.2958* | 1 | | | |
| (7) No. Rev. | 0.1619* | 0.0852* | 0.1140* | 0.1616* | 0.1913* | 0.0678* | 1 | | |
| (8) GTrends | 0.0561* | 0.1151* | 0.0109 | 0.0081 | 0.1189* | -0.2121* | 0.0244* | 1 | |
| (9) No. of Rest | 0.0769* | 0.2021* | 0.1629* | 0.1683* | 0.1735* | 0.0245* | 0.1282* | 0.3881* | 1 |

*Note. * p < 0.01, APD = advance-purchase discounts, Opt. Disc. = cancelation option discounts, Vol. = volatility, FC rate = free cancelation rate, Scale.= Hotel Scale, Rev. R. = review rating, No. Rev. = number of reviews, GTrends = Google trends search results, No. of Rest. = Number of Restaurants measurement.*

Table 5 presents the results of the hedonic pricing model. As expected, cancelation option discounts had a positive and significant effect on advance-purchase discounts (coef. = 0.6253, $t$ = 25.55, $p$ = 0.000). This suggested a positive relationship between cancelation option discounts and advance-purchase discounts in selected destinations. As expected, this finding supports H1.

Interestingly, room rate volatility was found to have a negative effect on advance-purchase discounts (coef. = –0.2798, $t$ = –13.63, $p$ = 0.000), which can be explained by major hotels' tendency to adjust their room rates rather than the amount of discount for early booking customers. This study hypothesized that hotels may offer greater discounts for early booking customers to avoid risks related to the room rate uncertainty, while the results suggested opposite direction and H2 was not supported. Based on the sample data, we found that hotels offered advance-purchase discounts ranging from 9% to 15% of the free cancelation rates for equivalent rooms, while the suggested discounts from the option pricing model ranged from 10% to 31%. Given that the mean room rate change was 17.99% in our observation, advance-purchase discounts can be applied more aggressively to reflect the actual room rate changes.

As anticipated, the high-demand period variable had a negatively significant effect on advance-purchase discounts (coef. = -6.5373, $t$ = –20.91, $p$ = 0.000). This confirmed H3, which posited that advance-purchase discounts were narrowed down in a high-demand period. To test H4a and H4b, the hedonic pricing model had variables representing hotels' awareness and customers' evaluation. In contrast to our expectation, the number of reviews, which reflected hotels' awareness, did not have a significant effect on advance-purchase discounts in the model. In comparison, review rating and consumers' evaluation had significant effects on advance-purchase discounts which supported H4b (coef. = –2.1233, $t$ = –8.11, $p$ = 0.000).

Table 5. Regression Results

| Dep. Var. = AP Discount | Coeff. | Robust Std. Err. |
|---|---|---|
| Cancelation Option Discount | 0.6159*** | (0.023) |
| FC Rate | 0.0829*** | (0.006) |
| Volatility | -0.3085*** | (0.020) |
| Review Rating | -2.1681*** | (0.256) |
| No. Review | -0.0001 | (0.000) |
| High Demand Period | -6.7785*** | (0.307) |
| Hotel Scale | | |
| Hotel Scale = 2 | 1.8616*** | (0.461) |
| Hotel Scale = 3 | 2.1821*** | (0.493) |
| Hotel Scale = 4 | 3.4427*** | (0.645) |
| Hotel Scale = 5 | 0.6363 | (1.393) |
| Google Trends | -0.0133 | (0.059) |
| No. of Restaurants | -0.0388*** | (0.006) |
| Destinations | | |
| Paris | 4.9276*** | (0.498) |
| Rome | 4.5791*** | (0.689) |
| Venice | 3.0064*** | (1.134) |
| Los Angeles | -1.8232* | (1.078) |
| Orlando | 2.8878*** | (0.959) |
| Observation Week | | |
| Oct. 28-Nov. 3 | 0.6585 | (0.448) |
| Nov. 4-10 | 1.4039*** | (0.425) |
| Nov. 11-17 | 2.3371*** | (0.447) |
| Nov. 18-24 | 2.7338*** | (0.476) |
| Nov. 25- Dec. 1 | 3.3935*** | (0.452) |
| Dec. 2-8 | 3.5453*** | (0.486) |
| Dec. 9-15 | 4.0158*** | (0.494) |
| Dec. 16-22 | 3.4310*** | (0.915) |
| Dec. 23-29 | -2.8071** | (1.189) |
| Constant | 3.3148 | (2.043) |
| Observations | 12,944 | |
| R-squared | 0.8189 | |

*Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Reference groups are Hotel Scale = 1, New York for destination categorical variables, Week1 (Oct. 21 – 27) for observation week dummies. High Demand Period represent high-demand period that room reservation for Dec. 30, 2019 – Jan. 1, 2020.*

The hedonic pricing models for each destination were analyzed, and the results were summarized (Table 6). A close observation of Table 6 reveals suggestive findings. First, the cancelation option discounts were positively significant in all subgroup analyses, implying that the value of cancelation option discounts from the B-S pricing approach was effective in multiple locations. Second, volatility was negatively related to the advance-purchase discounts in most of the destinations. The results hinted that the volatility in room rates was not a risk to hotels, rather it showed their ability to adjust their room rates and discounts dynamically. This result contradicts the interpretation of volatility, which implies risks, in the finance literature. It would be a worthwhile research topic in the future to further examine the relationship between room rate volatility and room rate attributes. In all destinations, advance-purchase discounts were smaller in the high-demand period and/or for hotels with better reviews. The results are in line with the outcomes of the integrated hedonic pricing model. The influence of the number of reviews was mixed, suggesting that the number of reviews did not fully represent hotels' awareness.

Table 6. Regression Results by Destination

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Paris | Rome | Venice | New York | LA | Orlando |
| Opt. Dis. | 0.7560*** | 0.3733*** | 0.2082*** | 0.4662*** | 0.3200*** | 0.3137*** |
| | (0.026) | (0.041) | (0.050) | (0.035) | (0.045) | (0.025) |
| FC Rate | 0.0776*** | 0.0395*** | 0.1181*** | 0.0667*** | 0.0572*** | 0.0713*** |
| | (0.011) | (0.007) | (0.010) | (0.006) | (0.008) | (0.004) |
| Vol. | -0.2435*** | -0.0173 | -0.0775** | -0.2149*** | -0.2397*** | -0.0704*** |
| | (0.031) | (0.025) | (0.038) | (0.018) | (0.035) | (0.018) |
| Rev. Rating | -3.3788*** | 8.4490*** | -0.8746** | -0.9906* | -6.0881*** | -0.8925*** |
| | (0.466) | (1.415) | (0.383) | (0.556) | (1.202) | (0.264) |
| No. Review | -0.0008*** | -0.0032*** | -0.0006** | 0.0002 | 0.0015*** | 0.0000 |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| HD Period | -4.8625*** | -3.9399*** | -0.8989** | -6.4886*** | -5.2455*** | -3.3956*** |
| | (0.287) | (0.644) | (0.374) | (0.713) | (0.997) | (0.427) |

Table 6 continued

| | | | | | | |
|---|---|---|---|---|---|---|
| Hotel Scale | | | | | | |
| 2 | 2.9982*** | | | | | |
| | (0.495) | | | | | |
| 3 | 1.3721** | | | 7.5398*** | -0.8563 | 1.3780*** |
| | (0.566) | | | (1.266) | (1.249) | (0.325) |
| 4 | 1.5080** | 2.9507*** | | 10.1733*** | 5.5205*** | 0.2559 |
| | (0.758) | (0.533) | | (1.327) | (1.397) | (0.533) |
| 5 | -5.1934*** | 4.6492*** | -2.2279 | 14.0880*** | -0.1203 | |
| | (1.819) | (0.881) | (1.513) | (3.858) | (2.554) | |
| G. Trends | -0.3948 | 0.9355 | -2.1722 | -2.0795*** | 0.4115 | -0.2066 |
| | (0.832) | (0.935) | (1.784) | (0.528) | (1.183) | (0.384) |
| No. of Rest. | 0.0192** | 0.0494*** | 0.0851*** | -0.0831*** | -0.1025*** | -0.0568*** |
| | (0.009) | (0.009) | (0.019) | (0.014) | (0.022) | (0.007) |
| Obs. Weeks | | | | | | |
| Oct. 28-Nov. 3 | -1.7389 | -0.1438 | 0.3721 | 3.0556*** | -0.2020 | 0.2699 |
| | (4.887) | (1.405) | (0.677) | (0.988) | (1.250) | (0.540) |
| Nov. 4-10 | -1.5694 | 0.3902 | 35.6253 | 4.2687*** | -0.5370 | 0.6929 |
| | (5.690) | (1.314) | (28.382) | (0.942) | (1.228) | (0.531) |
| Nov. 11-17 | -0.6545 | 1.2767 | 11.9855 | 3.4423*** | -0.7175 | 0.8294 |
| | (5.681) | (1.246) | (8.780) | (0.908) | (1.243) | (0.526) |
| Nov. 18-24 | -0.6806 | 2.9555 | 0.6212 | 2.0481* | 0.3790 | 1.0661 |
| | (6.490) | (2.651) | (0.623) | (1.132) | (1.227) | (0.702) |
| Nov. 25- Dec. 1 | 0.7849 | 2.5644 | -1.0096 | 8.6944*** | 2.2283 | 1.3968** |
| | (4.826) | (2.626) | (2.138) | (1.239) | (1.880) | (0.578) |
| Dec. 2-8 | 0.1610 | 0.5291 | -2.2972 | 5.4190*** | 3.7526** | 2.2038*** |
| | (5.604) | (1.783) | (3.743) | (0.975) | (1.877) | (0.590) |
| Dec. 9-15 | 0.5761 | 1.7794 | -1.3588 | 7.3160*** | 4.8605*** | 2.7276*** |
| | (4.731) | (3.479) | (2.063) | (1.225) | (1.645) | (0.619) |
| Dec. 16-22 | 5.5289* | | 1.0196 | 9.5014*** | 4.3087 | 5.4386*** |
| | (3.067) | | (1.218) | (3.585) | (4.193) | (1.917) |
| Dec. 23-29 | | -5.4054** | | | | |
| | | (2.361) | | | | |
| Constant | 19.1204 | -54.7182* | 18.2838 | 58.8245*** | 31.4919** | 10.5846** |
| | (29.760) | (29.428) | (15.896) | (14.824) | (13.351) | (4.800) |
| Observations | 5,832 | 812 | 428 | 2,672 | 937 | 2,262 |
| R-squared | 0.9032 | 0.8317 | 0.9671 | 0.6941 | 0.4342 | 0.5066 |

*Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Reference groups are Hotel Scale = 1 and Week1 (Oct. 21 – 27) for observation week dummies. Option Dis. is cancelation option discount, Vol. is room rate volatility, HD Period represent high-demand period (Dec. 30, 2019 - Jan.1, 2020), GTrends is google trends search results, and No. of Rest. refers to number of restaurants measurement.*

## 2.5. Conclusion

The hedonic pricing model demonstrates that the advance-purchase discount comprises the option value component and discount-adjustment component from hotel room-night market-specific attributes. Furthermore, the property-specific factors, such as hotel scales, customer reviews, and number of nearby restaurants, reflect each hotel's competitiveness in the local market. The results also suggest that property-specific factors have a significant impact on advance-purchase discounts, thus implying the relationship between hotels' competency and their rate discounts for early booking customers.

The results have theoretical implications to finance literature by extending the application of the option pricing model to real options for non-financial assets. The option value component—the cancelation option value embedded in room rates—was identified in this study using the Black–Scholes option pricing model. The method can be applied to evaluate cancelation options in other non-financial assets, such as airfares, car rentals, and restaurant reservations. To examine the total value of advance-purchase discounts, this study also identified the discount-adjustment component, which was found to be influenced by property-specific attributes at the property level. This heterogeneity is another distinctive feature of the hotel room-night market compared with the homogenous security market. Specifically, this study allowed perceived quality from customers to be a part of the hedonic pricing model for advance-purchase discounts. Perceived quality, which was measured by customer reviews, represented the uniqueness of hotels at the property level. This is a key difference of this model to the financial asset pricing model, which assumes the presence of uniform quality among financial products. Thus, similar price-adjustment components can be considered for examining assets with varied attributes, such as real estate, agricultural commodities, and precious metals.

These findings are important from a practical perspective, because many hotels offer advance-purchase discounts to attract price-sensitive travelers. The proposed approach provides a guide for hoteliers to systematically price their advance-purchase discounts. By applying the model to their own data, pricing decision-makers can effectively estimate property-specific advance-purchase discounts. This study, for example, observed that hotels offer low, last-minute free cancelation rates to attract travelers. Even for these cases, advance-purchase discounts are maintained at the normal-season levels. Thus, reducing room rates would be an effective strategy to increase booking intention if hotels only have free cancelation rates. However, because most of the hotels already have non-refundable rates or similar rate options for their customers, they can adjust advance-purchase discounts rather than adjust their free cancelation rates. If hotels apply the strategy suggested by this study, they can effectively manage room rates by maintaining free cancelation rates for less price-sensitive customers while reducing rates for early booking non-refundable rates for other types of customers.

Furthermore, this study empirically evaluated the effects of consumer preferences on various room- and property-specific factors related to the competitiveness of hotels in the local markets. In particular, the findings suggested that hotels can offer less discounts during high-demand periods when they already have high review ratings. This is a new addition to the extant research on the effect of positive reviews on booking intention and room demand in the local market. The results also confirmed that early booking discounts can be low for busy seasons even for the same type of rooms.

While this study examined the value of advance-purchase discounts in detail, some limitations must also be considered. First, it is possible that the estimated value of cancelation option discounts using the option pricing model may be more vulnerable than it is in reality. This is because hotel room nights are perishable and limited in quantity; transactions cease after all rooms are sold. Fewer observations closer to the check-in dates can be gathered, as there are fewer available rooms for reservation. Thus, more observations in the earlier weeks and fewer observations in the later weeks may have artificially increased the mean value of the cancelation option. Although this issue was addressed by collecting data from different cities during low- and high-demand periods, further research should take additional steps to account for the differences between a room reservation and a financial option.

Second, the empirical testing of the model was based on three hotel chains operating worldwide. Therefore, the resulting numerical estimations may not be valid for other types of accommodations (e.g., independent/boutique hotels, timeshare, Airbnb, etc.). Nevertheless, the conceptual framework and methodology employed in this study to measure advance-purchase discounts are still applicable to leisure/business markets and low/busy periods.

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# CHAPTER 3. RATE PARITY AGREEMENT AND ITS IMPACT ON ROOM-NIGHT MARKET EFFICIENCY

## 3.1. Introduction

Rate parity is an agreement between hotels and online travel agencies (OTAs) in which the hotels promise that they will use the equivalent rates for a certain type of room for all distribution channels. As online distribution channels become major booking channels, the benefits and costs of maintaining rate parity have been discussed by hotel industry practitioners and government authorities. In Europe, rate parity clauses have been regulated by European antitrust laws. For example, France has prohibited rate parity clauses since 2015, and a similar regulation has been enforced in Italy since 2017. Consequently, OTAs in Europe have lost their rate parity clauses, while rate parity agreement has been maintained in the United States.

In the hospitality industry, there have been debates about the need for rate parity agreements between hotels and OTAs. By maintaining rate parity agreements, hotels and OTAs have no worries regarding the showrooming effect and consumers' perceived fairness. However, the major criticism of rate parity agreements is that they may hinder hotels' flexibility in setting different room rates across distribution channels, including hotels' direct channels. The restrictions on price adjustment may prevent hotels from setting the optimal price for each distribution channel, rendering the limited supply not sufficiently allocated. This implies that rate parity clauses may impede the efficiency of room-night markets. Rate parity clauses could also potentially lead to price fixing and incite concerns about antitrust issues. While previous literature on rate parity has examined the direct effect of regulations on rate parity agreements in different regions, there has been limited research on the impact of such agreements on actual room pricing (Demirciftci et al., 2010; Hunold et al., 2018; Sharma & Nicolau, 2019; Toh et al., 2011).

Sharma and Nicolau (2019) discussed the economic significances of rate parity-related legislative actions in Europe and the United States and revealed that such regulations brought negative abnormal returns for OTAs but positive reactions for hotels. Hunold et al. (2018) examined the effect of regulation on rate parity in terms of the frequency of price offers and the price levels of hotels' direct channels and OTAs. Although previous research has suggested different patterns in room pricing for different distribution channels after regulating rate parity clauses, there has been lack of investigation of the intended purpose of regulating rate parity, to remove restrictions on room pricing. Thus, it is beneficial to answer the question of whether rate parity agreement really alters room rates and which property-specific attributes are affected by the rate parity agreement at the individual hotel level.

