11-10-2020

Do User-Generated Ratings Affect Hotel Valuations? – An Analysis of the Chicago Hotel Market

Shailesh Patel
University of Missouri-St. Louis, sspzh7@umsystem.edu

Do User-Generated Ratings Affect Hotel Valuations? – An Analysis of the Chicago Hotel Market

Shailesh Patel

MS-Taxation, University of Illinois Urbana-Champaign, 2015
MBA, Finance, Illinois State University,2008
MS- Computer Engineering, California State University, Long Beach,2001
BE – Structural Engineering, National Institute of Engineering, Surat Gujarat, 1993

A Dissertation Submitted to The Graduate School at the University of Missouri–St. Louis
in partial fulfillment of the requirements for the degree
Doctor of Business Administration with an Emphasis in Finance

December 2020

<u>Advisory Committee</u>

Thomas Eyssell, Ph.D., CSA
Chairperson

Bindu Arya, Ph.D.

Dinesh Mirchandani, Ph.D.

Abstract

Today's travelers are increasingly relying on aggregated online opinions to make purchase decisions. One of the sectors most impacted by these online reviews is the hospitality industry, where consumer review websites such as TripAdvisor, Expedia, and Bookings.com play a critical role in influencing consumer's choice of hotel and the price they will pay for the room. Recently, there have been studies investigating the various aspects of user-generated online reviews and ratings. The purpose of this paper is to investigate the impact of user-generated ratings on hotel valuations. Our paper does this using regression analysis to study the impact of TripAdvisor user ratings on Occupancy Rates, Average Daily Rate (ADR), and the corresponding market value of the hotels. The research was carried out on 33 properties operating in luxury through economy market segments and located within Chicago, Illinois. The results indicate user-generated ratings positively influence Occupancy rates and ADR. The findings indicate a robust relationship between higher user-generated ratings and higher Occupancy rates and ADR suggesting a corresponding increase in market values. The study also reveal a strong positive correlation between Seasonality and ADR. The academic and managerial implications of this research along with future directions have also been discussed.

Keywords: User-Generated Reviews, Electronic Word-of-Mouth, Hotel Valuations, Occupancy Rate, Average Daily Rate (ADR), TripAdvisor Ratings

ACKNOWLEDGEMENTS

I cannot express enough gratitude to my committee for their continued support and encouragement: Dr. Thomas Eyssell, my committee chair; Dr. Dinesh Mirchandani, and Dr. Bindu Arya. I extend my sincere appreciation for the learning opportunities and guidance provided by the committee.

The completion of this thesis could not have been accomplished without the support of all the wonderful professors and staff at UMSL DBA. I would also like to thank all my professors, who through their teachings had a profound impact on my DBA journey.

Finally, I would like to thank my family. First, I would like to express my deepest gratitude to my supportive, loving, and caring wife, Manisha: Your encouragement during rough times is much appreciated and duly noted. It was a great comfort and relief to know that you were willing to support my dreams and provide management of our business while I attended weekend classes for my DBA. My heartfelt thanks. Second, to my children Divit, Meesha, and Ruhee, who are the stars of my life. I am amazed by how much they teach me every day and how their bright smiles, no matter the situation, got me through some difficult and tiring times. A special thanks to Meesha, for helping me with my TripAdvisor data. She helped me assemble, organize, and categorize almost 37,000 lines of user rating into Excel data format.

Table of Contents

Chapter 1. Introduction

Purpose

Customer reviews have changed the way customers explore, discover, and buy products both online and in-store. Consumers making online purchase decisions tend to rely on user-generated online reviews for making buying decisions. Resnick & Zeckhauser (2002) and Melnik & Alm (2002) have documented the impact of online user generated reviews on the price and quality of transactions (Resnick et al., 2006). Further work by Chevalier and Mayzlin (2006); Berger et. al. (2010); and Chintagunta et. al (2010) examined the role of consumer reviews on product purchases online. The purpose of this research is to examine the impact of user-generated reviews and ratings on the valuation of hotels within the hospitality industry. This has been done by examining the user rating of hotels in the Chicago, Illinois market as posted by reviewers on the widely used travel review website TripAdvisor. This introductory chapter discusses and provides the origins of user-generated ratings and how these rating websites are influencing hotel occupancy and room rates and further affecting property valuations.

Customers looking to book hotel accommodations often refer to online user reviews for cues and indicators regarding the quality and service of the property. The widespread adoption of mobile devices makes it easy for users to review and create online reviews. Customers generally tend to trust user-generated reviews more than they do from the businesses themselves as customers assume that user reviews are independent and void of biases. Customer will at least review user feedback even if they do not plan on making an online travel reservation. Even businesses are using online reviews to their advantage by monitoring their customer feedback to better train their staff to meet guest expectations. The reviews are used by businesses in addition to the traditional market research used by many lodging establishments. Even though recently there have been issues raised around fake reviews and the erosion of trust, consumers still believe that just the sheer volume of user reviews generated negates the effect of few fake reviews that occasionally show up.

The Hospitality Industry

The origin of hospitality can be traced back to the very dawn of human existence or as far back as modern paleontology can take us. During the initial stages of human history, humans did not indulge in organized farming, organized collectively around settlements, or complex political hierarchies. They lived in scattered, living a nomadic life while hunting and gathering for food. Tanaka (1980), noted that the early humans, living in primitive societies would tend to be more accommodative to certain desirable groups. They would then associate with this group while offering food and creating new relationships.

Cassee & Reuland (1983) offered a relative comprehensive definition of hospitality as "a harmonious mixture of tangible and intangible components - food, beverages, beds, ambiance and environment, and behavior of the staff"; and contended that the hospitality "concept comprises much more than the classical ideas of preparing good food and providing a comfortable bed". This definition was further improved by Cassee & Reuland (1983) to include "a harmonious mixture of food, beverage, and/or shelter, a physical environment, and the behavior and attitude of people".

The hotel hospitality industry includes all revenues produced by lodging properties such as hotels, motels, and other accommodation providers through the provision of overnight lodging. According to the Bureau of Labor Statistics, the hotel and lodging industry "includes all types of lodging, from luxurious 5-star hotels to youth hostels and RV parks. While many simply provide a place to spend the night, others cater to longer stays by providing food service, recreational activities, and meeting rooms." Throughout history, travelers have sought comfortable places to dine and rest. While modern lodging properties feature provide new conveniences like in-room showers and televisions to help travelers ease into the night, they still accomplish the same purpose as the original inns and lodging houses. Even though the history of lodging goes back hundreds of years, they still have the fundamental essence of welcoming guests and making sure that their stay is comfortable. The term "hospitality" originates from latin word "hospitium," which literally translates to "a place of rest for travelers and pilgrims". Since the early 17th century, entrepreneurs built and developed guest houses and small hotels across America to serve the needs of explorers and entrepreneurs across the country. Initially, these properties provided very basic facilities like a bed and a safe environment, but as competition grew, they began providing more extensive services like hot showers and telephones, for those prepared to pay more. New York's first hotel, the City Hotel, opened in 1792. Designed by architect Isaiah Rogers, The Tremont House, opened in 1826 and was America's first five-star hotel. It was one of the first hotels to incorporate indoor plumbing, guest toilets, and bathrooms, rooms with locks, and provided free soap to travelers. The hotel featuring single and double rooms appealed to a new class of travelers who could afford these luxuries.

US Hotel Industry

The growth of the hotel industry during the last two decades has primarily been based on increasing business and leisure demand which outpaced supply, thus resulting in increased ADR, and improved Occupancy. The hotel occupancy rates in the United States reached a record 65.4% in 2016. The United States hotels & motels industry's total revenue was valued at $245 billion in 2015, depicting a compounded annual growth rate (CAGR) of 6.2% between 2012 and 2016. That was the fastest pace in the last 20 years. New construction properties additionally increased with a

CAGR of 1.0% between 2012 and 2016. The number of lodging properties increased to reach a multi-year high of 56,840 establishments in 2016. According to Smith Travel Research (STR, 2018), the U.S. hotel industry is projected to report an upward 0.6 % increase in occupancy to reach an all-time high of 66.3 %. The ADR (Average Daily Rate) is expected to grow 2.6 % to an all-time high $129.85, while RevPAR (revenue per available room) will increase on an annual basis from 3.2 % to $86.09. An analysis also shows that RevPAR (revenue per available room) has increased at least 3 % for each year of the past eight years. According to the 2016 AHLA (American Hotel & Lodging Association) report, 8 million people are directly and indirectly employed by this industry providing $74 billion in employee wages (Miller, 2019). Hotels and resorts generate approximately $167 billion in federal and local taxes and hotel guests spend an additional $238 billion on activities at local businesses during their stay (AHLA, 2015).

The number of hotel establishments in the United States is expected to rise to 61,520 by the end of 2021, representing a CAGR of 1.6% over 2016–2021. The number of Budget hotels has grown at a higher rate than those from any other class segment of the industry during 2012–2016. Hotels within the leisure market segment were the industry's most profitable in 2016, taking in total revenues of $108.2bn, equivalent to 57.2% of the industry's overall value. The business market segment trailed the leisure market by contributing revenues of $81.1bn in 2016, equal to 42.8% of the industry's overall value.

User-Generated Content (UGC)

While there are subtle similarities between User-Generated Content (UGC) and Electronic word-of-mouth (eWOM), they are not identical. UGC is broader and focuses on online user-generated reviews and content for others to view (Smith et al., 2012). UGC consists of textual material that has been published online and may include user comments, photographs, and personal opinions. With the arrival of Facebook and various social media networks within the last ten to fifteen years, there has been an explosive adoption of social media-based applications related to the hospitality and tourism domain. These technical advances made it easy for consumers to create and post user-generated content on web-enabled platforms like Twitter, Facebook, and YouTube. Gupta and Kim (2004) described such websites as "coffee shops" where virtual users can "find and then electronically 'talk' to others with similar interests". It is here that, people virtually "meet and discuss on forums and bulletin forms or exchange information on social networking sites" (Chung and Buhalis 2008, p. 1). UGC is now considered the predominant and premium source of information for leisure and business consumers. A study by Cox et al. (2009) found that "UGC is perceived as more trustworthy when compared to content from official destination websites, travel agents, and mass media." Per the study consumer trust of UGC was driven by users being able to get a peer perspective regarding lodging property before traveling. While the reliability of user-generated content and reviews is not vouched by the platforms, its influenced by many factors such as quality of the reviews, relevance with the product along with its usefulness, and even the user's experience with the online platforms. Recent studies conducted by Fotis, Buhalis, and Rossides (2012) and Cox et al. (2009) has confirmed that consumers are now turning to these UGS to make travel-related decisions and turning around to create their own UGC for others to review.