This study therefore aimed to examine how the regulation of rate parity affects room-pricing strategies used in hotels' direct channels by demonstrating hedonic pricing models for both free cancelation rates and non-refundable rates. This study also examined the moderating effect of rate parity on the relationship between property-specific attributes and room rates to test the sensitivity of room rates to property-specific attributes under rate parity clauses. This study thus constructed hedonic pricing models to test the direct and indirect impact of rate parity clauses on room rates by comparing hotels in Europe and the United States. The results suggested that the existence of rate parity agreement between hotels and OTAs has no direct impact on the direction of room rates. This study further investigated and confirmed that rate parity indirectly impacted room rates through property-specific attributes. This study also discovered that the existence of rate parity impeded the effect of property quality on room pricing. The findings supported this study's claim that rate parity reduced the efficiency of the hotel room-night market. This study also found hikes in room rates during high-demand dates, which indicated anti-trust behavior between hotels and OTAs. This is evidence to support the European Union's decision on rate parity agreement.

The results of this study contribute to the hospitality literature by identifying the impact of rate parity on specific room-pricing strategies and demonstrating the sensitivity of room rates to property-specific attributes under rate parity at the property level. The findings also extend the application of the efficient market hypothesis to rate parity and its impact on room rates in the hotel industry. Hotel managers have a new perspective from which to understand pricing dynamics under rate parity, as well as the extent to which their room rates are sensitive to each hotel's attributes under rate parity. Additionally, the findings can be evidence for policy makers to restrict rate parity and support channel-specific rates.

## 3.2. Rate Parity and Market Inefficiency

### 3.2.1. Rate Parity Agreement

The relationship between hotels and OTAs is a frequently discussed topic in the hospitality industry. Online reservation channels, such as hotel websites and OTAs, have become major booking channels for travelers. OTAs are third-party booking websites, such as Expedia, Priceline, and Booking.com; they allow travelers to search and book hotel rooms, air tickets, and rental cars. The market share for online reservation channels increased from 26% in 2011 to 47% in 2018 in the United States (Green & Lomanno, 2013; Phocuswright, 2018). Within the online hotel-booking market, hotel websites represented 49% of total reservations, while OTAs accounted for 51% of the total market in the United States (Phocuswright, 2018). In Europe, OTAs held a more dominant share (79%) of the online space, while hotel websites represented 21% of online distribution channels in 2018 (D-EDGE Hospitality Solutions, 2019). Accompanying the rise of OTAs, rate parity agreement has been a common practice between hotels and OTAs (Scott, 2015).

Rate parity is defined as a contractual arrangement between hotels and OTAs. Under the rate parity agreement, hotels guarantee that they will use the equivalent rate for a certain room type for all distribution channels (Trivago Business Blog, 2019). The agreements are generally grouped into two categories. The first group is a wide rate parity, which is a more restrictive form of parity agreement. Under wide rate parity, hotels agree to maintain the same room rates that OTAs charge for their hotel rooms. A narrow rate parity is a less restrictive form, which prohibit publicly offer lower rates in their own website than other OTAs but allows hotels to offer lower rates to other OTAs privately.

Previous literature on economics discussed the implications of rate parity clauses in different industries. Johnson (2017) analyzed suppliers and online retailers' adoption of price parity restrictions as one of the consequences of the shift from the wholesale model to the agent model. Price parity clauses in Amazon Marketplace, Amazon e-bookstore, and Apple's e-bookstore between suppliers (e.g., product suppliers and book publisher) and retailers (e.g., Amazon and Apple) and price comparison websites for auto insurance providers were examined as examples of such restrictions. Wang and Wright (2020) determined that platform fees increase the possibility of showrooming and that price parity clauses were adopted by suppliers and platforms. They showed that the existence of a multiplatform was able to reduce search costs but that the coexistence of price parity clauses can harm consumers.

In the hotel industry, the billboard effect (Anderson, 2009) is a form of showrooming because travelers gain information from OTA listings but reserve rooms through hotel direct websites. To avoid this effect, OTAs often request rate parity agreements when they post hotel rooms on their websites (Haynes & Egan, 2015). Thus, rate parity agreements influence the pricing and allocation of room inventory across online distribution channels (Demirciftci et al., 2010; Hunold et al., 2018; Mantovani et al., 2017; Toh et al., 2011). The existence of rate parity between OTAs and hotels may increase the level of reliance on OTA channels, and this reliance consequently increases hotels' commission payments to OTAs. This increased distribution cost and reduced price-competition in the marketplace could eventually push room rates upward. Thus, to enhance free and fair competition, European antitrust authorities started to regulate rate parity clauses between hotels and OTAs. In Europe, four countries—France, Austria, Italy, and Belgium—prohibit all rate parity agreement between hotels and OTAs. Countries such as Germany and Sweden regulate certain OTAs, while allow other OTAs to use wide and narrow rate parity agreements within these markets. In the United States, however, rate parity agreements were not been regulated (Table 7). Even though rate parity is still maintained in the United States, some hotels and OTAs voluntarily relax some rate parity clauses. Therefore, room-rate dispersions between hotels and OTAs were observed in the United States market (Kim et al., 2020). Hotels often offer extra benefits to customers who book through direct channels.

To evaluate the effect of rate parity agreements and regulations on such agreements, the pros and cons of rate parity agreement for hotels, OTAs, and potential travelers have been examined in the contexts of different markets. From the perspective of hotels, one of the advantages of parity clauses would be hotels' ability to maintain parity status with the minimum rates they set. The parity also prevented OTAs from offering lower rates than hotels. Accordingly, hotels maintained their room rates at reasonable levels, and this prevented the devaluation of their brands due to heavy discounts (Nicolau & Sharma, 2019). Additionally, potential travelers may perceive the rates from distribution channels as fair if all channels offer similar rates (Nicolau & Sharma, 2019).

While rate parity clauses may have a positive impact on hotels, one of the biggest disadvantages can be price inflexibilities in hotels' direct channels. Hoteliers cannot offer lower prices on their own distribution channels when they have rate parity agreements with OTAs. Under the dynamic pricing strategy with customization, price differentiation for each customer can be available for hotels to maximize their profit (Mohammed et al., 2017). However, hotels cannot fully employ their dynamic pricing strategy under the rate parity agreement. What is more, hotels' profit margins from OTAs can be lower than the margins from the hotels' own distribution channels under parity clauses because of the high commissions, which generally range between 10% and 30% (Sharma & Nicolau, 2019; Toh et al., 2011).

To see the effect of regulation on rate parity, room reservation environments without rate parity agreements have been investigated by Hunold et al. (2018). They found that hotels promoted their direct channels more actively and offered strictly the lowest prices more often when there was no use of rate parity agreement in Europe. In regard to the United States, however, the empirical analysis implied that rate parity exists in hotels' and OTAs' room rates at the aggregate level (Demirciftci et al., 2010). While the rate parity held in the aggregated market in the United States, there was some room-rate dispersion across OTA channels, such as Expedia.com, Orbitz, and Travelocity.com. This can be caused by competition and mark-ups.

Table 7. Regulation of the Rate Parity Agreement

| Country | Rate parity | Start From |
|---|---|---|
| France | Ban on narrow and wide rate parity clauses | July 2015 |
| Austria | Ban on narrow and wide rate parity clauses | November 2016 |
| Italy | Ban on narrow and wide rate parity clauses | August 2017 |
| Belgium | Ban on narrow and wide rate parity clauses | November 2017 |
| Germany | Rate parity clauses are prohibited for HTS and Booking.com | December 2013 |
| Sweden | Regulate rate parity clauses for Booking.com | July 2018 |
| European Union | Narrow rate parity agreement were maintained for Booking.com and Expedia | July 2015 |
| Switzerland | Swiss parliament made announcements to follow suit | September 2017 |
| USA | Rate parity has not been regulated | |

*Note. Contents are sourced from Trivago Business Blog (2019) and Scott (2015).*

### 3.2.2. Rate Parity and Market Efficiency

As discussed, rate parity agreement has been prohibited in many European countries. Consequently, the impact of regulation on rate parity can be estimated by comparing final transaction prices (i.e., free cancelation rates and non-refundable rates on check-in date) in Europe and the United States. The comparison is based on the efficient market hypothesis in the finance literature. The efficient market hypothesis states that "current prices reflect all available information such that no abnormal profits can be earned from arbitrage activities (Fama, 1970, 1991)." The market efficiency hypothesis can be divided as three forms by Fama (1970): weak, semi-strong, and strong. Under the weak form of efficiency, all information contained in past prices is irrelevant to price movement in the future. The semi-strong form of the efficient markets implies that prices should reflect all publicly available information. Prices reflect all information—both public and private—in strong forms of efficient markets (Brealey et al., 1988; Ross et al., 2008).

In the finance literature, the efficient market hypothesis has been widely tested. Researchers have determined that market inefficiencies or arbitrage opportunities can exist due to factors such as market imperfections, errors in valuation models, and noncontinuous data (Chiras & Manaster, 1978; Fama, 1998; Jensen, 1978; Schwert, 2003). Despite evidence of market anomalies in various markets, Fama (1998) argued that the efficient market hypothesis is still intact because long-term return anomalies are fragile. Schwert (2003) also mentioned that market anomalies can disappear, reverse, or attenuate in the long run. Financial market frictions are defined as anything that interferes with trade. Even in an efficient market, frictions such as trading restrictions, trading costs, and agency problems can exist, but they can be real costs or can create arbitrage opportunities for investors (Degennaro & Robotti, 2007).

Similar to the finance market, room rates were continuously adjusted by demand and supply in the hotel room-night market. Particularly under the dynamic pricing strategy, hotel managers frequently adjusted room rates, reflecting changes in demand. In hotel room-night markets, however, the markets' role in price adjustment can be hindered because of trading restrictions, such as perishability, limited liquidity, and rate parity clauses. First, the hotel room-night market is perishable. This means the value of hotel rooms becomes zero after the designated check-in date. Because of such perishability of inventory, room-night market trading for a particular night ends on the check-in date. Second, there is a limitation in quantity. The number of rooms trading on the hotel room-night market is fixed in the short term. Therefore, there is no trading once the rooms are sold out, further limiting trading activities. Finally, price restrictions caused by rate parity can create market friction and may increase trading costs for market participants.

Rate parity clauses force hotels to accept unfavorable rate conditions from their OTA channels. Thus, room-pricing independence is restricted from rate parity agreements. The rate parity agreement thus leads to higher room rates across channels for potential travelers because of the large OTA commissions and less price competition. First, when there were no price differences among distribution channels, booking through OTAs was more convenient for customers than using hotels' direct reservation systems, because OTAs offer a variety of hotel selections. Thus, rate parity may increase hotels' dependence on the OTA channel, which can cause large OTA commissions. In this case, hotels have an upward pressure on their room rates for offsetting larger commissions for OTAs (Nicolau & Sharma, 2019). Second, room rate may be fixed at a higher level than the actual value to customers by reducing natural competition between OTAs and hotels (Haynes & Egan, 2015). To prevent such anti-competitive consequences from the rate parity agreement between hotels and OTAs, European legal jurisdictions have regulated the use of rate parity clauses. While some OTAs and hotels in the United States ease such rate parity clauses between them, rate parity agreements are still available in the United States. Therefore, the imperfection derived from the rate parity agreements can be examined by comparing room rates in Europe to those in the United States. This study therefore claims that the existence of rate parity agreements between hotels and OTAs increases room rates on average. Thus, the following hypothesis is suggested:

*Hypothesis 1: Rate parity agreement increases room rates for both free cancelation rates and advanced booking rates.*

### 3.2.3. Moderating Effect of Rate Parity

Because rate parity clauses can be regarded as a form of market friction, the unique characteristics of hotels with such restrictions are less likely to be reflected in their room rates. Even if two hotels in the same area offer the same room types, the room rates would differ due to property-specific characteristics, such as reviews, hotel scale, and location. The existence of rate parity may impact the reflection of such attributes in room rates.

*3.2.3.1. Rate parity and hotel quality*

Hotel scale is a quality measure for hotels. This is an objective standard of the quality traditional classification system that allows customers to evaluate the quality of hotels. While there is no standardized method for rating, the rating system is based on 1 to 5 stars, with a greater number of stars indicating greater luxury. Similar to the star rating, the Smith Travel Research (STR) classified hotel chains into six categories: economy, midscale, upper midscale, upscale, upper upscale, and luxury. According to the STR's hotel segment, hotel chains are positioned in hotel scale groups based on their average daily rates. When hotels have higher scales, they have higher room rates for their customers. As an example, five-star hotels or luxury hotels, based on the STR classification, generally offer the highest rates among their counterparts in a competing region.

The average review rating can be viewed as a proxy for consumers' perceived quality given their expectations of the hotel, given its brand and hotel scale. This is also important information for consumers who have no prior experience with the property they are booking. The consumer can use the review information to help with the assessment of the property and then form their internal reference price. Previous studies on e-word-of-mouth have found that consumer reviews had a positive impact on hotel performance and consumers' hotel choices (Blal & Sturman, 2014; Book et al., 2018; Fang et al., 2016; Liu et al., 2019; Noone & McGuire, 2014; Xiang & Gretzel, 2010). Book et al. (2018) found that consumer reviews had a positive effect on consumers' evaluations and hotel choices. The characteristics of reviews were also examined to measure the impact of reviews on hotel performance (Fang et al., 2016; Liu et al., 2019). Previous literature has also focused on the positive effect of reviews on hotel-booking intention (Chan et al., 2017; Vermeulen & Seegers, 2009). Consequently, consumer ratings or positive reviews have a positive impact on hotel room rates (Öğüt & Onur Taş, 2012). In a similar vein, Ye et al. (2009) empirically revealed that positive reviews increase hotel revenues through higher booking rates. Because reviews can be viewed as a perceived value or quality from customers who have stayed at a hotel, the aggregated reviews can be a useful source for hotels and OTAs to estimate customers' booking intentions.

While such quality measures are closely related to room rates in the hotel room-night market, the existence of rate parity may hinder the reflection of such quality measures on room rates. For example, room prices may be less responsive to review ratings in hotels under rate parity than those without rate parity. Because hotels cannot offer lower rates than their OTAs and vice versa, the rates may not efficiently reflect the characteristics of hotels under rate parity agreements. Let us imagine a situation: Hotel managers detect bad reviews from recent visitors, and they need to do something to overcome this. One way to overcome such a bad reputation can be promotions through discounts. If hotels have a rate parity agreement, it would not be easy to offer discounted rates. This is because offering discounted rooms for hotels' direct channels means reducing room rates for all distribution channels. Therefore, the sensitivity of room rates regarding such quality measures can be slowed under rate parity agreements. Thus, room rates can be less responsive to changes in quality measures. Accordingly, the following hypotheses were suggested:

*Hypothesis 2a: Rate parity weaken the positive effect of hotel scale on room rates*

*Hypothesis 2b: Rate parity weaken the positive effect of review rating on room rates*

#### *3.2.3.2. Rate parity and room demand*

Demand volatility affects hotels' occupancy and room rates and may change the dynamics between hotels and OTAs. In the low-demand period, hotels may experience a relatively low level of occupancy. In a competitive market, hotels and OTAs may compete with each other to attract more customers to their own channels. Therefore, hotels and OTAs may offer different room rates depending on the demand from their own distribution channels when there is no parity restriction. However, rate parity clauses restrict such variety of room rate offerings and only allow to suggest one price for the same room types. Therefore, hotels and OTAs set a lowest price available for them in the low demand period. The average room rates, thus, may be higher in the cities without rate parity restrictions than those of in the cities with rate parity restrictions. In the high-demand period, however, high occupancy gives hotels incentives to increase their room rates. Rate parity clauses could further boost the room rate because both OTAs and hotels can increase the rate without worrying about being undercut by competitors. In this case, hotels and OTAs could cooperate more with regard to raising room rates. Thus, the following hypothesis was suggested:

*Hypothesis 3: Rate parity strengthen the positive effect of demand on room rates*

## 3.3. Methodology

### 3.3.1. Data Collection

Daily hotel room-rate information from Marriott, InterContinental Hotels Group (IHG), and Accor at six travel destinations was collected between October 21, 2019 and January 1, 2020. Given that this study assumed that room rates respond to market demand in similar ways, revenue management practice needs to be controlled in the sample. To control variations from revenue management practices, these three major hotel companies were selected because they have a similar level of revenue management expertise and global presence. This study thus excludes small and independent hotels in the sample because their revenue management practices may not be as sophisticated as those of major hotels. Information about non-refundable rates (e.g., prepay-and-save rates, prepaid rates, and saver rates) and free cancelation rates (e.g., flexible rates and standard rates) were obtained from hotels located in six popular travel destinations: Paris, Rome, and Venice from the European continent and New York, Los Angeles, and Orlando from the United States. All rates were recorded based on a one-night stay in a standard or standard-equivalent room from each hotel chain's website to control variations due to room type and distribution channels. Then, price characteristics, such as room-rate volatility, were calculated from the collected daily room rates. The individual hotels' characteristics—including hotel scales, review rating, number of reviews, and number of restaurants—were also obtained from various sources. Hotel scale was based on various sources, such as chain scale segmentation from STR, rating information from Google's hotel class ratings, online travel sites (e.g., TripAdvisor and Expedia), and each hotel's website. As a proxy for customers' perceived value of stay, review rating and number of reviews were obtained from TripAdvisor. The number of restaurants measurement was derived from TripAdvisor's "places to stay" indicator. Demand variations were obtained to classify six different check-in dates into two groups: December 16–18, 2019 as the low-demand period and December 30–January 1, 2020 as the high-demand period. The hotels' location information was also obtained to control for city-level price variations. The final sample included 4,013 observations from 399 hotels from three worldwide hotel chains.

### 3.3.2. Variables

#### *3.3.2.1. Last Available Room Rates*

Within the booking period, room rates change frequently, reflecting demand and supply, and these changes are affected by each day's market conditions. As discussed in the previous section, market frictions such as perishability and limited quantity in trading affect daily room rates. To control for these factors, this study used last available room rates as the final transaction prices. Theoretically, the final transaction price is the room rates for check-in dates, and they reflect all demand and supply information in the market. However, hotel rooms are limited in quantity, and there are no room rates available once sold out. Therefore, the last available free cancelation rates and non-refundable rates were obtained as the final transaction prices to examine the efficiency of the hotel room-night market.

#### *3.3.2.2. Parity*

To investigate the impact of rate parity agreements on the quality-adjustment component of advance-purchase discounts, the existence of rate parity was implemented in the model. This study selected six popular travel destinations located in Europe and the United States. Three cities in two European countries—France and Italy—were chosen because both countries have strictly prohibited rate parity agreements between hotels and OTAs, while there was no uniform regulation on rate parity agreements between two parties in the United States. Therefore, the parity variable was valued at 1 if the hotels were located in the two European countries, and 0 was assigned if they were in the United States.

#### *3.3.2.3. Hotel Scale*

To identify the quality of the hotel, star ratings of hotels were collected from Google, online travel review sites, and hotel websites. Based on the ratings that were collected from various sources, the hotel scales in this study were reclassified by the STR's chain scale segmentation, ranging from luxury to economy accommodations. The hotel scales were luxury (5), upper upscale and upscale (4), upper midscale (3), midscale (2), and economy (1). Similar to the adjustment for review ratings, the hotel scale variable was standardized to prevent possible statistical problems.

#### *3.3.2.4. Review Rating*

The aggregated reviews from customers were considered in the model to incorporate moderating impact from the perceived value on the sensitivity of divergence to the rate parity. The average review rating was based on a 1–5 rating system from TripAdvisor as of March 1, 2020. Hotels were categorized by review rating: excellent (4.5–5.0), very good (3.5–4.0), average (3.0), poor (2.0), and terrible (1.0). The collected review ratings were standardized to make interpretations easier and to avoid multicollinearity in the interaction term (Kutner et al., 2005).

#### *3.3.2.5. High-Demand Date*

To examine the moderating effect of rate parity on the demand variable, a high-demand dummy variable was included in the model. Among six check-in dates, the period between December 30, 2019–January 1, 2020 was selected as a high-demand period (New Year's holiday), and two weeks before this period (December 16–December 18, 2019) was recorded as a low-demand period.

#### *3.3.2.6. Control Variables*

Given that market inefficiency in regard to advance-purchase discounts can be influenced by other hotel characteristics, such as number of reviews and number of restaurants were controlled for in the model. To identify hotel segments, hotel scales of hotels were collected. Star ratings were based on the STR's chain scale segmentation, ranging from luxury to economy accommodations. The hotel scales were luxury (5), upper upscale and upscale (4), upper midscale (3), midscale (2), and economy (1). The number of restaurants variable was also collected from TripAdvisor and was included in the model to control for variations resulting from consumer convenience. A 0–100 scale measurement was used to show the ease of finding restaurants and things to do within walking distance. A destination categorical variable was also included in the model to control for city-level variations.

### **3.3.3. Regression Analysis**

A multivariate regression model was utilized to assess the deviations in advance-purchase discounts. Given that the final transaction price was employed as the dependent variable in the regression model, the existence of a rate parity agreement was implemented as a dummy variable. Review rating, hotel scale, and high-demand date were included in the model as other independent variables. As the transaction price can be influenced by other hotel characteristics, variables such as number of reviews, number of restaurants, and destination dummies were included to control for property-specific variations. Robust standard errors were implemented to control for heteroskedasticity. A regression model can be written as (Eq. 1):

$$Model\ 1:\quad Room\ Rates_i = \alpha + \beta_1 PARITY_i + \beta_2 RATING_i + \beta_3 SCALE_i + \beta_4 HIGH_i + \beta_5 NOREV_i + \beta_6 REST_i + \beta_7 DEST_i + \varepsilon_i \qquad (1)$$

, where *Room Rates* = last available transaction prices for free cancelation rates and non-refundable rates, PARITY = dummy variable for the existence of rate parity agreement, RATING = standardized review rating for each hotel, SCALE = standardized hotel scale for each hotel, HIGH = high-demand period dummy variable, NOREV = number of reviews for each hotel, REST = 0 – 100 scale measure that indicates travelers' access to restaurants and things to do within walking distance, DEST = a categorical variable for six different city-level destinations, and *i* refers to the hotel room rate.

To test hypotheses 2a, 2b, and 3, interaction terms between rate parity variable and independent variables were included in the model. The interaction term represented the moderating effect of rate parity on property-specific attributes. Models 2, 3, and 4 represented rate parity's interaction effects on review rating, hotel scale, and high-demand date, respectively. The interaction terms for Models 2, 3, and 4 were included in one model to see the overall significance in Model 5.

$$Model\ 2:\quad Room\ Rates_i = \alpha + \beta_1 PARITY_i + \beta_2 RATING_i + \beta_3 PARITY_i * RATING_i + + \beta_4 SCALE_i + \beta_5 HIGH_i + \beta_6 NOREV_i + \beta_7 REST_i + \beta_8 VOL_i + \beta_9 DEST_i + \varepsilon_i \qquad (2)$$

$$Model\ 3:\quad Room\ Rates_i = \alpha + \beta_1 PARITY_i + \beta_2 RATING_i + \beta_3 SCALE_i + \beta_4 PARITY_i * SCALE_i + \beta_5 HIGH_i + \beta_6 NOREV_i + \beta_7 REST_i + \beta_8 VOL_i + \beta_9 DEST_i + \varepsilon_i \qquad (3)$$

$$Model\ 4:\quad Room\ Rates_i = \alpha + \beta_1 PARITY_i + \beta_2 RATING_i + \beta_3 SCALE_i + \beta_4 HIGH_i + + \beta_5 PARITY_i * HIGH_i + \beta_6 NOREV_i + \beta_7 REST_i + \beta_8 VOL_i + \beta_8 DEST_i + \varepsilon_i \qquad (4)$$

$$Model\ 5:\quad Room\ Rates_i = \alpha + \beta_1 PARITY_i + \beta_2 RATING_i + \beta_3 PARITY_i * RATING_i + + \beta_4 SCALE_i + \beta_5 PARITY_i * SCALE_i + \beta_6 HIGH_i + \beta_7 PARITY_i * HIGH_i + \beta_8 NOREV_i + \beta_9 REST_i + \beta_{10} VOL_i + \beta_{11} DEST_i + \varepsilon_i \qquad (5)$$

## 3.4. Results and Discussion

### 3.4.1. Descriptive Statistics

Table 8 provides a summary of the variable statistics for the entire sample. The dependent variable, free cancelation rates, and non-refundable rates were higher in the United States than in Europe. Regarding the city level, New York City recorded the highest rates of US$313.16 and US$270.39 for free cancelation rates and non-refundable rates, respectively. The lowest rates were from hotels located in Orlando. All independent and control variables in the model were significantly different from zero.

Review rating, which indicated the perceived value of staying in a hotel room, had a higher mean of 4.40 in the United States, while it was 4.07 for Europe. Because the sample data were collected from three major hotel chains that have high quality standards, the overall review ratings were crowded at the levels of excellent, and very good (review ratings of 4 and 5). For example, among the six destinations, only five observations in Paris received poor ratings (review rating of 2) out of 924 observations. In other destinations, ratings ranged between average and excellent (review rating of 3–5). The mean of the hotel scale had a similar pattern. The mean of the hotel scale for Europe was 3.05, and it was 3.66 for the United States. For the city-level subgroup, Venice recorded the highest mean hotel scale of 3.99, and Paris had the lowest hotel scale of 2.91. Of the sample, 52% were collected during the high-demand period in Europe, and 61% of the sample rates were for the same period in the United States. Room-rate volatilities were higher in the United States than in Europe, but they varied by cities. Pairwise correlations were significant and ranged between -0.5 and 0.5, indicating moderate relationships among the variables (Table 9).

Table 8. Descriptive Statistics of Variables

| | By parity regulation | | By city-level | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Europe | USA | Paris | Rome | Venice | New York | Los Angeles | Orlando |
| FC | 201.68 | 242.78 | 205.23 | 187.94 | 182.36 | 313.16 | 252.75 | 171.42 |
| Rate | (148.37) | (271.25) | (144.70) | (138.44) | (200.32) | (392.93) | (106.51) | (82.60) |
| AP | 174.53 | 211.32 | 178.16 | 152.46 | 170.26 | 270.39 | 227.46 | 148.80 |
| Rate | (116.60) | (184.31) | (104.40) | (104.40) | (188.85) | (251.02) | (103.03) | (72.70) |
| Rate | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| Parity | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Review | 4.07 | 4.40 | 4.04 | 4.18 | 4.25 | 4.38 | 4.30 | 4.45 |
| Rating | (0.55) | (0.52) | (0.55) | (0.48) | (0.59) | (0.51) | (0.46) | (0.55) |
| Hotel | 3.05 | 3.66 | 2.91 | 3.45 | 3.99 | 3.74 | 3.91 | 3.50 |
| Scale | (1.04) | (0.59) | (1.05) | (0.77) | (0.55) | (0.59) | (0.62) | (0.53) |
| H. Demand | 0.52 | 0.61 | 0.53 | 0.49 | 0.46 | 0.75 | 0.63 | 0.48 |
| Date | (0.50) | (0.49) | (0.50) | (0.50) | (0.50) | (0.43) | (0.48) | (0.50) |
| No. of | 1178.82 | 1655.15 | 1108.00 | 1721.24 | 1062.16 | 2175.87 | 1388.45 | 1242.12 |
| Review | (1031.71) | (2208.93) | (1028.48) | (986.44) | (852.82) | (2766.37) | (1105.66) | (1730.38) |
| No. of | 85.61 | 79.46 | 89.93 | 66.71 | 64.18 | 93.61 | 70.27 | 67.79 |
| Rest. | (24.21) | (23.41) | (19.26) | (35.26) | (29.48) | (16.00) | (23.32) | (21.94) |
| Room Rate | 10.04 | 23.95 | 9.34 | 13.50 | 12.23 | 36.32 | 19.76 | 13.60 |
| Volatility | (13.56) | (28.53) | (10.82) | (15.73) | (28.88) | (36.57) | (20.37) | (14.00) |
| Obs. | 1,137 | 1,023 | 924 | 137 | 76 | 429 | 150 | 444 |

*Note. Standard deviations in parenthesis. FC Rate stands for the mean of free cancelation rates. AP Rate is the mean of non-refundable rates. Rate Parity is a dummy variable that is 1 for USA and 0 for Europe. Review Rating is based on 1 – 5 rating system acquired from TripAdvisor. Hotels are categorized as excellent (4.5-5.0), very good (3.5-4.0), average (3.0), poor (2.0), and terrible (1.0) for hotel scale. Acquired review rating and hotel scale were transferred to standardized review rating* $z = \frac{x-\mu}{\sigma}$*. No. of Review is number of reviews based on March 1, 2020 from TripAdvisor. No. of Rest. is a 0-100 scale measurement for number of restaurants in walking distance.*

Table 9. Pairwise Correlation Matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) FC rate | 1 | | | | | | | | |
| (2) AP rate | 0.7250* | 1 | | | | | | | |
| (3) Rate Parity | 0.0825* | 0.0909* | 1 | | | | | | |
| (4) Rev. Rating | 0.1931* | 0.2211* | 0.2951* | 1 | | | | | |
| (5) Hotel Scale | 0.2995* | 0.3280* | 0.3435* | 0.4854* | 1 | | | | |
| (6) H. Demand | 0.0815* | 0.0961* | 0.0885* | -0.029 | -0.0640* | 1 | | | |
| (7) No. Review | 0.1754* | 0.1374* | 0.1482* | 0.0648* | 0.2058* | 0.0252 | 1 | | |
| (8) No. Rest. | 0.1697* | 0.2086* | -0.1220* | 0.0332 | -0.0359 | 0.0515* | 0.1333* | 1 | |
| (9) Volatility | 0.3344* | 0.2982* | 0.3008* | 0.1583* | 0.2454* | 0.2004* | 0.1133* | 0.1628* | 1 |

*Note. * $p < 0.05$, Rev. Rating refers to the aggregated review rating, H. Demand stands for high demand period variable. No. review is number of reviews, and no. rest is the number of restaurants which is 0-100 measure for number of restaurants and things to do within walking distance.*

### 3.4.2. Multivariate Regression Model

The regression results in Table 10 suggested that the effect of rate parity on free cancelation rates and non-refundable rates was not significant at the 5% level. The findings indicated that there is no direct impact of rate parity on room rates. Thus, hypothesis 1—that there is a positive relationship between rate parity and room rates—cannot be supported.

Standardized review ratings had a significant effect on room rates, which implies that hotels had high levels of room rates when they obtained good reviews from customers. In Model 2, the interaction term between rate parity and standardized review rating, however, was negative and significant for both free cancelation rates and non-refundable rates (coef. = -15.9065, $t$ = -2.29, $p$ < 0.01 and coef. = -13.5840, $t$ = -2.35, $p$ < 0.05, respectively). The results imply that rate parity had a negative and significant moderating effect, supporting hypothesis 2a. Model 3 in Table 4 shows the interaction effect between rate parity and hotel scale on room rates. Similar to the results of Model 2, the results of Model 3 showed that the interaction term between rate parity and standardized hotel scale had a significantly negative effect on room rates. For free cancelation rates, the interaction term was -18.6528 ($t$ = -2.10, $p$ < 0.05), and it was -16.5860 ($t$ = -2.17, $p$ < 0.05) for non-refundable rates. While rate parity negatively affected the relationship between property quality-related attributes (i.e., review rating and hotel scale), it had a positive moderating effect on the high-demand dummy variable and room rates (Model 4 in Table 10). This indicates that in hotels under rate parity clauses, room rates were accelerated during the New Year holiday. The moderating effect of rate parity on all property-specific attributes was tested in Model 5. The results were similar to those from Models 2, 3, and 4, but the interaction term between rate parity and hotel scale was not significant in Model 5. This indicates that the moderating effect of rate parity on hotel scale was relatively weaker than the effect on other attributes. Among the control variables, number of restaurants and volatility variables had a significant effect on the quality-adjustment component. Destination dummies controlled for possible variations from each city. The results indicated that hotels in Paris had significantly higher room rates than those in Venice and that hotels located in New York and Los Angeles charged higher rates than those in Orlando. All variables in the model showed a Variance Inflation Factor (VIF) below 10, indicating that there were no serious multicollinearity issues in the model.