Hotel Valuation Issues

Hotel valuation is a highly specialized process that involves many variables and assumptions. Hence, the final value or value range can vary greatly from one model/method to the next. While hotel valuations are categorized under real-estate appraisals, valuing a hotel requires a thorough understanding of the general principles and procedures of appraisal along with and deep understanding of the lodging industry and their operations. Managing a lodging operation involves more than just taking care of guest expectations and physical assets. Hotels operations are very labor-intensive, require a very high level of managerial experience, and involve significant investment in FF&E that is subject to rapid depreciation, damage, and obsolescence. Hotel valuators usually consider the various factors as discussed above to derive a reasonable estimate of market value. Typically, property brokers and investors have used the financial statements created using the Uniform System of Accounts for the Lodging Industry (USALI) standards to forecast hotel cash flows. Their profit and loss statements contain departmental revenues and expenses, FF&E (Fixture, Furniture & Equipment) charges, and administrative costs. One major drawback of USALI pro forma is that it masks some of the key value drives that most investors care about like growth, market share, level of services, and user ratings.

Chapter 2 Literature Review

User-Generated Reviews Literature

Word-of-mouth (WOM)

Word of mouth has been one of the oldest ways of conveying information between consumers and producers (Dellarocas, 2003), and it has been defined in many ways. Katz and Lazarsfeld (1966, p. 1) described it as “the exchanging of marketing information between consumers in such a way that it plays a fundamental role in shaping their behavior and in changing attitudes toward products and services”. Arndt (1967) suggested that word-of-mouth (WOM) is a “person-to-person communication tool, between a communicator and a receiver, who perceives the information received about a brand, product, or service as non-commercial”. Previous research defined WOM was communication between consumers about a product or service independent of biases or company intervention (Litvin et al., 2008). These social and informal communications provide consumers access to information before they purchase a particular service or product, directly influencing user decision. These reviews provide in-depth information about the product or service that goes beyond the flashy communications provided by the companies themselves which aim to influence the individual’s decision-making (Brown et al., 2007).

Electronic word-of-mouth (eWOM)

Recent developments in telecommunications and mobile technology have provided a tremendous platform for electronic WOM (eWOM) which allows consumers and individuals to share their individual experiences and opinions online with other consumers via electronic web-based communication channels, such as community message boards, blogs, emails, online review platforms, chat rooms, and websites, all of which act as promotion and marketing tools to influence consumer decisions [Blal & Sturman, 2014].

While these technological advancements have led to wide adoption of electronic word of mouth (eWoM), eWoM messages cannot be disregarded anymore by any product/service provider. Fang et al., (2011) discovered that consumers trust online user-generated reviews 12 times more than sellers advertisements, leading to higher approval of eWOM messages. The adoption of an eWoM message refers to understanding the information and recommendations contained in an eWoM message. This further influence's consumers' rational and discernible propensity toward the referenced product and services (Filieri et al., 2018)

Online Reviews

Companies are increasingly using various web-based online platforms like social networking websites, online communities, and user review sites to decide how to structure and price their products and services. The tourism and hospitality industry is no exception to this trend (Chang, 2019). With the launch of TripAdvisor in 2000, travelers and web users began to share their experiences online for others to view and comment (H. Lee, Law & Murphy 2011). Lodging enterprises represent a significant portion of these reviews. Over one-third of travel businesses reviewed on TripAdvisor are related to accommodations (TripAdvisor 2014). The popularity and rapid increase in the number of hotel reviews online has mirrored the tremendous growth of hotel room bookings through web-based booking channels (Toh, Raven & DeKay 2011; O'Connor & Murphy 2008) like TripAdvisor, Expedia, and Booking.com.

Customers look for hotel review primarily on websites maintained primarily through online travel agencies (OTAs) or through websites that just host user reviews. Online travel agencies are companies that sell hotel rooms online through their websites. They act as a middleman between hotels and consumers, though their prices can often be cheaper than booking direct. Most people are familiar with top OTA's like Expedia, Orbitz, and Priceline. With the widespread popularity of mobile devices, OTA's have become popular booking sites for online customers as they provide users with a wide variety of booking options along with customer-generated reviews for instant feedback. Per eMarketer (2012), these OTA's generate $119 billion in revenues raking in almost 45% of all hotel bookings in the United States.

The purpose of this research project is to determine and understand the factors that impact the valuation of a hotel or lodging establishment within the city of Chicago, Illinois in relation to user-generated online ratings found on TripAdvisor. TripAdvisor is one of the most popular OTA websites that hosts the largest collection of users generated online ratings (HotelMarketing.com, 2012), We will be using the data downloaded from TripAdvisor for our research. The literature review helps us define the terms and components used within our research.

Hotel Classification System Literature

According to WTO (World Trade Organization) currently, there are no worldwide rating standards for hotel evaluation and classification, and hence hotel rating and classification systems vary from country to country (Tefera & Govender, 2015). Over time different countries have developed their own distinct classification systems reflecting local cultural and geographical preferences. For example, the United Kingdom has three main hotel rating systems, the English Tourist Boards, Automobile Association, and the Royal Automobile Club. The United States on the other hand does not have a national rating system, but various private associations maintain an independent hotel rating system. Cser & Ohuchi (2008) noted that various terms like "Hotel segmentation", "Hotel classification", "Hotel rating" and "Hotel grading" are used interchangeably to rate and differentiate hotels based on their nightly room prices, facility offerings, and services.

Even though hotel classification and guest reviews complement each other, they both provide distinct information to different travelers; whereas hotel classification concentrate on the amenities and services offered by the hotel, guest reviews and ratings focus more on the quality of services offered by the property (Blomberg-Nygard & Anderson, 2016). Traditionally consumer rating agencies like AAA or Forbes would send out experts to assess hotel quality and offerings and based on their 'expert' opinion the consumer ratings agency would assign a classification that was pre-defined by the agency. Reinsein & Synder (2005) found that "expert "assessment may not reflect user experience or preferences. These discrepancies among evaluators may lead to confusion among consumers resulting in uncertainty among buyers and property owners.

Star rating

With the advent of automobiles in the early 20th century, a group of motoring enthusiasts banded together to form the Motorists Mutual Association in the United Kingdom. Soon in 1912, they began assigning hotels using the various star ratings. The association name was formally changed to Automobile Association (AA) and published its first listing of hotels in 1908 with their star system of hotel rankings.

In the United States, hotels are usually assigned a star rating by third-party organizations like Forbes Travel Guide, AAA, or online aggregators like Travelocity and Expedia. Founded in 1958 by Mobil and Simon & Schuster, the Forbes Travel Guide is the oldest travel rating service in the United States. In late 2009, the Forbes Travel Guide integrated with Mobil Travel Guide and adopted the Star Rating system created by Mobil. The Forbes Travel Guide provides ratings and reviews of restaurants, hotels, and spas on a scale of one star to five stars (Bagdan, 2013). The Forbes Travel Guide uses its own scoring system based on a proprietary algorithm that weighs the facility at 25% and service quality at 75% to assign star ratings (Forbes, 2019). Specially trained inspectors from Forbes visit each property and analyze the property against approximately 900 objective standards. The inspectors do not themselves rate the property but submit their reports online. The proprietary algorithm then creates a star rating for the properties. Table No. 1 below offers a simplified definition of ratings from various major rating agencies.

Table 2.2

Star Rating	Expedia	Travelocity	Forbes
5 - Star	Luxury, Gourmet Dining, Spas, 24-hour guest services	Luxury setting, Flawless guest services	Outstanding, iconic properties with virtually flawless service and amazing facilities.
4 - Star	Superior, Up-scale, and high quality	Superior property offering a variety of services and amenities	Exceptional properties offering high levels of services and quality of facility to match
3 - Star	Quiet and comfortable, Upper-Up-Scale	High level of service offering additional services	Excellent properties with consistently good service and facilities.
2 - Star	Values-driven, clean, and comfortable, Mid-Scale Economy	Meets basic traveler needs	N/A
1 - Star	Basic no-frills, Economy	Meets Budget needs	N/A

Source - Expedia, Travelocity, and Forbes (Smith Travel Research)

Diamond Rating

Like various online rating services in North America, another widely used hotel and restaurant rating system is the AAA Diamond rating (Guillet & Law, 2010). After its merger with the American Motorist Magazine, AAA published its first stand-alone hotel directory in 1917 (AAA, 2020). AAA's Diamond rating system includes properties located in the United States, Canada, Mexico, and the Caribbean. Typically, to be included in the AAA guide, hotels do not pay any membership fees, but must apply for a rating. Historically, properties that are AAA listed meet a minimum of 27 basic requirements, relating to comfort, cleanliness, and safety. Once accepted, AAA sends out anonymous inspectors to assess the property and designate an appropriate diamond rating anywhere from one to five. Properties selected for evaluation must continue to demonstrate the strict quality guidelines laid out by AAA. Currently, about 32,000 hotels are listed in their travel guide (AAA, 2020). Depending on the market segment the property is operating in, AAA assigns a diamond rating anywhere from one to five. One rating is usually assigned to properties offering a very basic level or accommodations, while a rating of five indicates a luxurious hotel offering superior services and amenities. The Diamond ratings also indicates the extensiveness of services, amenities, and décor provided. Table 2.1 below breaks down AAA’s definition of its diamond ratings.