Table 10. Regression Model

| Dep. Variables | Free Cancelation Rates | | | | |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| Rate Parity | 1.7781 | 4.4097 | 8.6251 | -15.2350 | -7.9263 |
| | (16.151) | (16.794) | (15.877) | (17.566) | (17.204) |
| Rev. Rating | 18.0683*** | 26.6414*** | 17.0363*** | 18.3539*** | 24.4564*** |
| | (3.265) | (4.530) | (3.352) | (3.217) | (4.322) |
| Parity x Rev. Rating | | -15.9065** | | | -12.6191** |
| | | (6.928) | | | (6.403) |
| Hotel Scale | 61.0896*** | 57.9661*** | 65.3286*** | 60.1556*** | 60.5382*** |
| | (4.006) | (3.834) | (4.905) | (3.985) | (4.545) |
| Parity x Hotel Scale | | | -18.6528** | | -12.4285 |
| | | | (8.898) | | (8.153) |
| High Demand | 23.9610*** | 23.6095*** | 24.6350*** | 8.5472 | 9.3144 |
| | (7.062) | (7.007) | (7.185) | (6.392) | (6.402) |
| Parity x High Demand | | | | 35.2551** | 33.8899** |
| | | | | (14.269) | (14.082) |
| No. of Review | 0.0111 | 0.0111 | 0.0117 | 0.0112 | 0.0117 |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| No. of Rest. | 0.7624*** | 0.7173*** | 0.7614*** | 0.7672*** | 0.7305*** |
| | (0.096) | (0.100) | (0.096) | (0.096) | (0.994) |
| Volatility | 1.7909*** | 1.8022*** | 1.8125*** | 1.7474*** | 1.7723*** |
| | (0.373) | (0.374) | (0.375) | (0.384) | (0.387) |
| Paris | 82.9707*** | 83.6849*** | 87.5755*** | 82.4687*** | 86.1230*** |
| | (18.181) | (18.635) | (18.144) | (18.159) | (18.351) |
| Rome | 24.2965 | 22.7228 | 26.1090 | 24.1081 | 24.0747 |
| | (18.604) | (18.905) | (18.320) | (18.672) | (18.615) |
| New York | 39.6533*** | 39.7205*** | 41.0016*** | 35.2280*** | 36.3511*** |
| | (11.030) | (11.049) | (11.062) | (10.258) | (10.182) |
| Los Angeles | 47.8152*** | 46.3553*** | 52.2642*** | 45.3541*** | 47.2556*** |
| | (7.641) | (7.752) | (7.345) | (7.654) | (7.534) |
| Constant | 45.1654** | 49.8271*** | 41.0197** | 52.9815*** | 53.6147*** |
| | (17.862) | (17.257) | (18.168) | (16.887) | (16.204) |
| Observations | 2,051 | 2,051 | 2,051 | 2,051 | 2,051 |
| R-squared | 0.2694 | 0.2708 | 0.2707 | 0.2714 | 0.2733 |

Table 10 continued

| Dep. Variables | Non-refundable rates | | | | |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| Rate Parity | -7.9886 | -5.5276 | -1.7651 | -31.3458** | -24.8964 |
| | (15.143) | (15.657) | (14.830) | (15.679) | (15.467) |
| Rev. Rating | 14.4217*** | 21.5521*** | 13.5067*** | 14.8621*** | 20.0163*** |
| | (2.952) | (3.733) | (3.007) | (2.910) | (3.673) |
| Parity x Rev. Rating | | -13.5840** | | | -10.9986** |
| | | (5.756) | | | (5.586) |
| Hotel Scale | 49.4485*** | 46.8667*** | 53.1426*** | 48.0687*** | 48.4733*** |
| | (3.096) | (3.107) | (3.560) | (3.050) | (3.435) |
| Parity x Hotel Scale | | | -16.5860** | | -11.128 |
| | | | (7.638) | | (7.478) |
| High Demand | 31.9301*** | 31.6894*** | 32.7086*** | 10.4563** | 11.0425** |
| | (5.380) | (5.345) | (5.483) | (5.035) | (5.039) |
| Parity x High Demand | | | | 49.9832*** | 49.3809*** |
| | | | | (10.544) | (10.529) |
| No. of Review | 0.0071 | 0.0072 | 0.0076 | 0.0072 | 0.0076 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) |
| No. of Rest. | 0.7402*** | 0.7060*** | 0.7394*** | 0.7465*** | 0.7182*** |
| | (0.090) | (0.093) | (0.090) | (0.089) | (0.092) |
| Volatility | 1.9425*** | 1.9486*** | 1.9574*** | 1.8805*** | 1.8961*** |
| | (0.357) | (0.359) | (0.360) | (0.366) | (0.370) |
| Paris | 59.4058*** | 59.9402*** | 63.4340*** | 58.7183*** | 61.8618*** |
| | (16.301) | (16.634) | (16.099) | (16.278) | (16.270) |
| Rome | 12.2488 | 11.1494 | 13.9569 | 12.2685 | 12.5241 |
| | (17.175) | (17.384) | (16.935) | (17.271) | (17.201) |
| New York | 31.0004*** | 30.7802*** | 32.0096*** | 24.1018*** | 24.6837*** |
| | (9.319) | (9.302) | (9.264) | (8.722) | (8.577) |
| Los Angeles | 51.9571*** | 50.0652*** | 55.1275*** | 47.8256*** | 48.4707*** |
| | (7.862) | (8.066) | (7.599) | (7.761) | (7.806) |
| Constant | 38.0220** | 41.7626*** | 34.4527** | 48.9679*** | 49.4699*** |
| | (15.460) | (15.148) | (15.456) | (14.889) | (14.278) |
| Observations | 1,962 | 1,962 | 1,962 | 1,962 | 1,962 |
| R-squared | 0.3205 | 0.3220 | 0.3220 | 0.3267 | 0.3290 |

*Note. *** p < 0.01, ** p < 0.05, * p < 0.10. Robust standard errors in parentheses. Review Rating and Hotel Scale were standardized. Among destination variables, Venice and Orlando were omitted because of collinearity.*

### 3.5. Conclusion

This study examined the impact of rate parity agreement on free cancelation and non-refundable rates and the moderating effect of rate parity on the relationship between property-specific attributes and room rates. The results of the regression model demonstrated that the existence of rate parity agreement between hotels and OTAs has no direct impact on room rates but impedes market efficiency in terms of reflecting property characteristics on room rates. The results showed that room rates were less sensitive to property quality attributes under rate parity clauses. The findings implied that the reflection of property quality on room rates is less efficient when hotels have rate parity with OTAs. Furthermore, the results support the position that rate parity exacerbates the price increase in high-demand periods, which indicates possible collusion between suppliers (hotels) and distributors (OTAs).

The findings have theoretical implications for the hospitality industry and the finance literature. First, this study tested the market efficiency of the hotel room-night market by examining the moderating effect of rate parity on the relationship between room rates and property-specific characteristics. By examining the relative impact of property-level quality attributes, this study found that rate parity does not directly affect room rate. This indicates that rate parity affects market efficiency in reflecting product-specific characteristics. This may discourage suppliers from investing in product enhancement and produce differentiation. Eventually, this may slow innovative efforts and commoditize the product. Second, this study showed the impact of rate parity at the individual hotel property level and confirmed that the impacts of rate parity agreements may vary by property level. The findings addressed the gap in the existing literature, which was mainly based on corporate-level data, to measure the impact of rate parity agreement between hotels and OTAs. Third, the rate parity agreement can be evidence of market imperfection from the perspective of the market efficiency hypothesis. In the finance market, arbitrage opportunities, such as market anomalies or abnormal returns, can disappear by trading between buyers and sellers. Based on the market efficiency hypothesis, any market anomalies in security markets are chance results, and most arbitrage opportunities tend to disappear in the long run (Fama, 1998). However, in the hotel room-night market, the imperfections or deviations derived from the rate parity clauses cannot be easily faded away because of limitations in arbitrage trading. The hotel room-night market is a one-sided market: Hotels offer room rates, and customers accept or reject the prices for the limited supply of rooms. For these reasons, it was difficult to resolve the impact of rate party agreement on room-rate pricing. Thus, the inefficiencies derived from rate parity were observed by examining the moderating effect of rate parity on property-specific attributes and room rates.

The results also had managerial implications for the participants in the hotel industry. Hotel managers may obtain a new perspective on pricing analysis. They understand how rate parity agreements influence their pricing decisions and what can be a potential cost of maintaining rate parity clauses. By applying the model to their own data, they can estimate the impact of rate parity on their room rates at the property level. In particular, by analyzing the moderating effect of rate parity, they can measure the costs of maintaining rate parity for each property-specific attribute. In addition, the results indicate that this negative impact of rate parity can be bigger for high-quality hotels. Therefore, hotel managers must pay more attention to their rate parity clauses when they have a good reputation with customers or have high hotel scales of 4 or 5, because the indirect negative effect of rate parity can be widened for these hotels. This study also provided empirical evidence for policy makers and legislators to restrict rate parity agreement. In particular, this study supports policy makers in Europe, who restrict rate parity agreement between hotels and OTAs. The findings from the analysis supported such a restriction by showing the impact of rate parity on the anti-competitive behavior of raising transaction prices in a competitive period.

Although this study has contributed to the hospitality industry both theoretically and practically, it has some limitations. One limitation can be the sample data. As admitted in the data section, this study collected room-rate data from three major hotel companies. Therefore, this study had a relatively small sample of hotels in the midscale and economy segments. Collecting more data from hotels in these segments may give more insights into how to interpret the inconclusive results of the direct effect of rate parity on room rates. In addition, extending research on OTAs' pricing strategy can be a potential avenue for future study. This study incorporated pricing data from hotels' direct channels—that is, each hotel's website. Because the rate parity agreement affects the room-rate pricing of both hotels and OTAs, it may be worthwhile to examine data from other distribution channels. This can be a future research direction taken to extend the scope of the current study.

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# CHAPTER 4. PRICE DYNAMIC MODEL: PRICE DISCOVERY OF THE FREE CANCELATION RATE AND THE NON-REFUNDABLE RATE

## 4.1. Introduction

Consumer preferences for hotel rooms change over time. To meet the change in demand, hotels adjust their room rates continuously, which is referred to as a dynamic pricing strategy. There have been a number of studies on dynamic room pricing methods from the perspective of revenue management; however, there has been little examination of the price movement itself. Specifically, there has been a lack of investigation into how property-specific conditions are reflected in room rate adjustments for room-night markets with different cancelation policies. Hotels offer free cancelation rates (e.g., standard rates, flexible rates) for less price-sensitive customers who seek flexibility in their reservation. Non-refundable rates (e.g., prepay and save, book now and save, and advance purchase) exist for price-sensitive customers who are willing to sacrifice their flexibility. While two rates may be based on the same type of rooms for the same arrival day, they target different customer segments. Hotel managers, therefore, may set different pricing strategies for two different segments of customers. From this perspective, two rates can be independently priced. However, two rates have similar movement by time passes. This is partly due to the behavior of some customers who change their sensitivity on price under different circumstances and switch their reservations. Since both rates apply to the same room type for the same arrival day, customers can change their reservation from free cancelation rates to non-refundable rates when they fix their travel schedule to save the expense. This study, therefore, aimed to empirically examine hoteliers' response to the demand by observing the price movement of two rates with different cancelation policies—free cancelation rates and non-refundable rates.

By modifying the price discovery process in the literature of market microstructure theory, this study measured price discovery, which refers to the dynamic process by which market prices contain new information (Baillie, Booth, Tse, & Zabotina, 2002; Chakravarty, Gulen, & Mayhew, 2004; De Jong, 2002; Garbade & Silber, 1983; Gonzalo & Granger, 1995; Granger, 1986; Hasbrouck, 1995; O'Hara, 1997; Yan & Zivot, 2010). While these studies provided valuable insights into the price movement of two similar assets in different markets, there was a need to study price discovery in hotel room-night markets. First, there was no uniform conclusion as to the price discovery process across assets. For example, Garbade and Silber (1983) and Figuerola-

Ferretti and Gonzalo (2010) discovered that futures markets contribute more to the price discovery process than the those from cash markets, although Dimpfl, Flad, and Jung (2017) found evidence that the prices of agricultural commodities are decided mostly in spot markets and futures markets, as those commodities have limited impact. In the hotel room-night market, non-refundable rates can be comparable to forward contracts, which are based on a room for a specific night in the future. On the other hand, free cancelation rates can be explained as a combination of forward contracts and cancelation option value. Thus, free cancelation rates (e.g., forwards and option) can be interpreted as derivatives based on the value of non-refundable rates (e.g., forwards). The relationship between non-refundable rates and free cancelation rates is comparable to the relationship between underlying assets and derivatives in this context. Thus, this study examined the price discovery process between non-refundable rates (i.e., underlying assets) and free cancelation rates (i.e., derivatives of non-refundable rates) to identify which room rates provide more information on the pricing of hotel room-night markets.

Second, there was a gap in room pricing strategy and its conceptual pairs in the price discovery process. Generally, non-refundable rates are displayed as 10 to 20 percent discounted rates from free cancelation rates (e.g., standard rates, rack rates). However, non-refundable rates are comparable to underlying assets while free cancelation rates are classified as a combination of non-refundable rates and cancelation option. Therefore, non-refundable rates may contribute more to the price discovery process and this may lead to changes in hotel managers' attitudes toward pricing. Hotel managers may reflect the demand more accurately by starting to set prices from non-refundable rates if they contribute more to the price discovery process.

Third, modification was needed to examine price discovery in the hotel room-night market since the market is one-sided. In hotel room-night markets, hotel managers set prices and customers accept or reject the offers from hotels. Customers cannot trade room reservations themselves. They can only cancel the reservation when their reservation allows it. Therefore, customer demand was indirectly reflected in prices when hoteliers set room rates. Considering these similarities and differences between security markets and the hotel room-night market, this study examined the leadership role of non-refundable rates (i.e., underlying assets) in the price discovery process by applying a model suggested by Hasbrouck (1995).

The purpose of this chapter is thus to find how hotel managers reflected demand in pricing decision and factors that affected the reflection process. This study therefore measured the reflection of new information (room demand and supply) in the hotel room-night market particularly from the perspective of non-refundable rates by observing the contribution of price discovery from non-refundable rates. The results of the price discovery process thus show how hoteliers change room rates to meet the change in demand. Furthermore, this study investigated the factors affecting these reflection processes, such as contemporaneous hotel room-night market conditions and consumers' perception of value.

## 4.2. Literature review

### 4.2.1. Price Discovery in Security Market

The price discovery process was defined as the dynamic process of determining equilibrium market prices reflecting innovative information (Deb, McInish, Shoesmith, & Wood, 1995). Previous literature in finance has focused on price information and the price discovery process because liquidity and its discovery process were important functions in the security market (Leach & Madhavan, 2015; O'Hara, 2003). These market functions allowed individuals to reallocate their asset holdings in the security market. The mechanism of price discovery has been examined closely, particularly for assets that were traded in multiple markets. Thus, the price in any security market reflected new information in multiple markets in the price discovery process (Baillie et al., 2002).

In market microstructure literature, price discovery has been frequently analyzed in security markets. Garbade and Silber (1979, 1983) analyzed price discovery of stock markets (i.e., NYSE and regional exchange) and commodity markets (i.e., commodity futures and spot markets). Under the assumption of a common implicit efficient price for the diverse markets, Garbade and Silber (1979, 1983) argued that the actual prices in transactions are decided by a bid-ask spread component or an autoregressive adjustment component. The relationship between risk transfer (i.e., hedgers using futures contracts to shift price risk to others) and price discovery (i.e., the use of futures prices for pricing cash market transactions) were investigated in markets of spot and futures for storable commodities and found that futures markets dominated spot markets for those commodities. This implied that price changes in cash markets followed the price changes in futures markets more frequently than the opposite (Garbade & Silber, 1983).

Granger (1986) stated that the cointegration of pairs of economic variables should not diverge from each other too greatly. In a similar vein, this study concluded that the prices of spots and derivatives simultaneously reflected new information to avoid any arbitrage opportunities in a perfect market. However, market imperfections can be caused by transaction costs, lack of liquidity, and frictions in the security market. Although it was commonly assumed that the prices shared a common non-stationary component, the frictions in the market microstructure caused temporary deviations from the equilibrium price (De Jong, 2002). Therefore, price discovery can occur in the markets of spots and derivatives, which referred to the use of derivatives' prices to give an indication of spot prices (Granger, 1986). By using the lead-lag regressions, they found that "about 75 percent of new information is incorporated first in future prices."