Table 2.3

Diamond Rating	Definition
5 -Diamond	These establishments reflect the characteristics of the ultimate in luxury and sophistication. Accommodations are first class. The physical attributes are extraordinary in every manner. The fundamental hallmarks at this level are to meticulously serve and exceed all guest expectations while maintaining an impeccable standard of excellence. Many personalized services and amenities enhance an unmatched level of comfort.
4 -Diamond	These establishments are upscale in all areas. Accommodations are progressively more refined and stylish. The physical attributes reflect an obvious enhanced level of quality throughout. The fundamental hallmarks at this level include an extensive array of amenities combined with a high degree of hospitality, service, and attention to detail.
3 -Diamond	These establishments appeal to the traveler with comprehensive needs. Properties are multifaceted with a distinguished style, including marked upgrades in the quality of physical attributes, amenities, and level of comfort provided.
Approved	These establishments appeal to the traveler seeking more than the basic accommodations. There are modest enhancements to the overall physical attributes, design elements, and amenities of the facility typically at a moderate price.
Approved	These establishments typically appeal to the budget-minded traveler. They provide essential, no-frills accommodations. They meet the basic requirements pertaining to comfort, cleanliness, and hospitality.

Source - https://www.aaa.com/diamonds/

Hotel Segmentation

Hotel’s operate in different markets segments depending on their franchise affiliation, number of rooms, function, and location. Majority of lodging properties and management companies that operate these hotels follow widely accepted industry standards to classify their hotel properties.Hotels can be further classified based on their location, the number of rooms, the markets they serve, the level of service provided, and brand affiliation. Location is one of the most important factors that affect the success of hotel property (Kim & Okamoto, 2006). Desirable urban locations can lead to higher RevPAR (Revenue Per Available Room) (Sainaghi, 2011), better occupancy (Chung & Kalnins, 2001), and increased guest satisfaction ((Sim, Mak & Jones, 2006) along with great long term growth and success (Baum & Mezias, 1992). A hotel can be further segmented by urban and rural locations. Another way to segment a hotel is by its size and room count. Previous research confirms that there is a high positive correlation between hotel size and the number of online reviews it receives (Martin-Fuentes and Mellinas, 2018; Viglia et al. 2014). Hospitality brands and chains are commonly slotted by chain scale which is based on the previous year's annual system-wide Average Daily Rate (ADR). Smith Travel Research (STR) uses Chain Scales to classify hotels based on the services offered. The categories include Luxury, Upper Upscale, Upscale, Upper Midscale, Midscale, and Economy (STR, 2019). Hotels included in the Luxury segment typically offer five-star accommodations and high-end range of on-property services and amenities, including 24 hour restaurants, spas, health clubs, concierges, room service, and transportation. Upper Upscale and Upscale offer services similar to the Luxury segment but with reduced benefits. Midscale properties are positioned between Upscale and Economy segment. Midscale properties offer basic accommodations with minimum amenities. Amenities often include complimentary breakfast, a fitness center, and business center. Economy hotels are small properties that offer little or no services. Our research focuses on all market segments of hotels located within the City of Chicago, Illinois.

The AAA guidebook published annually and available online and in print. The guidebook encompasses AAA ratings for almost 58,000 lodging properties and restaurants, about 21,000 attractions, over 7,400 tourist destinations and around 20,000 events (AAA, 2017). For our study, the hotel market is segmented based on the AAA diamond rating of the hotel property. Table 2.4 provides a summary of the data included from each category. Recently AAA combined the previously One-Diamond and Two-Diamond sub-categories to create a new segment called "Approved" to provide uniform marketing for value customers. AAA continues to rate properties as Three-Diamond, Four-Diamond, and Five-Diamond.

The Approved category provides clean and basic budget accommodations that meet the minimum requirements of the economy traveler. These accommodations are tailored for someone looking for value at an affordable price. Hotel chains such as EconoLodge, Motel 6, Days Inn, and La Quinta Inn are included in this category. Data collected for our research includes 5 properties from this category and is labeled as Mid-Scale Economy (Table 2.4).

Three-Diamond rated hotels include properties that provide comprehensive amenities with style and comfort, yet they are still considered affordable. They are not luxurious; they offer simple options that will not break the bank. These properties are typically located by business areas that attract business and casual travelers. Franchise hotels similar to Holiday Inn and Hilton are typically included in this category. Our data includes 6 properties from this category and are labeled as Upscale.

Four-Diamond rated hotels include properties that provide an upscale style with higher-end amenities and the right level of service. These hotels provide the guest with well-lit, nicely furnished rooms with continental breakfast and valet services. They are upscale, high-quality, and comfortable. Examples of four-diamond hotels include Marriott and Hyatt. Our data includes 15 properties from this category and are labeled as Upper Upscale.

Five-Diamond rated properties are world-class hotels treat their guest to luxury, high-end amenities, and once-in-a-lifetime experiences. These properties feature lavish hotel lobbies, stylish room furniture, heated pools, garden tubs or jacuzzies, 24-hour room service, and valet parking services. Examples of five-diamond hotels include Ritz Carlton and Four Seasons. Our data includes 15 properties from this category and are labeled as Luxury.

Revenue Management Literature

From a research perspective, not much attention was paid to revenue management until 1971, when Rothstein (1971, 1974) started looking into models to optimize airlines and hotels overbookings. Further contributions were made by Belobaba (1987; Smith et al. 1992) who formalized revenue management as an essential part of a company's financial strategy. Revenue management aims to maximize revenue and profits by improving sales and increasing operating efficiencies (Wirtz et. al., 2003). The airline industry provided researchers with practical examples of the tremendous impact that revenue management models can have on other similar industries like hotels and restaurants. Revenue management can help hotel owners to focus on the most profitable mix of available business.

Financial Indicators

Hotel owners use top-line financial indicators such as ADR, Occupancy, RevPAR, and bottom-line indicators like Gross Operating Profit (GOP) or Net Operating Income (NOI) to provide crucial operating information to executives and managers (Singh & Schmidgall, 2002; O'Neill & Mattila, 2006). O'Neill (2003) suggested that top-line financial indicator such as ADR is a better predictor of a hotel's market value compared to market value based on its net operating income. Even though hotel RevPAR, ADR, and Occupancy rates explicate the various discrepancies within hotel's bottom-line financials, research literature points to additional factors like branding which can affect top-line revenues (Johnson & Selnes, 2004). Financial performance is primarily measured using financial and operational dimensions (Hu & Cai, 2004). The principal indicators used in the hotel industry are Revenue per available room (RevPAR), Average daily rate (ADR), and Occupancy (Hung et al., 2010)

Revenue per available room (RevPAR)

Many researchers consider RevPAR to be the strongest performance indicator in the hospitality industry (Jacobs, C. C., 1997). Multiplying the ADR by its Occupancy Rate will provide the hotels RevPAR. Traditionally hotel properties are evaluated based on their ADR and Occupancy rate individually, but RevPAR combines them to provide one important indicator for investors (Woods Jr., D, 1994). Both, investors, and the lodging industry rely heavily on RevPAR as a benchmark for hotel performance and valuation (Ismail et al., 2002a, 2002b). Many investment firms use RevPAR for pricing hospitality-related stocks (Anwar R., 2000). RevPAR is also used by many appraisal companies to compare lodging properties in terms of revenue stability and future growth. RevPAR successfully captures the interaction of Average Daily Rate and Occupancy levels at various stages of hospitality lifecycles and reveals both the demand and supply aspects of the lodging market cycle in one very useful indicator.(Gallagher & Mansour, 2000).

$$\boxed{\text{RevPAR} = \text{Average Daily Rate x Occupancy \%}}$$

Average daily rate (ADR)

The relationship between the average daily rate (ADR) and the corresponding variables Occupancy rate and RevPAR is used not only to determine the productivity of a hospitality property but also to benchmark competitors within the hotel market (Mauri, 2013). Revenue growth for hotel property depends on several variables including location (Barros, 2005), number of rooms (O'Neill

& Mattila, 2006) age of the property (Park & Jang, 2010), and several endogenous factors outside of firms' control. There is also a positive impact of higher ADR with growth in revenues (Skalpe & Sandvik, 2002). ADR is positively influenced by hotel occupancy (Qu et al., 2002). Demand and supply affect hotel room prices (Baum & Haveman, 1997, Min et al., 2002). ADR is also likely to be influenced by existing competition (Falk & Hagsten, 2015) and are higher in the presence of limited competitors (Abrate et al., 2011)

$$\boxed{\text{ADR = Room Revenue / Rooms Sold}}$$

Occupancy Rate

Hotel occupancy has been used by property owners as a yardstick to improve revenues. Occupancy rate is measured by dividing the number of rooms occupied by the number of rooms available (Bardi, 2007). The higher the occupancy rate, the higher the revenues and profits. Hotel occupancy rates depend on several external and internal factors. Some of the external factors involve include tourism, economy, technologies, demographics, politics, etc. Internal factors that can influence occupancy rates include service quality, management, room prices, quality of accommodations, and location of the property (Lau et al., 2005). Factors such as room design and layout (Ruys & Wei, 1998), Cleanliness (Lockyer, 2005), overall comfort (Salleh & Ryan, 1992), and meeting customer expectations (Abdullah & Hamdan, 2012) positively affect Occupancy rates.

$$\boxed{\text{Occupancy Rate = Rooms Sold/ Rooms Available}}$$

Like other assets, the hotel market value corresponds to its capacity to generate future cash flows. Historically, the valuation of hotels and other types of hospitality properties has been constrained because of the challenges in analyzing and separating values between tangible and intangible components as well as separating values within the tangible assets. Due to the complexity involved, lodging evaluators use a mix of different approaches to estimate the value of their assets. The various approaches include using existing theories and models to empirically estimate asset values while the informal approach may include ad hoc rules of thumb, each having their own benefits and limitations. While there are many approaches to valuing hospitality properties, four approaches generally utilized to estimate the value of lodging properties include the cost approach, the sales comparison approach, the income capitalization approach, and the gross revenue multiplier approach.

Although real estate valuation companies estimate the value of their properties using various methods, the most widely used trend in lodging valuation has been to employ any of the following Four approaches approach (Lesser, 1992; Rushmore, 1992b; Walsh and Staley, 1993, Nilsson et al ., 2002).

1) The cost approach,

2) The sales allocation approach,

3) The income capitalization,

4) Gross Revenue Multiplier Approach

Rushmore (1992) concluded that hotel valuation is a complex task and often requires a deep understanding of how hotels operate along with a thorough understanding of existing valuation techniques and processes.

The Cost Approach

The Cost Approach calculates the values-based how much would it cost to rebuild the hotel less any depreciation. The land on which the hotel currently is built on is also taken into consideration for the valuation. Per Stefanelli (1982) research, this approach does not consider the prevailing market value of the existing property nor does it consider the potential future cash flows.

The Sales Comparison Approach

The Sales Comparison Approach uses the valuation of similar properties in comparable market segment to estimate the selling price for a particular hotel. To estimate accurate values, specific features and other characteristics of the property will also be considered. Sikich (1983) found that the sales comparison approach uses the most recent transaction as a benchmark for similar hotel sales regardless of the replacement cost or future cash flows.

The Income Approach

The Income Approach for property valuation looks at the estimate of future cash flows to determine the value of the hotel. (Rushmore, 1975; Rushmore, 1992b). They look at historical revenue streams as an indicator of future performance. Some of the indicators this approach examines includes ADR, RevPAR, occupancy rates and room revenues.

Gross Revenue Multiplier Approach

Under the Gross Revenue Multiplier Approach, a hotel is valued based on the last 3 to 5 years of gross room revenue using an appropriate multiplier. Hotel brokers and hospitality property buyers have used the Gross Revenue Multiplier method for years as a simple but informative measure to value properties (Bjorklund & Soderberg, 1999). This multiplier varies with the location and the type of property (Hinton, 2008). For our analysis, we use a multiplier ranging from 3.5 to 5.0 depending on the hotel franchise affiliation and the market segment it operates in. While it is difficult to accurately assign revenue multiplies to each hotel, hotel owners and brokers use average multiple values based on history and local market conditions. For the Chicago market, our values for the revenue multipliers are shown in Table 2.2 and are based on existing practitioner estimates for FY2018. The revenue multiplier increases as the AAA Diamond rating of the property goes higher. This is because a luxury hotel provides more upscale accommodation and amenities compared to a Mid-Scale Economy hotel. Also, Luxury and Upscale properties are located in more desirable locations, giving it a higher land valuation. Due to desirable locations and high-end services, Luxury and Upscale hotels can command a higher ADR and Occupancy compared to hotels located in other market segments. Table 2.2 shows the estimated multipliers used for each market segment within the Chicago hotel market based on their assigned AAA Diamond rating.

Table 2.4

Revenue Multiplier's

Hotel Market	Revenue Multiplier
MidScaleEconomy	3.5
UpScale	4
Upper UpScale	4.5
Luxury	5

The Cost Approach method of valuation is based on the idea that the hotel is valued at what it would cost to rebuild a new similar property less any depreciation. The major weakness of this method is the fact that this approach ignores a range of dissimilarities. Although all hotels have rooms, many other aspects affect value including, location of the property, onsite restaurants, health clubs, land size, and so forth. For this reason, the Cost Approach is not the preferred method for the market valuation of hotels. As discussed above, the Sales Comparison is Approach uses recently sold comparable properties in related markets to determine the market value of a specific hotel. While this method is commonly used by real estate agents, some of the limitations include, finding similar properties that sold recently, also this approach becomes less reliable if large adjustments have to be made, and is not considered to be the best method for income properties or special purpose properties. The Sales Comparison is commonly used to value single-family homes. Finally, the income approach method for valuation looks at future cash flows to determine the likely revenue streams for the hotel to assess property market values. However, a major weakness of the income approach method is that it is difficult to estimate the hotel's future income cash flows and difficult to predict market uncertainty, which could lead to income fluctuations. For example, the income approach method would not have anticipated the 2007 financial meltdown, which temporarily depressed hotel incomes and their revenues. Also, this method does not accurately forecast the future room supply, leading to inaccurate calculations of future occupancy and ADR rates. With these limitations combine with subjective estimates and unpredictable appraiser assumptions, we have decided to use the revenue multiplier method to value the hotel properties used in our data set.

While the Cost Approach, Sales Allocation, and Income approach methods are intuitively appealing and widely used, hotel owners, operators, and brokers are increasingly turning to the gross revenue multiplier method to value hotel properties due to its simplicity and user-friendly way of assessing property value. The gross revenue multiplier method is a useful tool that helps to compare hotel properties that have different levels of profits but operate in similar business segments. This can be valuable for our research as our data includes hotel properties that operate in a different market segment. Using revenue multiples in valuation estimation helps investors and property owners to quickly estimate market values in relation to the properties they are assessing. This method is particularly useful when appropriate multiples are used in combination with local market values based on gross revenues. The multiples are relevant as they incorporate a key indicator of company financial performace. Additionally, the straightforward and uncomplicated simplicity of the gross revenue multiples method makes it easy to use and analyze. While equity multipliers have been used to value technology and software companies, they are recently gaining popularity as a valuation tool among hotel owners and operators.

Model and Hypothesis

To compare the effect of TripAdvisor user ratings on hotel performance, this study identified one independent variable, two dependent variables, and ten control variables. Table 2.3 illustrates the variables and their measurements.

The STR data include the company's performance metrics such as ADR, RevPAR, and Occupancy rates. In terms of user review ratings, we collected the data from the website TripAdvisor. For TripAdvisor, the ratings are based on a 1-5 scale. ADR and Occupancy are the variables that drive the value of RevPAR. So, if ADR or Occupancy increases RevPAR increases as well, and hence RevPAR was not included in our regression. Given the fact that ADR and Occupancy are popular metrics of hotel valuation and research literature, we selected them as Dependent variables and TripAdvisor user ratings as independent variables to determine whether it can predict the overall ADR and Occupancy of lodging properties. Research by Butler (2001) confirms that seasonality is an unavoidable situation for the tourism and hospitality industry, and it further causes the underutilization and overutilization of hospitality facilities. As we use Chicago, Illinois for our study, its geographic location impacts the ADR and Occupancy of hotels. To study the effect of user ratings on seasonality, we created three Independent dummy variables (FALLD, SPRD, SUMD). Another six Independent dummy variable (TA_LAG1, TA_LAG2, TA_LAG31, TA_LAG4, TA_LAG5, TA_LAG6) were created to study the correlation of TripAdvisor user ratings and the monthly lags for months one through six. The market segment in which the hotel operated was selected in the model as control variables to see if they moderate the relationships. The following regression model and the corresponding hypothesis is proposed for our research:

Table 2.5

Variable	Measures
Control Variables	
Market Segment	The market segment hotel operates in
Dependent Variables	
Occupancy Rate	Rooms Occupied/Total rooms available
ADR	Room revenue/number of rooms sold
MktValue	Based on Gross Room Revenue Multiplier
Independent Variables	
User Ratings	TripAdvisor Customer review rating
FALLD	Seasonality Fall Dummy Variable
SPRD	Seasonality Spring Dummy Variable
SUMD	Seasonality Summer Dummy Variable
TA_LAG1	TripAdvisor User Rating at 1-month Lag
TA_LAG2	TripAdvisor User Rating at 2-month Lag
TA_LAG3	TripAdvisor User Rating at 3-month Lag
TA_LAG4	TripAdvisor User Rating at 4-month Lag
TA_LAG5	TripAdvisor User Rating at 5-month Lag
TA_LAG6	TripAdvisor User Rating at 6-month Lag

H1: User ratings positively affect ADR

Several studies have shown that higher customer ratings and a greater number of online reviews improves business performance indicators like Occupancy and RevPAR (Zhu & Zhang, 2010; Viglia et al., 2016). Higher consumer reviews online can boost hotel performance indicators while lower reviews will produce opposite results (Chevalier & Mayzlin, 2006; Anderson, 2012). Anderson (2012) also reported that for every 1% increase in a property's online rating there was a corresponding increase in hotels occupancy by 0.54% and a 1.42% increase in RevPAR, which includes ADR. We hypothesize that higher online ratings will lead to higher ADR and greater RevPAR, which in turn leads to higher market valuation of hotels.

H2: User ratings positively affect Occupancy Rates

Previous research by Viglia et. Al (2015) and Pelsmacker et. al. (2018) shows the positive effects of eWOM on hotel occupancy rates and performance. Also, customers use online reviews and cues from these reviews to make a purchase (Noone & McGuire, 2013). We hypothesize that a higher TripAdvisor rating is associated with higher Occupancy, leading to higher revenues and in turn positively influencing the market values of hospitality property.

H3: User ratings positively affect Market Value of Hotels

Recent studies have tried to understand how online user reviews affect hotel financial performance. Research by Torres et al. (2015) found that higher overall rating and a large number of reviews lead to higher-value transactions and the generation of more revenue per customer. This leads to higher Occupancy and ADR. We hypothesize that a higher TripAdvisor rating is associated with higher overall revenue generation in turn positively influencing the market values of hospitality property.