Hasbrouck (1995) and Gonzalo and Granger (1995) developed two distinguished models for price discovery. While both studies were based on the vector error correction model (VECM hereafter), they have differing perspectives in markets' contribution to the price discovery process. Hasbrouck (1995) focused on the information share, which is defined as the proportion of price discovery variance for a certain market, but Gonzalo and Granger (1995) examined the permanent component which indicated one market's contribution to price discovery.

Hasbrouck (1995) stated that price discovery is "innovations (unpredictable change) in the efficient price." Then contribution to price discovery of each market was defined as information share (IS hereafter). The author applied this approach to gauging the information shares of stocks trading in the New York Stock Exchange (NYSE) versus the same stocks trading in the regional stock markets and found that price discovery dominantly took place in the NYSE. Based on the vector error correction model (VECM), Hasbrouck (1995) pointed out that results of the information share examination of the VECM has similar characteristics with extant market microstructure models (Baillie et al., 2002). Hasbrouck (1995) also reported that the upper and lower bounds in his study of price discovery between the NYSE and off-NYSE quotes were very similar because short interval of prevailing quotes were used. The method also applied to investigating price discovery in equity index markets (e.g., S&P 500, S&P MidCap 400, and Nasdaq-100) to see the relationship among indices, ETFs, and futures contracts. Chakravarty et al. (2004) investigated the contribution of option markets to price discovery, modifying Hasbrouck's (1995) information share approach. The study from Chakravarty et al. (2004) revealed that the option market contribute about 17% percent on average to price discovery. It was also found that the relative rate of price discovery in the two markets was associated to market characteristics such as trading volume, spreads, and volatility.

Another approach developed by Gonzalo and Granger (1995) placed great emphasis on the cointegration of the common factor and the error correction process. Gonzalo and Granger (1995) defined "permanent-transitory decomposition" (PT decomposition hereafter), which grouped cointegration into two parts: the permanent component (trend) and the transitory component (cyclical part). Then, the characteristics of price discovery were examined by focusing on the permanent factor implied by cointegration from PT decomposition. An econometric approach the author used was based on an implicit unobservable efficient price, which is supposed to be the same in all markets assuming the markets are efficient. While Hasbrouck (1995) decomposed the implicit efficient price variance by using the price volatility, Gonzalo and Granger's (1995) PT approach examined the common factor itself. The PT approach had some advantages, such as allowing the hypotheses testing of a market's contribution of price discovery and providing a unique price discovery measure; however, the model ignored the correlation among markets and attributes. The leading role solely to the price movement in the other markets. The argument for using this approach was based on the consideration that the permanent component represented the fundamental or efficient price (Lien & Shrestha, 2009).

Two models suggested by Hasbrouck (1995) and Gonzalo and Granger (1995) were related as they were based on the same VECM. Therefore, the equivalent information flow (i.e., with similar volatility) influence the markets, the results provided from two models were consistent. For example, the market with the greatest contribution to the price discovery may have the largest dependent on the common factors. However, if the residuals are correlated, the Hasbrouck (1995) models' upper and lower bounds may not be the same. The spread between the two bounds also can be positively related to the degree of correlation (Baillie et al., 2002). This is because the residual correlation can be determined in two different ways. First, it can be influenced by the information flows between the markets. Secondly, the frequency of the price data can affect the residual correlation. Also, the information share model depends on the arrangement of the series. Thus, information share approach demonstrates upper and lower bounds of information share rather than a unique measure for the price discovery.

To determine which model is more appropriate for analyzing the price discovery process in hotel room rates, the present study reviewed previous price discovery research in commodities and real estate markets. The pricing dynamics of hotel rooms have some similarities to commodities and real estate markets, such as their scarcity, perishability, and illiquidity (Garbade & Silber, 1983).

### 4.2.2. Price Discovery in Commodities and Real Estate Markets

The hotel room-night markets are limited in trading volume, and illiquid with limited inventory. To determine price discovery methods for hotel room-night markets, it would be helpful to examine the price discovery process of commodities and real estate markets under market imperfections (e.g., finite elasticity of arbitrage, inventories, speculations, and illiquidity). Figuerola-Ferretti and Gonzalo (2010) demonstrated an equilibrium model of commodity spot and future prices, with assumptions of limitation in the elasticity of arbitrage services and convenience yields. The finite elasticity of arbitrage services assumption was more realistic in that context since it reflected factors such as basis risks, storage costs, and convenience yield, that existed in the commodity futures markets. Based on the PT decomposition of Gonzalo and Granger (1995), the presence of backwardation or contango in the long-run spot futures equilibrium relationship had been incorporated in the theoretical model by using convenience yields. Backwardation existed when prices declined with time-to-delivery, so that spot prices were larger than futures prices, while contango occurred when prices increased with time-to delivery. The paper also claimed that the futures price represented more information share for all liquid futures metal markets.

Kao and Wan (2012) examined the ability of West Texas Intermediate (WTI) to reflect market conditions by applying a rolling estimation of IS of WTI to Brent over time. The time series of WTI rolling IS regressed on the price discount and the accumulated crude oil inventory to test the distortions of the benchmark status of WTI. The modified IS approach was also applied to reveal the relationship between spot and futures prices of agricultural commodity markets such as corn, wheat, soybeans, and live cattle (Dimpfl et al., 2017). They revealed that the long-run efficient price of agricultural commodities was decided on the spot market, which implied that speculations in futures markets were not a key factor in determining commodity prices.

To analyze a Real Estate Investment Trust (REIT) premium/discount puzzle in real estate markets, price discovery between securitized and private market pricing of real estate has been explored. Previous studies found that the securitized market contributed to the price discovery process while they captured long-term cointegration relationships. They also revealed that such relationships can be varied by time. Barkham and Geltner (1995) estimated the temporal cross-correlation structure between securitized and private real estate markets in the US and UK. They found the existence of price discovery for the securitized market structure in both countries. Price discovery of Singapore's public and private real estate market was also examined with a Granger causality-error correction framework (Ong & Sing, 2002). The error correction term captured any long-term cointegrating relation, while the short-term dynamics were captured in the lagged returns. A unidirectional causality between REIT returns and Net Asset Value (Elliott & Navin, 2002) returns was examined for different types of real estate assets (Yavas & Yildirim, 2009). By utilizing the dynamic conditional correlation GARCH model, they were able to confirm that the correlation between returns of NAV and REIT changed continously.

### 4.2.3. Hotel Room Pricing and Price Discovery

To meet the different demand by segment, hotels offered different rates with various rate fences (Chen & Xie, 2013; Guo, Ling, Yang, Li, & Liang, 2013; Kimes, 2002; Toh, Raven, & DeKay, 2011). For the same type of room, room rates can be varied by the length of the lead time (e.g., the advance-purchase restrictions for early booking), by the distribution channel (e.g., hotel website, OTAs, or travel agencies), or level of risk accepted (e.g., refundability). These can be classified into rate fences by transaction characteristics (Kimes, 2002). By adapting dynamic pricing strategy with rate fences, hotels can better adjust to fluctuations in demand to optimize their revenue structure.

Dynamic pricing strategy—continuously changing prices according to demand and supply—was one of the most frequently discussed topics in the hotel revenue management field. Because hotel rooms are perishable, the unsold rooms cannot be kept in inventory for future use. Dynamic pricing enabled hotels to charge different prices for each market segment, but the prices (room rates) were constantly updated for each segment by demand. Many hotel chains have therefore adapted the dynamic pricing strategy for their rooms in different segments. This segmentation aimed to maximize revenue by separating travelers into groups and charging different rates based on their varied needs and behavior (Hanks, Cross, & Noland, 2002). The market for hotel rooms can be classified into two main segments: group and transient. According to STR, fewer than 10 rooms per night were occupied by individuals or groups who could be classified as transient. The room market for the transient segment can be categorized further into two groups: leisure travelers and business travelers. These two groups in the transient segment decide their rooms based on the particular circumstances of time, place, and purpose of trip (Hanks et al., 2002). While business travelers had inflexible destination and schedule, leisure travelers were generally able to make an advance purchase, be flexible in their location, and price elastic. Accordingly, hotels can set higher rates for business travelers who tend to reserve rooms with a short lead time, while offering lower rates for leisure travelers who book rooms a longer time before the check-in date (Guo et al., 2013). For the same type of rooms, hotels additionally offered a different layer of rates by adopting a different cancelation policy. Hotels often offered discounted rates for non-cancelable advance-purchase rooms. These non-cancelable non-refundable rates targeted travelers who were price-sensitive and had a confirmed travel schedule. Travelers can secure their stay with discounted non-refundable rates but cannot cancel nor refund their payment. Travelers such as business travelers who were less price-sensitive and had flexible schedules would choose free cancelation rates. While these travelers may pay higher rates (e.g., free cancelation rates) for the reservation, they can change or cancel their reservation without any penalty before the prescribed date. If hotels could distinguish price-sensitive and less price-sensitive travelers clearly, dynamic pricing for these two rates would be paralleled. Under this perfect market scenario, price movement for the two different segments could be independent and follow their own demands. However, because of the following reasons, the movement of the two rates are not the same, but interrelated.

First, some price-sensitive travelers choose to book their rooms with free cancelation rates and look for better deals even after their booking (Chen, Schwartz, & Vargas, 2011). Travelers considered various factors in their room reservations, such as price, room condition, service quality, room availability, and their travel schedule. Even after booking, these conditions can change. Travelers therefore secured their rooms by booking their rooms with free cancelation rates, and then searched for better deals. When they found a better one, they could cancel their original reservations and switch to a better deal. These travelers were defined as book-and-search travelers (Schwartz, 2006). In these arbitrage opportunities, book-and-search travelers who booked with free cancelation rates in advance could switch to the lowest available rates for the later date to reduce their cost. Because of the existence of book-and-search travelers, the price movement between non-refundable rates and free cancelation rates were interrelated.

Second, two rates are based on the same type of room for the same day. Many hotels offer a few rate options depending on specific rate conditions, such as the cancelation option, free breakfast, and additional benefits even for the same type of rooms. Generally, hotels offer non-refundable rates by discounting from their free cancelation standard rates. Since all other conditions except the cancelation option are identical, the movement of two rates should be related.

For the reasons stated above, non-refundable rates and free cancelation rates are interrelated, but the movement of two rates cannot be the same because hotels have different demands for two rates by time. For example, hotels may offer additional discounts only for non-refundable rates in the early booking period to boost their occupancy. In this case, the total discount travelers can get would be higher than the cancelation option value imbedded in free cancelation rates. Thus, arbitrage opportunities exist for travelers. From the hotels' perspective, the amounts of discount from non-refundable rates can be offset by reducing overall cancelation risk by selling those rooms for sure. A recent study by D-Edge Hospitality Solutions into reservation revenue revealed that overall cancelation rates across all channels were approximately 40% in 2018 (Hertzfeld, 2019). Offering non-refundable rates can be one of the attractive options for hotels that want to increase booking rates and to reduce cancelation rates at the same time. In a high demand period, on the other hand, hotels are highly likely to have reservations and expect more room demand in the future, so they may focus on selling rooms with free cancelation rates. In this case, vacancy risk does not cause concern, but revenue maximization can be key for hotel managers.

According to the studies in market microstructure, the price discovery process is applicable when assets are traded on the multiple markets but are connected by arbitrage opportunities. In the hotel room-night market, the non-refundable rate is an arrangement that allows customers to book and pay for a hotel room before they arrive, at a discount rate. This can be equivalent to a forward contract, which is defined as a contract to buy or sell an asset at a pre-determined future time at a price arranged upon at the time of the contract. On top of non-refundable rates, free cancelation rates have options to cancel the reservation within the cancelation window. Therefore, a free cancelation rate can be identified as the combination of a forward contract with an option to cancel the contract. Free cancelation rates, therefore, can be viewed as derivatives based on non-refundable rates.

Among these two rates, some arbitrage opportunities exist. Travelers who booked rooms with free cancelation rates have several options before their check-in. One of the possible moves they can make is switching their reservation to non-refundable rates when they see some arbitrage opportunities. The market frictions and different market structure in the hotel room-night market accelerated such arbitrage opportunities. Travelers may enjoy a large discount at the last minute, since hotels often offer deeply discounted rates when the date of check-in approaches. Arbitrage opportunities can be amplified in the hotel room-night market because the market is one-sided, where sellers (hotels) offer room rates. Buyers (potential travelers) accept prices (reserve rooms) or reject the offer (no reservation). Buyers cannot trade room nights themselves, but they are able to cancel their reservations before their check-in if their reservations allow cancelation. Additionally, there is no full disclosure of information about room inventory. In the stock market, buyers and sellers recognize real-time price changes and trading volume. On the other hand, customers in the hotel room-night market have limited information about room inventory or transaction volume. Therefore, customers use current rates and availability of rooms to estimate future rates. To see the price discovery process in the hotel room-night market for these arbitrage opportunities, an examination of underlying assets' (non-refundable rates') contribution to price discovery in the derivatives (free cancelation rate) would be a relevant topic to uncover information content in dynamic pricing. While non-refundable rates are often regarded as discounted rates from free cancelation rates, this study expected non-refundable rates (underlying assets) to contribute to the price discovery process. Accordingly, the following hypothesis is suggested:

*Hypothesis 1: The non-refundable rate contributes to the price discovery process more than the free cancelation rate.*

### 4.2.4. Determinants of Price Discovery

To examine price discovery in the hotel room-night market, the contemporaneous market conditions as well as property-specific attributes that affect room demand were investigated. Market conditions such as trading volume, volatility, and bid-ask spreads between markets are related to the trading costs of markets. Previous literature in market microstructure revealed that markets with low trading costs respond rapidly to new information (Fleming, Ostdiek, & Whaley, 1996; M. Kim, Szakmary, & Schwarz, 1999). Based on the theoretical support from previous studies, Chakravarty et al. (2004) found that price discovery in the option market is higher when the option market has high trading volume, low volatility, and narrow option spread. To investigate the effect of determinants on the price discovery process in the hotel room-night market, this study selects room demand as analogous to trading volume in market microstructure literature. This is because each hotel's room demand represents how many rooms were occupied by travelers for a specific date. In the security market, volume of trade refers to the total number of contracts exchanged between buyers and sellers of a security during a day. In the hotel room-night market, room demand can be equivalent to trading volume in the security market because the trade only occurred once a day when rooms were occupied. Thus, the following hypothesis is suggested:

*Hypothesis 2: The contribution of the non-refundable rate to price discovery is higher in hotel markets that have high levels of room demand than those with low demand.*

Similar to Chakravarty et al.'s (2004) study, the present study includes room rate volatility in hotel room-night markets as a price volatility measure. Chakravarty et al. (2004) found a negative (positive) coefficient on underlying assets' volatility to option (stock) information share, which is in line with the estimation by Capelle-Blancard (2001) that informed traders selected stock market rather than option market when they had great uncertainty. Similar to the behavior of informed traders in the capital market, hotels' revenue managers may pay more attention to non-refundable rates under high volatility because room rate volatility may imply the uncertainty in demand estimation and revenue managers may be motivated to use non-refundable rates to lock travelers into the non-cancelable reservation to mitigate the effect of uncertainty in forecasting.

In a similar vein, Gale and Holmes (1992) claimed that non-refundable rates contribute to the efficient allocation of capacity under demand uncertainty. McCardle, Rajaram, and Tang (2004) examined the benefits of advance-purchase discount programs under high demand uncertainty. With non-refundable rates, sellers can extend the selling season without immediate delivery, increase accuracy in demand forecast, and improve cash flow by receiving payments in advance. Thus, the following hypothesis is suggested:

*Hypothesis 3: The contribution of the non-refundable rate to price discovery is higher in hotel markets that have high volatility in non-refundable rates than those with low volatility.*

While the non-refundable rate and the free cancelation rate were based on the same room for a specific date, the reflection of new information on two rates can be diverged due to property-specific demand factors. From the perspective of hotels, the purposes of offering non-refundable rates are to increase early booking and reduce cancelations. For example, hotels can offer non-refundable rates more aggressively when they have a low booking rate or a high cancelation rate.

Thus, the factors that affect demand were examined to estimate the degree of price discovery in the hotel room-night market.