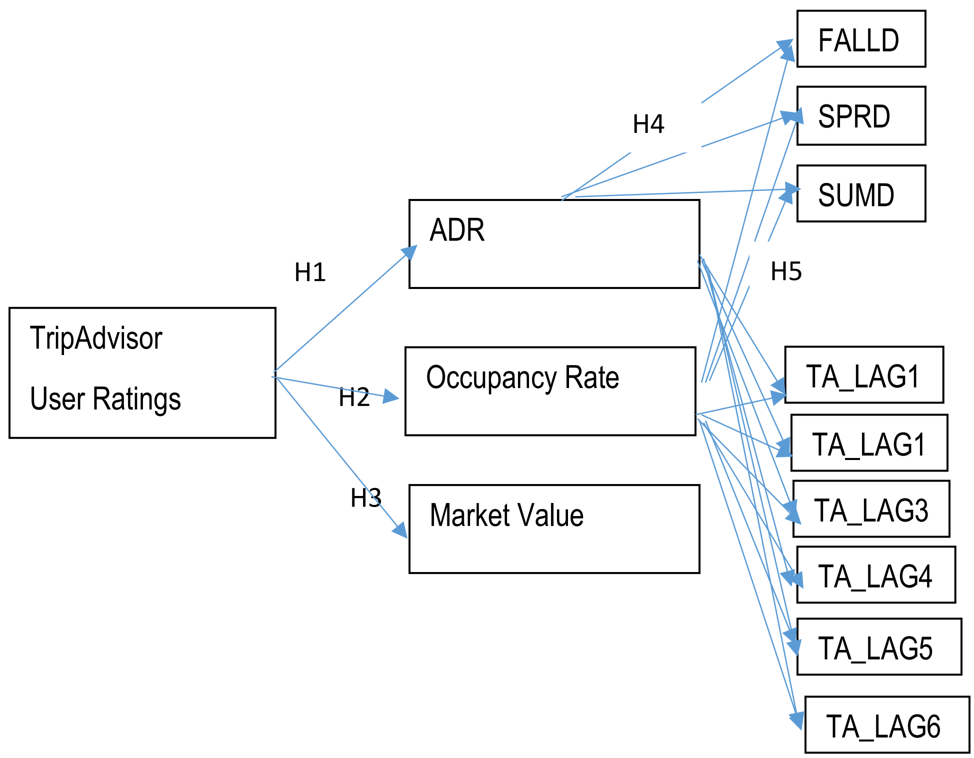
H4: Seasonality positively affects ADR

Seasonality causes high fluctuations in demand during the peak seasons compared to low seasons, which results in hotel rooms being sold at different prices at different times of the seasons. We hypothesize that there is strong positive correlation between seasonality (FALLD, SPRD, SUMD) and ADR.

H5: Seasonality positively affects Occupancy Rates

Coenders et al. (2003) observed that demand for rooms could double during the peak seasons compared to low seasons, affecting the Occupancy rates of hotels. We hypothesize that there is a strong correlation between seasonality (FALLD, SPRD, SUMD) and Occupancy Rates.

Model 1


FALLD
SPRD
SUMD
H4
ADR
H1
H5
TripAdvisor
User Ratings
H2
Occupancy Rate
H3
Market Value
TA_LAG1
TA_LAG1
TA_LAG3
TA_LAG4
TA_LAG5
TA_LAG6

Chapter 3. Method

The purpose of this research project is to determine and understand the factors that impact the valuation of a hotel or lodging establishment in Chicago, Illinois in relation to user-generated online ratings found on TripAdvisor. This will be accomplished by conducting research based on the following query:

> *To what extent can variation in the dependent variables (i.e. ADR, Occupancy, Market Value) be explained by User-Generated Content (i.e. overall user rating)?*

Data

Our research will utilize secondary data downloaded from third-party websites along with hotel property data provided by Smith Travel Research. This helps to reduce cost and time as the data already exists without the need for the researcher to collect new data. (Cowton, 1998; Lazar et al., 2010). While there are advantages of using pre-existing data, there are potential disadvantages of using secondary data as well. As the research does not own or generate their own data, their control over the data is limited. But to ascertain the authenticity of the data, the research will use data from reliable sources such as Smith Travel Research (STR) and TripAdvisor. In our case, hotel property performance reports will be provided by STR and TripAdvisor data will be downloaded from their website.

Smith Travel Research (STR)

STR is a company based in Hendersonville, Tennessee, United States. STR works with hotel owners and operators around to word to acquire proprietary performance metrics from these participating properties. The company works in about 16 countries around the world with its corporate headquarters located in Hendersonville, Tennessee. STR provides data driven performance indicators and trends, which is used to benchmark the property against its competitors. Its international headquarters is in London, England.

We plan to use STR provided data for the hotel market in Chicago for 11 years, dating from January 2008 up through December 2018. STR will provide occupancy, ADR, RevPAR, and revenue data for all the hotels in the Chicago, Illinois market, consisting of 184 hotels. Being a big metropolitan city, Chicago has hotels that operate in every single market segment. This allows us to select hotels operating within different segments for our data.

TripAdvisor

TripAdvisor is the world's largest travel and consumer review platform used by nearly 500 million travelers every month. After it launched in early 2000, TripAdvisor has grown rapidly with travelers and consumers across the globe using its traditional website and mobile phone app to browse more than 800 million user reviews and ratings on more than 9 million hotels, cruises, airlines and restaurants. TripAdvisor makes it easy for consumers and users to compare prices on hotels, flights, cruises and popular attractions. As of 2019 TripAdvisor was operating in 49 countries. Currently TripAdvisor is one of the most popular and leading discussion board for hospitality travelers to share their reviews, comments, and pictures (Jeacle & Carter, 2011). TripAdvisor users trust the reviews written by fellow travelers more than what is presented by hotel owners on their website (Gretzel & Yoo, 2008). Due to this popularity most of the hotel owners now provide potential guest with their hotels TripAdvisor rating right on their own reservation site.

While users must register and verify their identity on TripAdvisor to post reviews, their reviews are available to be viewed by everyone. The reviewer can gain credibility and status based on the number of reviews and providing feedback to community questions.

Data Collection

Chicago Hotel Industry

While the hotel and lodging industry in the US is very large and highly dispersed, for our research we focus on the Chicago hotel industry. Within the last two decades, the Chicago metro area has been experiencing rapid economic growth. Due to its strategic location, more than two dozen Fortune 500 companies have moved their headquarters to the Chicago area creating jobs and growing the local economy. The companies are associated in a variety of segments and industries, including defense, finance, hospitality, food services, and manufacturing. New startup companies are drawn to the Chicago area due to its sprawling transportation infrastructure, dominant location, available manpower, reasonable cost of living, and easily accessible sports, cultural, and entertainment attractions. Several areas of Chicago are experiencing new growth and revitalization. Recently, West Loop, a former manufacturing and meatpacking district, was redeveloped into a new "technology hub" with companies such as Dyson, Google, and Accenture opening new offices. Even McDonald relocated its world headquarters from the suburbs to Downtown Chicago. As such, the city's well established and diversified economy presents growth opportunities for hospitality and related industries. The financial crisis of 2007 led to slow growth in the tourism and hospitality sectors, but that trend began to reverse in in 2012 with steady increase room inventories and new hotel construction. About 12,000 hotel rooms and 37 new hotels have opened in Downtown Chicago since 2015, including a new 1,200-room Marriott Marquis hotel, which opened in late 2017 adjacent to the McCormick Place Convention Center. This growth includes a new wave of boutique hotels coming up in neighborhoods like Fulton Market and Hyde Park, away from the city's traditional hotel district along North Michigan Avenue.

The Chicago hotel industry enjoyed a pretty good year in 2018. According to the hotel-analysis company STR (Smith Travel Research), the Chicago hotel occupancy rate rose from 68 % to 75.2 % in 2017. In Chicago, the average daily rate rose $4.60 to $210.64, RevPar rose $5.40 to $158.27 and total revenue rose 9.4 % to $2.654 billion. Per 2018 STR report Chicago now has 184 providing approximately 46,996 rooms for guest. That is up from 173 hotels and 45,166 rooms at the end of 2017 (Miller, 2019). For 2018, a record of 55 million domestic and international tourists visited Chicago, nearly 2.5 % increase from the 2016 total of 53.8 million. Driven by this surge of visitors, the hotels experienced a 7.6 % year-over-year surge in occupancy for the peak tourist season which usually starts in June and ends by September. Overall, Chicago hotels saw a 3.3 % Occupancy rate growth for 2017.

For our research, data were obtained from two independent sources. The first data set contains user ratings downloaded directly from TripAdvisor.com between the years 2008 - 2018. Expedia, Google, and Yelp all have a significant presence in the online travel review space, but TripAdvisor has the highest number of unique visitors to its site boosting its online presence compared to its competitors. A recent study by Oxford Economics (2017) found that user reviews posted on TripAdvisor encouraged travelers to take additional trips which resulted in longer stays and had a net positive impact on spending per trip. For 2017, TripAdvisor facilitated almost $546 billion (10.3%) of tourism worldwide. According to TripAdvisor, it's ranking of hotels is based on its own proprietary algorithm which is based on quality, recency, and quantity of reviews that users post to its website online. The algorithm is updated periodically to reflect a non-biased and more consistent form of ranking that stresses property performance over time. TripAdvisor uses the bubble rating system from One to Five, where One is the lowest rating that a guest can give to property and Five being the highest. The user ratings directly affect the quality score of the hotel property. TripAdvisor algorithm also places greater weight on the recency of reviews. This ensures that users get the most current information about the hotel. Our original TripAdvisor data included user ratings from 358 hotels located within the City of Chicago. The downloaded data included TripAdvisor user ratings, from a scale of 1 – 5 for every month. A rating of 5 is the highest rating a user can provide, while a rating of 1 is the lowest possible rating for a hotel property. In total, we had approximately 37,000 unique monthly user ratings. Next, we cleaned the TripAdvisor data by selecting hotels that were operational during years 01/2008 – 12/2018. This was done by importing the data to an Excel spreadsheet and sorting the ratings by year and month. Only those hotels were selected that had TripAdvisor rating starting from the year 2008 through 2018. The subset of hotels was further vetted to include only those hotels that had a tangible improvement in their user ratings. These hotel properties were further grouped by the market segments they serve.

The second set of data for our survey was provided by Smith Travel Research. Due to privacy concerns, STR was not able to provide us with individual property data, hence we had to group them by market segments. This list of properties was provided to STR, who grouped the individual hotel performance metrics like ADR, Occupancy, RevPAR, Revenue, and Census Rooms for every month. Table 2.4 provides a summary of the data used.