The overall demand for a hotel room is an aggregation of individual travelers' hotel selections. Accordingly, the demand depends on customers' booking intentions and their decisions on cancelation. Examples of the factors that motivate hotel selection would be prices, hotel quality, consumer reviews, hotel location, complimentary services, familiar brand name, and past experiences (Carroll & Sileo, 2014; Chow, Garretson, & Kurtz, 1995). While price information is referred to as an influential determinant of consumer behavior, the role of non-price information has also received academic attention recently (Zeithaml, 1988). Because consumers have substantial exposure to the non-price information through the Internet, both user-generated content (e.g., consumer reviews and ratings) and hotel-generated content (e.g., information about reward/loyalty programs, hotel segment information, room descriptions on hotel websites, amenity information with photographs, and distances from major attractions) are frequently used to compare hotels and make a choice (Noone, 2016; Noone & McGuire, 2013).

In the e-word-of-mouth literature, many studies emphasized the significant effect of consumer reviews and ratings on consumers' hotel choice and on hotel performance (Book, Tanford, Montgomery, & Love, 2018; W. G. Kim, Lim, & Brymer, 2015; Noone & McGuire, 2014; Öğüt & Onur Taş, 2012; Xie, Zhang, & Zhang, 2014; Ye, Law, Gu, & Chen, 2011). The results of Noone and McGuire's (2013) study demonstrated that consumer reviews, aggregate consumer ratings, TripAdvisor rankings, and brand names are meaningful determinants of hotel selection in online channels. Book et al. (2018) also showed that social influence in the form of traveler reviews and price had a strong effect on consumer decisions and post decision dissonance.

In the capital market, investors hardly consider the hedonic value of possessing assets or derivatives in their portfolio. The value is only measured by risks and returns associated with the investment. In contrast to capital markets, buyers in the hotel room-night market actually stay in a selected room for a specific date. Therefore, the hedonic value perceived by customers is one of the major considerations in room reservation.

The aggregated review rating from previous customers is a proxy of such hedonic value. In the context of price discovery in the hotel room-night market, the hedonic value of rooms, which is reflected as consumer reviews, can affect the price discovery process. If travelers book a room with free cancelation rates, they can change their reservation within the cancelation window. After booking rooms with non-refundable rates, however, travelers cannot cancel their reservation nor change the schedule. Therefore, travelers more carefully evaluate the quality of hotel rooms when they consider advance booking. From the buyers' perspective, positive reviews might promote more reservations through non-refundable rates since they reduce uncertainties related to overall qualities such as location, room amenities, and services. This study expected that more reservations (high trading volume) through non-refundable rates would lead to greater contribution to the price discovery process from non-refundable rates. This is consistent with findings of Chakravarty et al. (2004). The following hypothesis is thus proposed:

*Hypothesis 4: The contribution of the non-refundable rate to price discovery is higher in hotels that have high review ratings than hotels with low review ratings.*

## 4.3. Methodology

### 4.3.1. Sample and Data Collection

The sample was derived from hotel room rate information from three major hotel chains' online reservation sites for two different demand seasons. Daily hotel room rate information for checking in on the second week of December and the New Year's holiday was collected from Marriott, IHG, and Accor in six travel destinations (Paris, Rome, Venice, New York, Los Angeles, and Orlando) between October 21, 2019 and January 1, 2020. Then, price characteristics such as room-rate volatility for both non-refundable rates and free cancelation rates were calculated. Individual hotels' information was also obtained, such as hotel scale, review rating, number of reviews, and number of restaurants. Hotels' scales were based on the STR's chain scale segmentation, which were luxury (5), upper upscale & upscale (4), upper midscale (3), midscale (2), and economy (1). Review rating (1 – 5 rating system), number of reviews, and the attractiveness measure (0 – 100 scale measurement to grade ease of finding restaurants and things to do within walking distance) were collected from TripAdvisor. Aggregated hotel performance data by subgroup (e.g., average daily rate, occupancy rate, revenue per available rooms, room demand and supply) were obtained from STR and room demand for each destination by hotel scale were included as one of the regressors.

To examine the price discovery process of non-refundable rates and free cancelation rates, daily room rate data were grouped by five segments (1 – 5 hotel scale), six destinations (major travel destinations in US and Europe), and six hypothetical check-in dates (Dec. 16 – 18 for low demand dates, and Dec. 29 – Jan. 1 for high demand dates). To calculate representative price discovery coefficients for non-refundable rates and free cancelation rates by these subgroups, the mean level of hotel-level daily rates was calculated by segment, destination, and check-in. The final sample included 118 observations.

Of the initial sample of 118 observations, 11 were not retained for use in the regression models. These transactions either lacked sufficient details in hotel/destination characteristics (e.g., attractiveness, room demand). A total of 107 observations were included in the regression model.

#### 4.3.2. Price Discovery Coefficient

The price discovery process demonstrates which market contains new information in advance about the underlying fundamental asset (Yan & Zivot, 2010). As discussed in section 4.2.1. *Price Discovery in Security Market*, the proportion of the efficient price innovation variance is identified as one market's IS (Hasbrouck, 1995), while Gonzalo and Granger (1995) focused on one market's contribution to efficient price innovation. Among the two approaches, the information share approach was chosen to estimate the price discovery process in room rates for several reasons. First, the IS model enables this study to incorporate the flow of information. By calculating the proportional contribution to the variance of efficient price, this study considers the flow of information since price volatility (variance) reflects the flow of information. Because the PT model only considers permanent shocks in the markets, transitory shocks were ignored in the model. Second, the IS approach is appropriate when prices are cointegrated and highly correlated in two markets. Two rates in hotel room-night markets (non-refundable rates and free cancelation rates) have high correlations, since both rates are based on the same type of rooms for the same hotel in a specific date range.

The price discovery coefficient of hotel room rates is thus estimated by using Hasbrouck's (1995) information share approach. Let $Y_t = (y_{1t}, y_{2t})'$ is the vector of prices for the same underlying asset in two markets. The error correction term is $z_t = \beta' Y_t = y_{1t} - y_{2t}$ and the cointegrating vector is $\beta = (1, -1)'$. The vector error correction model (VECM) allows to calculate the multivariate price process:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{j=1}^{k} A_j \, \Delta Y_{t-j} + e_t \qquad (1)$$

, where $\alpha$ is an error correction vector and $e_t$ is a zero-mean vector of serially uncorrelated innovations with a covariance matrix $\Omega$ such that,

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}. \tag{1a}$$

$\sigma_1^2(\sigma_2^2)$ is the variance of $e_{1t}(e_{2t})$ and $\rho$ is the correlation between $e_{1t}$ and $e_{2t}$. The VECM is divided in two parts. The first part, $\alpha\beta' Y_{t-1}$, denotes the long-run dynamics between two markets, and the second portion, $\sum_{j=1}^{k} A_j \, \Delta Y_{t-j}$, demonstrates the short-run dynamics brought by market imperfections (Baillie et al., 2002).

The VECM can be converted to a vector moving average (VMA)

$$\Delta Y_t = \psi(L) e_t \tag{2a}$$

$$Y_t = \psi(1) \sum_{s=1}^{t} e_s + \psi^*(L) e_t \tag{2b}$$

, where $\psi(L)$ and $\psi^*(L)$ are matrix polynomials in the lag operator, L. The impact matrix, $\psi(1)$, is the sum of the moving average coefficients, with $\psi(1)e_t$ being the long-run impact of an innovation on each of the prices.

Denote $\psi = (\psi_1, \psi_2)$ as the common row vector in $\psi(1)$, Eq. 2b can be stated as

$$Y_t = \iota\, \psi\left(\sum_{s=1}^{t} e_s\right) + \psi^*(L) e_t \tag{3}$$

, where $\iota = (1,1)'$ is a column vector of ones. In Eq. 3, $\psi e_t$ is the common factor component while $\psi^*(L)e_t$ is the transitory component.

The common factor can be stated as $f_t = \Gamma Y_t$, where $\Gamma$ is the orthogonal to the error correction coefficient vector $\alpha$, denoted by $\alpha_\perp = (\gamma_1, \gamma_2)'$ (Gonzalo & Granger, 1995). The relationship between IS and PT models indicated a direct relationship of $\psi$ and $\Gamma$ (Baillie et al., 2002; Johansen, 1991),

$$\frac{\psi_1}{\psi_2} = \frac{\gamma_1}{\gamma_2}. \tag{4}$$

Since the price innovations in hotel room-night markets are significantly correlated, the Cholesky factorization is used to eliminate the correlation between two variables in the same time period in time series analysis (Hasbrouck, 1995). Hasbrouck (1995) denoted $\Omega = MM'$, where M is a lower triangular matrix. The information shares are suggested as,

$$IS_j = \frac{\left([\psi M]_j\right)^2}{\psi\Omega\psi'} \tag{5}$$

, where $[\psi M]_j$ is the *jth* element of the row of matrix $\psi M$. In Eq. 4,

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{pmatrix}. \tag{5}$$

Therefore, using Eq. 4 and Eq. 5,

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} = \frac{(\gamma_1 \sigma_1 + \gamma_2 \rho \sigma_2)^2}{(\gamma_1 \sigma_1 + \gamma_2 \rho \sigma_2)^2 + \left(\gamma_2 \sigma_2 (1-\rho^2)^{1/2}\right)^2}, \tag{6}$$

$$IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} = \frac{\left(\gamma_2 \sigma_2 (1-\rho^2)^{1/2}\right)^2}{(\gamma_1 \sigma_1 + \gamma_2 \rho \sigma_2)^2 + \left(\gamma_2 \sigma_2 (1-\rho^2)^{1/2}\right)^2}. \tag{7}$$

When two markets are highly correlated, a larger information share were examined on the first price by Eq. 6 and Eq. 7. The upper and lower bounds are thus calculated by trying alternative rotations. The present study estimates the information share for the hotel room-night market from aggregated daily room rates for each market segment by different check-in dates.

#### 4.3.3. Cross-Sectional Regression

The first step of the analysis is to find the price discovery coefficient, which measures the reflection of new information in changed room rates. The results of the price discovery process show how hoteliers change room rates to meet changes in demand. This study further investigates what creates differences in the level of price discovery of non-refundable rates. To answer this question, the contribution of price discovery from non-refundable rate (dependent variable) regresses on the determinants of price discovery (independent variables) in the OLS regression model as a second step. The three determinants (e.g., rooms demand, price volatility, review rating) were selected considering trading costs and their reflection of the advance-purchase booking demand.

To compare upper and lower bounds of price discovery to the determinants of price discovery, the dependent variable is calculated as the mean of the lower and upper bound on the non-refundable rate price discovery across destinations and hotel scales for each hypothetical check-in date (Baillie et al., 2002; Chakravarty et al., 2004). The selected destinations are New York, Los Angeles, Orlando, Paris, Rome, and Venice. Hotels' hotel scales of 1 – 5 were recorded based on the chain scale segmentation from Smith Travel Research (STR) to control for room rate. The hotel scales are luxury (5), upper upscale & upscale (4), upper midscale (3), midscale (2), and economy (1).

Room-demand information is based on the number of rooms occupied for six destinations by market class obtained from STR's daily market performance data. To calculate relative demand, number of rooms occupied is divided by room supply. Price volatility for non-refundable rates and free cancelation rates are measured as the standard deviation of daily room rates. The average review ratings and number of reviews measures a degree of reputation and popularity for a hotel in the specific location and obtained from TripAdvisor. The average review rating is based on a 1 – 5 rating system. Hotels are categorized as excellent (4.5 – 5.0), very good (3.5 – 4.0), average (3.0), poor (2.0), and terrible (1.0). Other variables that can affect the overall price discovery process, including the number of restaurants, hotel scale, estimated date of stay, and destination were controlled for in the model. Thus, the OLS regression model is suggested as,

$$PD_i = \alpha_i + \beta_1 DEMAND_i + \beta_2 VOL\_AP_i + \beta_3 VOL\_FC_i + \beta_6 RATING_i + \beta_7 NOREVIEW_i + \beta_8 REST_i + \beta_8 SCALE_i + \beta_9 HIGH_i + \beta_{10} DEST_i + \varepsilon_i \quad (8)$$

, where $PD_i$ = the non-refundable rate's information share of hotel property *i*, *DEMAND* = room demand/room supply for each destination for each hotel scale, VOL_AP = standard deviation of daily non-refundable rate, VOL_FC = standard deviation of daily free cancelation rate, RATING = review ratings for each hotel, *NOREVIEW* = number of reviews for each hotel, *REST* = 0 – 100 scale measure that indicates travelers' access to restaurants and things to do within walking distance, *SCALE*= 1 – 5 hotel scale segmentation, *HIGH* = high demand date dummy variable, *DEST* = destination categorical variable, *i* refers to hotel markets.

## 4.4. Results

### 4.4.1. Price Discovery Coefficients

Table 1 provides a summary of variable statistics for the entire sample and subgroup. Price discovery for non-refundable rates is found to have a significant higher mean of 0.536 than the mean of free cancelation rate of 0.464 ($t$ = 1.657, $p < 0.05$), indicating that the room market for non-refundable rate leads the market for free cancelation rate. Hypothesis 1, which states that the non-refundable rates contribute to the price discovery process, is thus supported.

Non-refundable rates dominant the price discovery process for hotels that are luxury and highly rated by travelers (Table 11). Subgroup analysis by hotel scale and review rating indicates that volatility, review ratings, hotel scale, and number of reviews are positively related, while room demand and attractiveness are not linearly correlated with them. Table 4.2 shows lower and upper bounds on the price discovery of non-refundable rates along with room demand, volatility, review rating, number of reviews, and attractiveness. The study estimates one price discovery coefficient over the 60-day period for each hotel. The lower and upper bounds of the estimates are organized by city, hotel scale, and check-in date. The price discovery coefficients range from 0.19 – 0.70 for Rome to 0.15 – 0.88 for Venice. The lower and upper bounds of each destination for six check-in dates are shown in Figure 4. The bound is wide in Venice and narrow in New York for different check-in dates (Figure 11). The mean of lower-bound price discovery is 0.30 (29.61%) and of upper-bound is 0.78 (77.51%) (Table 12). Among six destinations, the city of New York records the highest numbers in room demand, volatility, review rating, and number of reviews, while these variables are the lowest for Venice, except the attractiveness measure. Pairwise correlations and the variance inflation factor (VIF) are also examined to determine multicollinearity (Table 13). As all variables in the model show a VIF below 10, multicollinearity is not an issue.

Table 11. Descriptive Statistics by Subgroups

| Variable | Pooled | by Hotel Scale | | | | |
|---|---|---|---|---|---|---|
| | | 5 | 4 | 3 | 2 | 1 |
| Price Discovery (AP) | 0.536 | 0.463 | 0.521 | 0.592 | 0.569 | 0.523 |
| | (0.233) | (0.271) | (0.210) | (0.228) | (0.204) | (0.273) |
| Price Discovery (FC) | 0.464 | 0.537 | 0.479 | 0.408 | 0.431 | 0.477 |
| | (0.233) | (0.271) | (0.210) | (0.228) | (0.204) | (0.273) |
| Demand | 0.714 | 0.616 | 0.716 | 0.754 | 0.778 | n/a |
| | (0.168) | (0.220) | (0.160) | (0.111) | (0.125) | n/a |
| Volatility (AP) | 19.287 | 26.142 | 20.301 | 19.596 | 12.403 | 5.472 |
| | (17.027) | (17.906) | (15.755) | (19.751) | (10.809) | (1.665) |
| Volatility (FC) | 20.499 | 30.196 | 20.112 | 17.389 | 17.701 | 5.299 |
| | (19.606) | (15.250) | (17.762) | (24.805) | (16.815) | (1.795) |
| Review Rating | 4.255 | 4.735 | 4.372 | 4.109 | 3.961 | 3.286 |
| | (0.399) | (0.293) | (0.053) | (0.211) | (0.063) | (0.000) |
| No. of Review | 1520.097 | 2227.992 | 1707.311 | 1111.844 | 1079.326 | 1056.143 |
| | (813.421) | (1143.770) | (512.653) | (235.671) | (639.317) | (0.000) |
| Hotel Scale | 3.449 | 5.000 | 4.000 | 3.000 | 2.000 | 1.000 |
| | (1.174) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| No. of Restaurants | 81.784 | 96.802 | 74.871 | 77.426 | 80.672 | 77.286 |
| | (15.542) | (6.145) | (11.523) | (12.555) | (24.087) | (0.000) |
| Obs. | 118 | 27 | 32 | 32 | 21 | 6 |

Table 11 continued

| Variable | Pooled | by Review Rating | | |
|---|---|---|---|---|
| | | 4.5-5.0 | 4.0-4.5 | 3.5-4.0 |
| Price Discovery (AP) | 0.536 | 0.462 | 0.549 | 0.559 |
| | (0.233) | (0.288) | (0.233) | (0.200) |
| Price Discovery (FC) | 0.464 | 0.538 | 0.451 | 0.441 |
| | (0.233) | (0.288) | (0.233) | (0.200) |
| Demand | 0.714 | 0.653 | 0.740 | 0.723 |
| | (0.168) | (0.193) | (0.156) | (0.161) |
| Volatility (AP) | 19.287 | 27.084 | 23.987 | 11.408 |
| | (17.027) | (18.797) | (19.894) | (8.131) |
| Volatility (FC) | 20.499 | 31.220 | 22.618 | 13.488 |
| | (19.606) | (15.875) | (24.820) | (12.185) |
| Review Rating | 4.255 | 4.827 | 4.367 | 3.883 |
| | (0.399) | (0.133) | (0.076) | (0.229) |
| No. of Review | 1520.097 | 2478.928 | 1519.767 | 1060.148 |
| | (813.421) | (942.064) | (536.332) | (494.667) |
| Hotel Scale | 3.449 | 5.000 | 3.727 | 2.460 |
| | (1.174) | (0.000) | (0.451) | (0.930) |
| No. of Restaurants | 81.784 | 96.403 | 76.243 | 79.406 |
| | (15.542) | (6.418) | (11.973) | (17.327) |
| Obs. | 118 | 24 | 44 | 50 |

*Note. AP stands for non-refundable rates and FC is free cancelation rates. Standard deviations in parentheses*

Table 12. Price Discovery for Non-refundable rates over Destinations

| | Lower Bound | Upper Bound | Mid point | Demand | Vol. (AP) | Vol. (FC) | Rev. Rating | No. of Rev. | No of Rest. |
|---|---|---|---|---|---|---|---|---|---|
| Paris | 0.33 | 0.83 | 0.58 | 0.72 | 10.69 | 12.22 | 4.08 | 1113.62 | 89.55 |
| Rome | 0.19 | 0.70 | 0.44 | 0.68 | 15.01 | 16.64 | 4.32 | 1807.56 | 72.30 |
| Venice | 0.15 | 0.88 | 0.52 | 0.45 | 10.01 | 11.29 | 4.14 | 884.79 | 74.94 |
| New York | 0.26 | 0.72 | 0.49 | 0.83 | 33.30 | 40.82 | 4.35 | 2359.55 | 96.29 |
| Los Angeles | 0.35 | 0.74 | 0.54 | 0.73 | 23.41 | 22.47 | 4.35 | 1551.67 | 73.96 |
| Orlando | 0.46 | 0.85 | 0.65 | 0.71 | 21.40 | 14.74 | 4.31 | 944.44 | 67.89 |

*Note. Lower-bound and upper-bound on the price discovery are attributable to non-refundable rates for each destination. Price discovery for free cancelation rates can be calculated as 1- information share for non-refundable rates. Each number represents the average estimated bound across hypothetical check-in dates and across destinations. Average volatility of non-refundable rates, room demand, number of reviews, review rating (1-5 scale), No. of restaurants measure (1- 100 scale) are also reported by destination.*

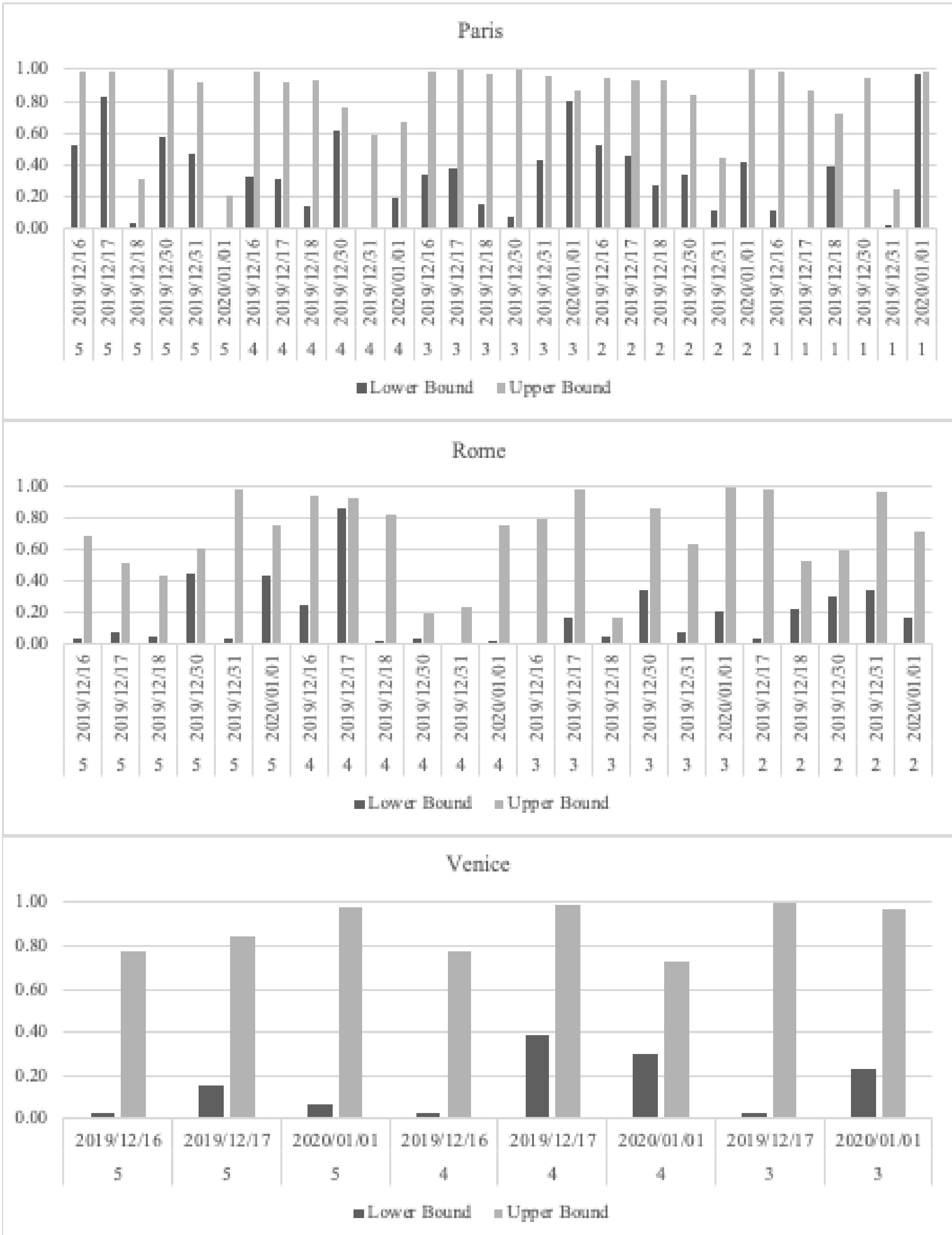
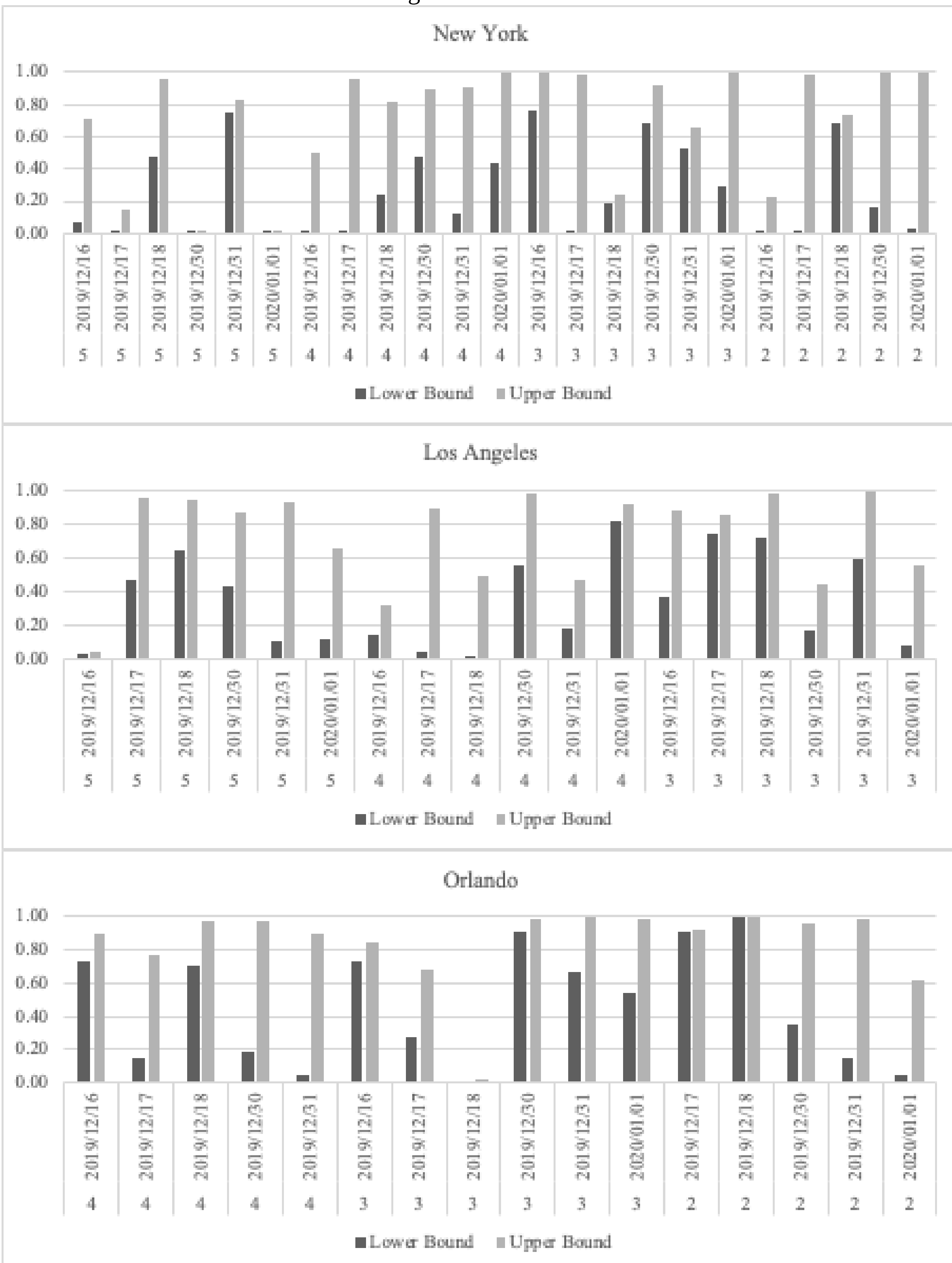



Figure 4. Upper and Lower Bounds on the Price Discovery by Destinations

Figure 4 continued




*Note. Each bar graph is cross-sectional time series averages across hotel scales and across for six check-in dates in each destination. The x-axis is check-in dates x hotel scales, y-axis is price discovery coefficient*

Table 13. Pairwise Correlations

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) Price Discovery (AP) | 1 | | | | | | | | |
| (2) Demand | 0.0333 | 1 | | | | | | | |
| (3) Volatility (AP) | -0.0723 | 0.2646* | 1 | | | | | | |
| (4) Volatility (FC) | -0.0596 | 0.3144* | 0.6286* | 1 | | | | | |
| (5) No. of Review | -0.2647* | 0.1218 | 0.4071* | 0.3694* | 1 | | | | |
| (6) Rev. Rating | -0.0853 | -0.2163* | 0.3499* | 0.3128* | 0.5439* | 1 | | | |
| (7) No. of Restaurants | -0.029 | -0.0758 | 0.1405 | 0.3026* | 0.3467* | 0.3101* | 1 | | |
| (8) Hotel Scale | -0.154 | -0.3350* | 0.3049* | 0.2794* | 0.5285* | 0.8674* | 0.3281* | 1 | |
| (9) High Season | 0.0142 | 0.5603* | 0.2193* | 0.2933* | 0.0011 | -0.0191 | -0.0312 | -0.0000 | 1 |
| VIF | | 3.83 | 3.38 | 2.3 | 1.95 | 1.84 | 1.74 | 1.64 | 1.27 |

*Note. * $p < 0.05$*

### 4.4.2. Cross-Sectional Regression

The results of cross-sectional regression analysis show that the contribution of non-refundable rate to price discovery has a positive relationship with room demand but is not significant at 5% (Table 14, Model 1). Therefore, there is no evidence to support hypothesis 2 that price discovery is associated with high room demand. This insignificant relationship between room demand and price discovery can be explained by the different aspects of two variables. The demand variable in this study was based on the final room demand which derived from the total rooms supply divided by the total rooms demand for each room for the specific check-in date. However, the dynamic pricing movement of room rates for different reservation times for the same check-in dates were captured in the price discovery process. Thus, price discovery would be more related to the real-time changes of occupancy for different reservation time than the final demand for each room.

Model 1 in Table 14 indicates a negative coefficient on volatility in the cross-sectional regression, but the results are not significant. This finding implies that there is no linear relationship between volatility and price discovery associated with non-refundable rates to support hypothesis 3. The effect of consumers' evaluation on price discovery is positive and significant ($t = 5.43$, $p = 0.012$), supporting hypothesis 4 that there is an increasing impact of consumer reviews on non-refundable rates' contribution to price discovery. This implies that positive reviews promote more reservations through non-refundable rates.

In the hotel room-night market, there are two market participants—travelers and hotels. Because two market participants interact with each other, the dynamics of the hotel room-night market can be different in the period when the rates are volatile. While room rates are set by hotels, travelers' preferences indirectly affect room rates through room demand. Potential travelers, especially book-and-search customers, may pay less attention to free cancelation rates under low volatility, because the chance of finding a better deal after their reservation is lower under this situation. In this case, they may select non-refundable rates to save money. In the high volatility case, on the other hand, hotels tend to actively manage non-refundable rates to reduce the uncertainty in demand. Therefore, the present study examined a possible U-shaped relationship between price discovery coefficient and volatility in Model 2 (Table 14).

To examine the U-shaped relationship of volatility and price discovery coefficient, a U-shape test is conducted (Lind & Mehlum, 2007) for volatility variables. The test results indicate that the volatility of non-refundable rates has a U-shaped relationship ($t$ = 3.79, $p$ = 0.016), while there is no evidence of U-shaped relationship between the volatility of free cancelation rate and price discovery coefficient ($t$ = 0.77, $p$ = 0.248). Therefore, Model 3 is suggested without a quadratic term of volatility for free cancelation rates (Table 14). Model 3 shows the U-shaped relationship between volatility and the price discovery contribution from non-refundable rates. To test the linear relationship of volatility and the price discovery coefficient, therefore, quadratic terms of volatility for non-refundable rates and free cancelation rates are included. The non-refundable rates' volatility is found to have a negative effect on price discovery from non-refundable rates ($t$ = -3.35, $p$ < 0.04), which can explain the negative relationship between the uncertainty in room pricing and travelers' room market choice. The positive coefficient in quadratic terms ($t$ = 3.41, $p$ < 0.04) suggests a U-shaped relationship of volatility and price discovery, which implies that the non-refundable rate strongly contributes to price discovery in the case of extremely high/low volatility.

To verify the results from Model 3, this study did a subgroup analysis by the level of volatility. Volatility of non-refundable rates are divided into five groups. As anticipated, the mean of non-refundable rates' contribution to price discovery decreases from group 1 to group 4 (mean: 0.593 to 0.461), and rebounds to 0.482 in group 5 (Table 15). The results further support the U-shape relationship between volatility and price discovery from non-refundable rates in Model 3.