Table 3.1

Summary of Hotel Properties

Hotel Market Segment	# of Properties	# of TripAdvisor Ratings	Average Property TripAdvisor Ratings for 2008 (Scale 1-5)	Average Property TripAdvisor Ratings for 2008 (Scale 1-5)
Luxury	7	131	3.6	4.4
Upper UpScale	15	255	3.7	4.3
UpScale	6	129	3.4	44
MidScaleEconomy	5	132	2.1	3.9
Total	33	647	3.2	4.25

Data Analysis

As shown in Model 1, our study will use one control variable (Market Segment), ten independent variables, and three dependent variables. The dependent variables include the Average Daily Rate (ADR) and occupancy rate. The ten independent variables include FALLD, SPRD, SUMD, TA_Rat, TA_LAG1, TA_LAG2, TA_LAG3, TA_LAG4, TA_LAG5, and TA_LAG6. The secondary data downloaded from STR will provide us with values for dependent variables. Once the raw data was converted into financial indicators, Excel was used to further manipulate the data to create monthly averages and market values.

Chapter 4. Results and Discussions

Descriptive Statistics

Table 4.1 below provides the means, standard deviations, and correlations between the model variables in our research study. The correlations in Table 4.1 show the significance of our relationships between our dependent variables and TripAdvisor user ratings. The overall TripAdvisor user rating was significantly correlated with ADR (r = .451, p < .001), RevPAR (r = .401, p < .001), Market value of the property (r = .302, p < .001), Room Revenue (r = .297, p < .001) and Occupancy (r = .175, p < .001). As we had discussed in our theoretical section, Occupancy and ADR are influenced by several internal and external factors including star rating of the property, franchise affiliations, location, and seasonality.

Table 4.1

Correlations

	Occupancy	ADR	Revenue	RevPar	MktVal	TA_Rat
Occupancy	1					
ADR	.491**	1				
Revenue	.418**	.642**	1			
RevPar	.751**	.931**	.652**	1		
MktVal	.441**	.657**	.996**	.673**	1	
TA_Rat	.175**	.451**	.297**	.401**	.302**	1

**. Correlations is significant at the 0.01 level (2-tailed), N = 657

Analysis

The normal distribution graph showed that Occupancy and ADR, for all market segments, were normally distributed for our data (n = 657). The exploratory regression analysis between Occupancy/ADR and TripAdvisor user ratings did not detect any heterogeneity and hence linear regression was used. Our empirical model as shown below in Equation 1,2 and 3 includes dummy factors that accounted for seasonality and monthly lags of user ratings against Occupancy and ADR. The sequence chart (Fig. 4.2) below shows the effect of seasonality on Occupancy. The graph displays the seasonality of Occupancy rate against the months of the year for year 2008-2018. We can see from the graph that Occupancy is seasonal and highly corelated to monthly data. Specifically, we coded three dummy variables (FALLD, SPRD, SUMD) to account for the impact of seasonality on user ratings. The seasonality dummy variables were coded with a value of 1 for the months of March, April, May (SPRD), June, July, August (SUMD), and September, October, November (FALLD), and has a value of 0 for all other months. We also coded dummy variables for TripAdvisor user rating Lag. The Lag variables were included for months one through six (TA_LAG1, TA_LAG2, TA_LAG31, TA_LAG4, TA_LAG5, TA_LAG6). The adjusted R^2 of our model improved significantly by adding the above dummy variables. Multicollinearity was also checked, and no significant multicollinearity was found.

Equation - 1

Occupancy = β0 + β1TripAdvisorRating + β2FallMonthsSeasonality + β3SpringMonthsSeasonality + β4SummerMonthsSeasonality + β5TripAdvisorRatings_LAG1 + β5TripAdvisorRatings_LAG2 + β5TripAdvisorRatings_LAG3 + β5TripAdvisorRatings_LAG4+ β5TripAdvisorRatings_LAG5 + β5TripAdvisorRatings_LAG6 +ε0

Equation - 2

ADR = β0 + β1TripAdvisorRating + β2FallMonthsSeasonality + β3SpringMonthsSeasonality + β4SummerMonthsSeasonality + β5TripAdvisorRatings_LAG1 + β5TripAdvisorRatings_LAG2 + β5TripAdvisorRatings_LAG3 + β5TripAdvisorRatings_LAG4+ β5TripAdvisorRatings_LAG5 + β5TripAdvisorRatings_LAG6 +ε1

Equation - 3

MltVal = β0 + β1TripAdvisorRating + β2FallMonthsSeasonality + β3SpringMonthsSeasonality + β4SummerMonthsSeasonality + β5TripAdvisorRatings_LAG1 + β5TripAdvisorRatings_LAG2 + β5TripAdvisorRatings_LAG3 + β5TripAdvisorRatings_LAG4+ β5TripAdvisorRatings_LAG5 + β5TripAdvisorRatings_LAG6 +ε0

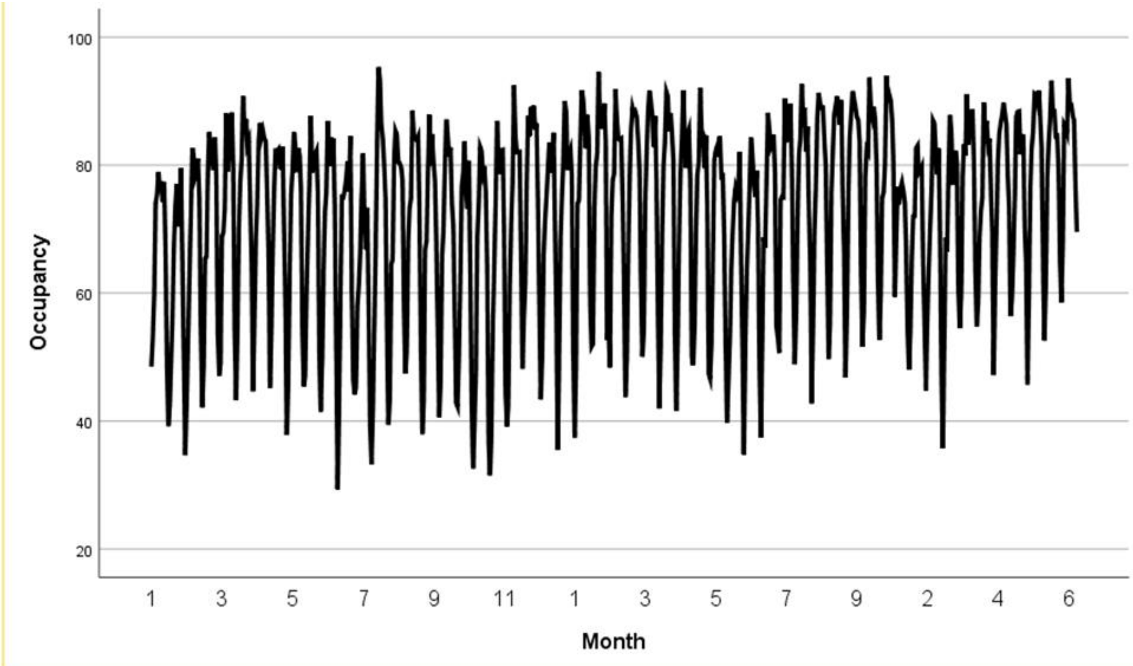


Figure 4.2

H1: User ratings positively affect ADR

Table 4.3 below provides the estimates of regression analysis against the determinants of ADR. We can see that where the relationship between ADR and TripAdvisor is positive, it is strongest at the lags of three (B = 19.45, $p < .001$) and four months (B = 17.47, $p < .001$). The data did not support a strong relation for hotel properties operating in the Upscale and Mid-Scale Economy segment.

H2: User ratings positively affect Occupancy Rates

Table 4.4 below provides the estimates of regression analysis against the determinants of Occupancy. As was the case in Hypotheses H1, we again see that where the relationship between ADR and TripAdvisor is positive, it is strongest at the lags of three (B = 3.94, $p < .001$) and four months (B = 6.78, $p < .001$).

H3: User ratings positively affects Market Value of Hotels

Table 4.5 below provides the estimates of regression analysis against the determinants of Market value. As was the case in Hypotheses H1 and H2, we again see that where the relationship between Market Value of hotel and TripAdvisor is positive, it is strongest at the lags of two ($p < .001$) and four months ($p < .001$).

H4: Seasonality positively affects ADR

Table 4.3 below provides the estimates of regression analysis against the determinants of ADR. We can see that the relationship between ADR and seasonality (FALLD, SPRD, SUMD) is positive, and strong across all the market segments with FALLD ($B = 86.80$, $p < .001$), SPRD ($B = 56.16$, $p < .001$), SUMD ($B = 83.57$, $p < .001$) for Upscale properties.

H5: Seasonality positively affects Occupancy Rates

Table 4.4 below provides the estimates of regression analysis against the determinants of Occupancy Rate. We can see that the relationship between Occupancy and seasonality (FALLD, SPRD, SUMD) is positive, and strong across all the market segments with FALLD ($B = 30.51$, $p < .001$), SPRD ($B = 23.72$, $p < .001$), SUMD ($B = 35.85$, $p < .001$) for Upper Upscale properties

Tables 4.3 – ADR

ADR/Luxury

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.	F	*df*
	B	Std. Error	Beta			
Model					15.09	*125*
(Constant)	39.71	43.687		0.365		
FALLD	80.172	7.733	0.811	.000**		
SPRD	42.535	8.009	0.417	.000**		
SUMD	66.831	7.944	0.669	.000**		
TA_Rat	-8.479	9.709	-0.071	0.384		
TA_LAG1	-5.94	10.876	-0.05	0.586		
TA_LAG2	9.088	10.568	0.076	0.392		
TA_LAG3	9.749	10.734	0.083	0.366		
TA_LAG4	27.693	10.128	0.234	0.007		
TA_LAG5	-4.326	9.658	-0.039	0.655		
TA_LAG6	14.735	8.965	0.136	0.103		

Notes.

a. Dependent Variable: ADR
b. R^2 = .568
c. **. Correlations is significant at the 0.01 level (2-tailed)

ADR/Upper UpScale

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.	F	*df*
	B	Std. Error	Beta			
Model					61.73	*251*
(Constant)	42.897	17.041		0.012		1
FALLD	83.551	3.763	0.959	.000**		
SPRD	49.79	3.992	0.553	.000**		
SUMD	64.158	3.825	0.729	.000**		
TA_Rat	-3.477	5.464	-0.033	0.525		
TA_LAG1	-14.866	5.337	-0.142	0.006		
TA_LAG2	1.066	5.066	0.011	0.834		
TA_LAG3	19.452	5.19	0.2	0		
TA_LAG4	17.476	5.129	0.181	0.001		
TA_LAG5	8.797	5.297	0.092	0.098		
TA_LAG6	-5.764	5.074	-0.061	0.257		

Notes.

a. Dependent Variable: ADR
b. $R^2 = .719$
c. **. Correlations is significant at the 0.01 level (2-tailed)

ADR/Upscale

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					24.44	*122*
(Constant)	-113.949	50.731		0.027		
FALLD	86.808	7.044	0.878	.000**		
SPRD	56.161	7.056	0.556	.000**		
SUMD	83.574	6.655	0.827	.000**		
TA_Rat	-0.296	7.041	-0.002	0.967		
TA_LAG1	10.662	6.879	0.087	0.124		
TA_LAG2	14.821	6.791	0.121	0.031		
TA_LAG3	13.299	6.733	0.113	0.051		
TA_LAG4	8.839	6.548	0.08	0.18		
TA_LAG5	7.612	6.138	0.071	0.218		
TA_LAG6	0.509	6.037	0.005	0.933		

Notes.

d. Dependent Variable: ADR
e. R^2 = .686
f. **. Correlations is significant at the 0.01 level (2-tailed)

ADR/MidScale Economy

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.	F	*df*
	B	Std. Error	Beta			
Model					33.11	*125*
(Constant)	45.201	7.332		.000**		
FALLD	48.71	3.529	0.845	.000**		
SPRD	31.764	3.696	0.534	.000**		
SUMD	52.907	3.446	0.909	.000**		
TA_Rat	-5.74	3.396	-0.146	0.094		
TA_LAG1	5.328	3.304	0.136	0.11		
TA_LAG2	0.243	3.178	0.006	0.939		
TA_LAG3	-0.148	3.449	-0.004	0.966		
TA_LAG4	3.099	3.302	0.083	0.35		
TA_LAG5	3.529	3.197	0.1	0.272		
TA_LAG6	4.727	3.052	0.134	0.124		

Notes.

a. Dependent Variable: ADR
b. R^2 = .742
c. **. Correlations is significant at the 0.01 level (2-tailed)

Tables 4.4 - Occupancy

Occupancy/Luxury

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					*79.9*	*125*
(Constant)	-8.235	7.804		0.294		
FALLD	29.49	1.381	0.901	.000**		
SPRD	21.629	1.431	0.64	.000**		
SUMD	33.158	1.419	1.003	.000**		
TA_Rat	1.606	1.734	0.04	0.357		
TA_LAG1	0.798	1.943	0.02	0.682		
TA_LAG2	3.344	1.888	0.084	0.079		
TA_LAG3	1.959	1.918	0.05	0.309		
TA_LAG4	6.785	1.809	0.173	0		
TA_LAG5	-3.153	1.725	-0.085	0.07		
TA_LAG6	1.911	1.601	0.053	0.235		

Notes.

a. Dependent Variable: Occupancy
b. $R^2 = .874$
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/Upper UpScale

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					*168.47*	*251*
(Constant)	14.838	4.398		0.001		
FALLD	30.516	0.971	0.906	.000**		
SPRD	23.721	1.03	0.682	.000**		
SUMD	35.853	0.987	1.054	.000**		
TA_Rat	1.909	1.41	0.047	0.177		
TA_LAG1	-0.619	1.377	-0.015	0.654		
TA_LAG2	3.106	1.307	0.081	0.018		
TA_LAG3	3.942	1.339	0.105	0.004		
TA_LAG4	1.368	1.324	0.037	0.302		
TA_LAG5	2.003	1.367	0.054	0.144		
TA_LAG6	-2.32	1.309	-0.063	0.078		

Notes.

a. Dependent Variable: Occupancy
b. R^2 = ..875
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/UpScale

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					*51.62*	*122*
(Constant)	-21.474	11.43		0.063		
FALLD	22.806	1.587	0.771	.000**		
SPRD	20.174	1.59	0.668	.000**		
SUMD	29.915	1.499	0.99	.000**		
TA_Rat	3.98	1.586	0.109	0.014		
TA_LAG1	5.723	1.55	0.156	0		
TA_LAG2	2.427	1.53	0.066	0.115		
TA_LAG3	2.05	1.517	0.058	0.179		
TA_LAG4	2.532	1.475	0.077	0.089		
TA_LAG5	2.707	1.383	0.084	0.053		
TA_LAG6	-0.382	1.36	-0.013	0.78		

Notes.

a. Dependent Variable: Occupancy
b. $R^2 = .822$
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/MidScaleEconomy

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					*57.06*	*125*
(Constant)	38.689	3.829		.000**		
FALLD	32.342	1.843	0.867	.000**		
SPRD	24.437	1.93	0.635	.000**		
SUMD	39.925	1.799	1.059	.000**		
TA_Rat	-1.538	1.774	-0.061	0.388		
TA_LAG1	4.345	1.725	0.171	0.013		
TA_LAG2	-0.388	1.66	-0.015	0.816		
TA_LAG3	-0.395	1.801	-0.016	0.827		
TA_LAG4	2.057	1.725	0.085	0.235		
TA_LAG5	-2.287	1.67	-0.1	0.173		
TA_LAG6	-0.446	1.594	-0.02	0.78		

Notes.

a. Dependent Variable: Occupancy
b. $R^2 = .832$
c. **. Correlations is significant at the 0.01 level (2-tailed)

Tables 4.5 – Market Value

MktVlu/Luxury

Coefficients[a]

	Unstandardized Coefficients		Std Coefficient	Sig.		
	B	Std. Error	Beta		F	*df*
Model					3.3	125
(Constant)	-87943726.06	22551809.87		.000**		
FALLD	61560219.74	3992065.064	0.89	.000**		
SPRD	39490944.73	4134602.985	0.553	.000**		
SUMD	62562907.4	4100776.161	0.896	.000**		
TA_Rat	159854.659	5012197.803	0.002	0.975		
TA_LAG1	-3711923.118	5614341.438	-0.044	0.51		
TA_LAG2	7995801.33	5455314.121	0.096	0.145		
TA_LAG3	4283070.922	5541062.694	0.052	0.441		
TA_LAG4	18818538.44	5228286.254	0.228	0		
TA_LAG5	-4384971.828	4985474.901	-0.056	0.381		
TA_LAG6	8966373.969	4627721.242	0.118	0.055		

Notes.

a. Dependent Variable: MktVlu
b. $R^2 = .764$
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu /Upper UpScale

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					6.86	251
(Constant)	-48053367.84	38204932.96		0.21		
FALLD	58361701.88	8437091.009	0.497	.000**		
SPRD	38782109.45	8949495.544	0.32	.000**		
SUMD	54995028.01	8576368.558	0.464	.000**		
TA_Rat	379541.697	12249713.57	0.003	0.975		
TA_LAG1	-7905243.581	11965893.6	-0.056	0.509		
TA_LAG2	1759436.541	11357525	0.013	0.877		
TA_LAG3	13215770.96	11635976.89	0.101	0.257		
TA_LAG4	9636066.117	11499428.81	0.074	0.403		
TA_LAG5	6403078.938	11875853.77	0.05	0.59		
TA_LAG6	-2295436.932	11376469.97	-0.018	0.84		

Notes.

a. Dependent Variable: MktVlu
b. $R^2 = .222$
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu /UpScale

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					31.85	122
(Constant)	-43654566.56	9622497.789		.000**		
FALLD	17231205.33	1336043.68	0.836	.000**		
SPRD	12302971.02	1338410.263	0.584	.000**		
SUMD	19251283.43	1262376.9	0.914	.000**		
TA_Rat	791954.758	1335525.739	0.031	0.554		
TA_LAG1	2486577.512	1304875.68	0.098	0.059		
TA_LAG2	2672649.357	1288003.78	0.105	0.04		
TA_LAG3	2567991.349	1277163.338	0.105	0.047		
TA_LAG4	2107536.867	1241959.083	0.092	0.092		
TA_LAG5	2292998.452	1164263.932	0.102	0.051		
TA_LAG6	370491.026	1145059.306	0.018	0.747		

Notes.

a. Dependent Variable: MktVlu
b. R^2 = .740
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu / MidScaleEconomy

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients	Sig.		
	B	Std. Error	Beta		F	*df*
Model					49.19	125
(Constant)	97919.307	585921.63		0.868		
FALLD	4539297.3	282050.43	0.845	.000**		
SPRD	3044787.3	295368.91	0.549	.000**		
SUMD	5555879.4	275370.16	1.024	.000**		
TA_Rat	-346914.17	271418.73	-0.095	0.204		
TA_LAG1	526446.41	264037.8	0.144	0.049		
TA_LAG2	55836.069	253991.21	0.015	0.826		
TA_LAG3	-181682.55	275609.03	-0.051	0.511		
TA_LAG4	420208.08	263922.05	0.12	0.114		
TA_LAG5	-3741.089	255504.27	-0.001	0.988		
TA_LAG6	261555.21	243931.9	0.08	0.286		

Notes.

a. Dependent Variable: MktVlu
b. $R^2 = .811$
c. **. Correlations is significant at the 0.01 level (2-tailed)