Table 14. Cross-Sectional Regression Models

| VARIABLES | (1)<br>Model1 | (2)<br>Model2 | (3)<br>Model 3 |
|---|---|---|---|
| Demand | 0.1154 | 0.0429 | 0.0745 |
| | (0.449) | (0.370) | (0.354) |
| Volatility (AP) | -0.0001 | -0.0153** | -0.0138** |
| | (0.003) | (0.003) | (0.004) |
| $\text{Volatility}^2$ (AP) | | 0.0002*** | 0.0002** |
| | | (0.000) | (0.000) |
| Volatility (FC) | 0.0003 | 0.0043 | 0.0007 |
| | (0.001) | (0.005) | (0.001) |
| $\text{Volatility}^2$ (FC) | | -0.0000 | |
| | | (0.000) | |
| No. of Review | -0.0000 | -0.0001* | -0.0001* |
| | (0.000) | (0.000) | (0.000) |
| Review Rating | 0.1884* | 0.1452** | 0.1378** |
| | (0.068) | (0.030) | (0.030) |
| No. of Restaurants | 0.0027 | 0.0033 | 0.0032 |
| | (0.002) | (0.002) | (0.002) |
| Hotel Scale | | | |
| - Hotel Scale = 3 | 0.0027 | 0.0199 | 0.0127 |
| | (0.025) | (0.028) | (0.023) |
| - Hotel Scale = 4 | -0.0829 | -0.0204 | -0.0115 |
| | (0.038) | (0.035) | (0.035) |
| - Hotel Scale = 5 | -0.2273* | -0.1569* | -0.1183 |
| | (0.072) | (0.058) | (0.055) |
| High Demand Date | 0.0043 | 0.0247 | 0.0322 |
| | (0.073) | (0.063) | (0.068) |
| Destinations | | | |
| - Paris | 0.0931 | 0.0176 | -0.0021 |
| | (0.063) | (0.078) | (0.068) |
| - Rome | 0.0262 | -0.0119 | -0.0282 |
| | (0.111) | (0.082) | (0.086) |
| - Venice | 0.1500 | 0.0204 | -0.0043 |
| | (0.195) | (0.129) | (0.132) |

Table 14 continued

| | | | |
|---|---|---|---|
| - Los Angeles | 0.1187 | 0.1015 | 0.0882 |
| | (0.100) | (0.057) | (0.070) |
| - Orlando | 0.1331* | 0.0884 | 0.0751 |
| | (0.044) | (0.046) | (0.042) |
| Constant | -0.5176 | -0.1719 | -0.1202 |
| | (0.730) | (0.438) | (0.441) |
| | | | |
| Observations | 107 | 107 | 107 |
| R-squared | 0.1353 | 0.2067 | 0.1998 |

*Note. *** p < 0.01, ** p < 0.05, * p < 0.10. Robust standard errors in parentheses. References: Hotel Scale = 2, New York City for a city level destination.*

Table 15. Subgroup Analysis by Level of Volatility

| | by level of volatility | | | | |
|---|---|---|---|---|---|
| Level of Volatility | 1 | 2 | 3 | 4 | 5 |
| Volatility (AP) | <8 | 8-12 | 12-16 | 16-20 | >20 |
| Price Discovery (AP) | 0.593 | 0.589 | 0.541 | 0.461 | 0.482 |
| | (0.242) | (0.167) | (0.251) | (0.210) | (0.264) |
| Price Discovery (FC) | 0.407 | 0.411 | 0.459 | 0.539 | 0.518 |
| | (0.242) | (0.167) | (0.251) | (0.210) | (0.264) |
| Demand | 0.629 | 0.730 | 0.691 | 0.674 | 0.776 |
| | (0.162) | (0.122) | (0.214) | (0.186) | (0.144) |
| Volatility (AP) | 5.139 | 9.734 | 14.069 | 17.548 | 40.611 |
| | (1.872) | (1.287) | (1.279) | (1.339) | (18.827) |
| Volatility (FC) | 6.665 | 10.983 | 18.343 | 22.229 | 38.080 |
| | (4.084) | (3.108) | (9.631) | (3.667) | (28.151) |
| Review Rating | 3.872 | 4.124 | 4.357 | 4.452 | 4.460 |
| | (0.380) | (0.315) | (0.380) | (0.379) | (0.273) |
| No. of Review | 1163.563 | 1241.225 | 1111.844 | 1760.039 | 2047.323 |
| | (428.983) | (441.083) | (631.969) | (849.225) | (1038.863) |
| Hotel Scale | 2.333 | 3.143 | 3.591 | 4.000 | 4.091 |
| | (1.065) | (0.932) | (1.141) | (1.038) | (0.914) |
| No. of Restaurants | 73.411 | 76.168 | 87.284 | 89.076 | 84.775 |
| | (15.264) | (14.759) | (13.795) | (12.514) | (15.531) |
| Observations | 21 | 28 | 22 | 14 | 33 |

*Note. AP stands for non-refundable rates and FC is free cancelation rates. Standard deviations in parentheses.*

## 4.5. Conclusion

The price discovery effect of non-refundable rates and free cancelation rates was estimated by Hasbrouck's (1995) information share approach. This estimated price discovery effect illustrates how new information about room rates are best reflected in two rates. The present study aimed to reveal the price discovery contribution of non-refundable rates, which have been regarded as a discounted room rate from the free cancelation rate. The findings showed that non-refundable rates contributed more to the price discovery process than free cancelation rates, indicating that non-refundable rates were more sensitive to the price information (i.e., unexpected information related to price) than free cancelation rates. This study also identified the determinants of price discovery process from non-refundable rates. The analyses also demonstrated the positive effect of consumer evaluation on price discovery from non-refundable rates. Overall, the findings suggest that non-refundable rates contributed more to price discovery than free cancelation rates in both high and low volatility periods.

These findings present several theoretical implications. First, this study identified the reflection of information content in the hotel room-night market by revealing that non-refundable rates were more sensitive to price information. There has hitherto been a lack of investigation into the role of non-refundable rates in dynamic pricing, which the majority of studies focusing on free cancelation rates or standard rates. The present findings accordingly address this gap in the existing literature. Second, this study expands the application of the price discovery process to the non-security market. Previous studies in market microstructure theory have predominantly explored price discovery in security markets. The present study showed that the price discovery process can be applied to non-financial assets in a one-sided market, which is a novel addition to the finance literature. In the hotel room-night market, hotels set room rates and customers accept or reject them. Security markets are, in contrast, two-sided markets in which buyers and sellers meet to exchange a product or service through an intermediary or platform. In spite of this disparity between the hotel room-night market (one-sided) and security market (two-sided), the price discovery process can be applied to the hotel room-night market when sufficient price data is available. The present study thus illustrates that this method can be applied to one-sided markets that are frequently traded with multiple price ranges under a dynamic pricing strategy (e.g., airline tickets, car rentals). Third, this study included review rating as a determinant of price discovery. This variable implies perceived quality for market participants, while previous literature in price discovery only considered contemporaneous market conditions, such as trading volume, spread, and volatility. This can be a new addition to the market microstructure literature as industry-specific conditions can be used to analyze the price discovery process in markets that have different perceived values in each asset class. As an example, such hedonic value can be employed to investigate the price discovery process in markets for real estate assets or agricultural commodities.

These findings also have practical implications for market participants in the hotel industry. Given that myriad dynamics affect room pricing, it would be beneficial to ascertain how non-refundable rates respond to demand. This is because non-refundable rates were found to be more sensitive to the new information derived from demand variations than free cancelation rates. For example, the demand of price sensitive travelers plays a key role in the determination of room rates when non-refundable rates contribute more to the price discovery process than the free cancelation rates. Additionally, the results indicated that the reflection of demand in the hotel room-night market varied according to certain hotel characteristics, such as quality of hotel services, location, segmentation, and seasons.

Understanding aggregated demand and its impact on pricing is therefore crucial for all participants in the hotel industry. By examining the conditions affecting price discovery for each room-night market, hotel managers can better understand which room-night market is effective in specific context. Hotel managers can compare their own price discovery coefficient with an aggregated coefficient to examine their response to demand. Hoteliers can thereby increase the precision of their revenue forecast by comparing obtained price coefficients to actual demand. The results of the current study can also guide small- and medium-sized hotels in understanding how larger hotel chains adjust room rates to changes in demand. These findings have further implications for revenue managers in hotels as they support the importance of pricing non-refundable rates. Non-refundable rates are regarded as rates discounted from standard rates (e.g., free cancelation rates, rack rates), but the results of this study suggest that hoteliers should carefully consider their pricing strategy for non-refundable rates. By closely monitoring non-refundable rates, revenue managers can acquire invaluable information, particularly for hotels that have extreme volatility in room rates. Revenue managers should assess market supply and demand as well as customer reviews to maintain competitive non-refundable rates.

Although this study contributes to the hospitality literature both theoretically and practically, there were some limitations. First, the study used a limited sample taken from six hypothesized check-in dates in December. Analysis of data from the summer peak season could yield additional implications for hotel room pricing strategy. However, the validity of the current study remains intact as all hypotheses are based on the both high- and low- demand periods within a short timeframe. Additionally, the subgroup analysis of determinants in midscale hotels was inconclusive, which may be due to the insufficient sample size. Although the specific implications of this insignificant effect are beyond the scope of the present study, it can be a worthwhile topic for future research using an extended sample.

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# CHAPTER 5. CONCLUSION

In this dissertation, pricing decisions for non-refundable rates and free cancelation rates were examined from the hotel room-night market's perspective. Financial market models and theories were applied to understand the movement of room rates in this market under various circumstance. To consider heterogeneity of quality in units, property-specific attributes such as quality, hotel scale, location, and seasonality were incorporated in the model as the adjustments.

In the first study, the advance-purchase discounts were decomposed into two components: the cancelation option value component and the adjustment component based on property-specific attributes. This study found that the cancelation option component positively affects the overall advance-purchase discounts. This study also found that the perceived quality which indicated hotels' competitiveness in the local market affect the level of early booking discounts. In the second study, the effect of market efficiency under rate parity agreement was diagnosed with the final transaction prices. The findings suggested that the existence of rate parity weaken the market efficiency in reflecting hotel quality (e.g., consumer reviews, hotel scales) of room rates. The results further indicated possible anti-competitive behavior between hotels and OTAs in the high-demand periods. The third study examined the price movements in the hotel room-night market and showed non-refundable rates' significant contribution to the price discovery process. Similar to the prior two studies, the last study also showed the reflection of demand in the hotel room-night market varied according to certain hotel characteristics, such as property quality, location, and segmentation.

To conclude, the findings of this dissertation bear implications for both academia and practitioners. First, this dissertation demonstrated an approach in applying financial market models to examine the pricing decision of the hotel room-night market. To apply financial market models in the product market, differences of two markets should be considered. One of the major differences is the market structure. The hotel room-night market is a one-sided product market, which means prices are offered from sellers (hotels or other distribution channels) and buyers (customers) can only decide to accept or reject the offers. Security markets are, in contrast, two-sided markets in which buyers and sellers meet to exchange a product or service through an intermediary or platform. Perishability is another factor to limit the trading between buyers and sellers in the hotel room-night market. To overcome these differences, this study collected data from both high- and low- demand periods in chain hotels in the major travel destinations. To avoid such discrepancies between the hotel room-night market and the financial market, this study also used hedonic pricing models with the results from financial models and property-specific attributes. The three studies in this dissertation thus illustrated that financial market models need to be adjusted to account for property characteristics.

This study also demonstrated the importance of consideration of property-specific characteristics in pricing decisions. Among various characteristics, this study found that variables related to the property quality take a key role in adjusting financial market models to the hotel room-night market. This indicated that the consideration of the heterogeneity of quality in unit of the product market may increase the explanatory power of financial market models in the non-security market.

Furthermore, this study found a new perspective of volatility, which interpreted as risks in the finance literature. In the first study, volatility was negatively related to the advance-purchase discounts in most of destinations. These results hinted that the volatility in room rates was not a risk to hotels, rather it showed their ability to adjust their room rates and discounts dynamically. In the third study in this dissertation, the results implied U-shaped relationship between volatility and price discovery coefficient for non-refundable rates. This can be caused by the interaction between buyers and sellers in the hotel room-night market. While room rates are set by hotels, travelers' preferences indirectly affect room rates through room demand. Book-and-search customers may pay more attention to non-refundable rates under low volatility, while hotels tend to actively manage non-refundable rates in the high volatility period. These distinctive interpretation of volatility in the product market would be a worthwhile topic for future research. For future researches, including data from other distribution channels may give additional implications on room pricing decisions. For example, the effect of rate parity on room rates collected from OTA channels would be a good reference to compare the impact of rate parity on market efficiency for different distribution channels. Additionally, extended data from other distribution channels may incorporated to check the responsiveness of non-refundable rates on property-specific attributes.

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- Portfolio management

Revenue management

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## PUBLICATIONS AND WORKING PAPERS

**Kim, H.**, & Tang, C. H. **“**Experienced Buyers, Long-Term Fee Contracts, and the Value of Property Transactions in the Hotel Industry.”

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- ***Revise & Resubmit: Cornell Hospitality Quarterly*.**
- Role: First & Corresponding author

Legg, M., Tang, C. H., & **Kim, H.** “An economic sensitivity analysis of Las Vegas gaming revenues.”

- Working paper.

**Kim, H.**, & Tang, C. H. “Price Dynamic Model: Non-refundable rates’ Contribution to Price Discovery.”

- Working paper

**Kim, H.**, & Tang, C. H. “Rate Parity Agreement and its Impact on Market Efficiency in Advance-Purchase Discount.”

- Working paper

## ACADEMIC PRESENTATIONS

**Kim, H.** & Tang, C.H. “What is in an advance-purchase discount? An analysis based on stock option pricing model and consumer market factors.”

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- Managerial Accounting and Financial Management in Hospitality Operations (Undergraduate: HTM241), *Fall 2018, Spring 2019*

**Teaching Assistant,** Purdue University, West Lafayette, IN, USA

- Advanced Hospitality Accounting & Finance Systems (Graduate: Online HTM541), *Summer 2018, Fall 2018*

**Research Assistant,** Purdue University, West Lafayette, IN, USA

- Research topics: “The value of hotel property transactions to sellers.” and “Do hotels and mixed-use projects benefit each other?”, *Fall 2017*

## CERTIFICATIONS

**College Teaching Development**, Purdue University, West Lafayette, IN, USA

- Certificate of Practice in College Teaching, *Spring 2019*

**Graduate Teacher Certificate,** Purdue University, West Lafayette, IN, USA

- Graduate Instructional Development Certificate (GIDC), *Fall 2018*

## PROFESSIONAL EXPERIENCE

**Mirae Asset Global Investments,** Seoul, Korea, *Nov. 2006- Jan. 2014*

Investment Manager / Senior Investment Analyst, Research Division,

- Investment manager of $35Million Korea Consumer Equity Investment Trust Fund; specialized investment in Korean consumer sector with thirty investee companies in the portfolio; outperformed KOSPI for three consecutive years between 2009 and 2011 by average 80 basis points, resulting in thirty times increase of fund size in 2012; continuously ranked Korea Best Theme Fund in 2011 and 2012
- Senior Investment Analyst covering hospitality and tourism, retailing, chemical/oil/gas, steel, Internet/Gaming, and transportation sector; perform multi-aspect review including competitor analysis and on-site due-diligence both domestic/overseas, consult with industry/academic experts and practitioners, create earnings/valuation model to and publish opinions; communicate with domestic and overseas sell-side equity analysts who provide company information, conduct company calls, and hold investment conferences.

Investment Analyst, Global Asset Allocation Division

- Analyzed investment feasibility focusing around emerging markets, including BRICs, to help top-management decision-making for per-country investment size of Mirae Asset's multi-country investment funds; reviewed macro-economic factors and country-strategy reports supplied by each country analysts.
- Conducted quantitative research of countries in emerging markets to produce input into Quantitative Country Allocation Model, which calculates optimal per-country investment size numerically; input included GDP growth rates, per-country aggregated corporate earnings, and regulation/policy.

**Nemo Partners,** Seoul, Korea, *Feb. 2006- May 2006*

Intern, Strategic Consulting Group

- Team member of Request for Proposal project to pitch Microsoft's corporate solutions to prospective media clients

**Samsung SDI**, Selemban, Malaysia, *Jul. 2005- Aug. 2005*

Intern, Summer Internship Program

- Performed on-site interviews with plant personnel of Samsung SDI in Malaysia; composed research paper themed 'Glocalization of Samsung SDI in Malaysia', discussing success factors of localization in Malaysia

## HONORS AND AWARDS

Compton Graduate Student Research Travel Award, College of Health and Human Sciences, Purdue University, *2018, 2017*

Second place winner, 2015 Student Managed Investment Fund (SMIF) Widiger Essay Contest, Krannert School of Management, Purdue University, *2015*

MBA Scholarship, Krannert School of Management, Purdue University, *2014*

Fourth place winner, Amore Pacific Marketing Competition, Amore Pacific Co., *2005*

Four times Merit-based honors scholarship, Korea University Business School, Korea University, *2002- 2006*

## SKILLS

Statistical Software: Proficient in SAS, STATA, R, and MS Office

Data: Compustat, CRSP, Reuters, Bloomberg Terminal, Capital IQ, and Thomson One Analytics

Other: Certified Investment Manager (2007); CFA Level 2 candidate