Chapter 5. Conclusions

Implications for Research

Hospitality and lodging enterprises rely on various approaches to estimate the value of their property and assets. Depending on the type of asset and its functionality, some approaches are formal, based on pre-established theories and models while others are informal, operated by ad-hoc rules of thumb. These valuation techniques have their benefits and limitations based on the inherent complexity and the variations within each evaluation techniques. The overall valuation of hotel properties can be influenced by external factors such as location, market competition, economic conditions (Hospitality Marketing Management, 2014) and internal factors like cash flows, productivity levels, number of rooms, payroll expenses, and the quality of service provided (Ruggero, 2010). While there have been various studies where user-generated reviews on TripAdvisor have been used to understand the impacts of online reputation on overall hotel performance as measured by revenue per available room (RevPAR) (Anderson, 2016), our study focuses on the impact of hotel ratings from TripAdvisor and Smith Travel Research (STR) on hotel market values. Our research findings suggest an additional external factor (user-generated TripAdvisor ratings) that influences the market value of hotel properties. The information can be used by real estate brokers, investors, hedge funds to value hospitality properties more accurately. This can also guide existing property operators to estimate the returns on renovations and its corresponding effect on market values. The study also found an interesting relation between occupancy/ADR rates and user ratings lag. From our results, we can see that there is a strong positive correlation between ADR and seasonality ($p < .001$) for all the different market segments. Additionally, for the Luxury segment, the correlations between TripAdvisor user ratings and ADR is positive and strong at a lag of 4 months ($p = .007$). Similar results were found for hotels operating in the Upper Up Scale market segment where the relations is positive with TripAdvisor ratings lag at 3 ($p < .001$) and 4 ($p < .001$) months. The data did not support a strong relation for hotel properties operating in the Upscale and Mid-Scale Economy segment. Our results also suggest a strong positive correlation between Occupancy and seasonality ($p < .001$) for all the different market segments. Within the Luxury segment, the correlations between TripAdvisor user ratings and Occupancy is positive and strong at a lag of 4 months ($p = .007< .001$). Similar results were found for hotels operating in the Upper Up Scale market segment where the relations is positive with TripAdvisor ratings lag at 3 months ($p = .004$). The data also support's a strong relation for hotel properties operating in the Upscale ($p < .001$ and Mid-Scale Economy ($p = .013$) segment. This information can be used by the property manager and management companies to effectively manage Average Daily rates and Occupancy rates and increase property performance. This study can easily be replicated in other markets to assess the effect of user-generated ratings on hotel valuations.

Implications for Practice

Our research findings suggest an additional external factor (user-generated TripAdvisor ratings) that influences the market value of hotel properties. The information can be used by real estate brokers, investors, hedge funds to value hospitality properties more accurately. Also, this can guide existing property operators to estimate the returns on renovations and its corresponding effect on market values.

Limitations

Like any other research, this study also has its limitations. While our research contributes to the emerging field of UGC and its influence on hotel market valuation, especially with ADR and Occupancy having a significant correlation to TripAdvisor Ratings. As our research was limited only to the Chicago, Illinois market, our results may not reflect the market valuations in other major cities within the United States. The modeling was done with available accommodation data related to Chicago, IL which can be influenced by the socio-economic environment. Any changes in the economic variable or to supply of room availability can change the estimated elasticity in our study.

Our research primarily relied on data supplied to us by STR and TripAdvisor.com. While STR is the industry-leading provider or hospitality analytical data, TripAdvisor with more than 463 million unique monthly visitors is the world’s leading user review website. While STR collects data directly from their partner hospitality properties, TripAdvisor is sometimes not perceived as a reliable source of data due to a lack of customer validation procedures. A 2017 study by Agusaj et. al. shows that TripAdvisor reviews are just as reliable as Booking.com which uses customer validation procedures before letting users post their reviews and feedback. Additionally, results may be biased as we only reviewed one city within the US, had we included data from diverse cities or even international locations we may have had different results.

Our data set includes hotel information from January 2008 to December 2018. This represents information of 33 hotel properties within five market segments representing approximately 14,000 rooms. This may present a minor limitation as we used data for only 18% of the total hotel rooms in Chicago. Had we included all the hotels within the City of Chicago, we may have obtained different results.

Finally, our study used hotel ratings on TripAdvisor only. But recently, many TripAdvisor competitors like Expedia, Booking.com, and Yelp have created their rating websites. We did not include the user ratings from these websites. Thus, this limitation may have led to different results for the various demographics of customers who tend to use different online rating websites for their feedback. In addition, fake reviews and ratings are also limitations for researchers since there is no easy way to remove these postings from our dataset.

Future Directions

Future research may include analysis of hotels located within different cities around the country and including hospitality properties from international markets. This study could explore and include qualitative data to elicit more detailed insight like demographics and user perceptions. Another potential future direction may include adding data from more than one website. For our analysis we used TripAdvisor, future research may consider including user ratings from Expedia, Booking.com, and Yelp. This may reveal additional factors and rating biases as well.

Future research may also further explore the seasonality of the hotel occupancy within the various markets. Another area is the correlation between user ratings and the monthly lag. As our research shows there seems to be a lag of 2-6 months between when the rating is posted on the website to ADR and Occupancy. Future research may want to study the parallels between stock price drifts post-earnings announcement and hotel valuation post-consumer reviews.

General Conclusions

By evaluating the relationships between user-generated ratings and its effect on market values as measured by ADR and Occupancy rates, our results provided strong support to the correlation that exists between user-generated ratings and the market value of the property. This curvilinear nature of the relationship allows the practitioners to look at property valuations not only based on its future cash flows, but also consider user ratings when evaluating and valuing properties that are underperforming or underrated by users. As the market segment was a significant moderator, the practitioners can customize the effect of user ratings for different markets the property operates in.

References

Abdullah, A., & Hamdan, M. (2012), Internal success factor of hotel occupancy rate, *International Journal of Business and Social Science,* Vol. *3* No. 22

Abrate, G., Fraquelli, G., Viglia, G. (2012). Dynamic pricing strategies: Evidence from european hotels. *International Journal of Hospitality Management. 31*. 160–168.

American Hotel & Lodging Association. (2015). *U.S. hotel industry: Driving growth, jobs & the economy.* http://ahla.com/sites/default/files/Driving%20Growth%2C%20Jobs%20and%20the%20Economy.pdf

Anderson, C. (2012). The impact of social media on lodging performance. *Cornell Hospitality Report, 12*(15), 6-11.

Arndt, J. (1967). Role of product—Related conversations in the diffusion of a new product. *Journal of Marketing Research*, 4, 291-295.

Bagdan, P. (2013). *Guest service in the hospitality industry*. John Wiley & Sons Inc

Barros, C., (2005). Measuring efficiency in the hotel sector. *Annals of Tourism Research*, 32. 456-477.

Baum, J., & Mezias, S. (1992). Localized competition and organizational failure in the manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, 37(4), 580-604.

Baum, J., & Haveman, H. (1997). Love thy neighbor? Differentiation and agglomeration in the manhattan hotel industry, 1898-1990. *Administrative Science Quarterly,* 42(2), 304-338.

Bardi, J. (2007). *Front office management 5th edition,* John Wiley & Sons, Inc New Jersey.

Belobaba, P. (2005). Air travel demand and airline seat inventory management. Thesis (Ph. D.). *Massachusetts Institute of Technology, Dept. of Aeronautics and Astronautics*, 1987.

Berger, J., Sorensen. A., & Rasmussen, S. (2010)., Positive effects of negative publicity: when negative reviews increase sales. *Marketing Science*, 29. 815-827.

Bjorklund, K., & Soderberg, B. (1999). Property cycles, speculative bubbles, and the gross income multiplier. *Journal of Real Estate Research*, Vol. 18, No. 1, 151-174.

Blal, I., & Sturman, M. C. (2014). The differential effects of the quality and quantity of online reviews on hotel room sales. *Cornell* Hospitality Quarterly, 55(4), 365-375

Blomberg-Nygard, A., & Anderson, C. (2016). United nations world tourism organization study on online guest reviews and hotel classification systems: An Integrated Approach. *Service Science*., 8, 139-151.

Brown, J., Broderick, A. J., & Lee, N. (2007). Word of mouth communication within online communities: Conceptualizing the online social network. *Journal of Interactive eMarketing*, 21(3), 2–20.

Butler, R.W. (2001). Seasonality in tourism: issues and implications. *Advances in Tourism Research*, 5–21.

Cassee, E., & Reuland, R. (1983). *The management of hospitality*. Oxford, Pergamon.

Chang, K., Liao, S., & Hsu. H. (2019). OTA's selection for hot spring hotels by a hybrid MCDM model. *Mathematical Problems in Engineering*.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.

Chintagunta, P., Gopinath, S., & Venkataraman, Sriram. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science,* 29, 944-957.

Chung, J., & Buhalis, D. (2008). Information needs in online social networks. *Information Technology and Tourism*, Vol.10(4), 267-282.

Chung, W., & Kalnins, A. (2001**).** Agglomeration effects and performance: A test of the texas lodging industry. *Strategic Management Journal*, 22. 969 - 988.

Coenders, G., Espinet, J., Saez, M. (2003). Predicting random level and seasonality of hotel prices: a latent growth curve approach. *Tourism. Analysis*, 8 (1), 15–31.

Cowton, C. J. (1998). The use of secondary data in business ethics research. SpringerLink, 17(4), 423–434.

Cox, C., Burgess, S., Sellitto, C., & Buultjens, J. (2009). The role of user-generated content in tourists' travel planning behavior*. Journal of Hospitality Marketing & Management,* 18. 743-764.

Cser, K., & Ohuchi, A. (2008). World practices of hotel classification systems. *Asia Pacific Journal of Tourism Research*, 13. 379-398.

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, 49(10):1407–1424.

Guillet, B. D., & Law, R. (2010). Analyzing hotel star ratings on third-party distribution websites. *International Journal of Contemporary Hospitality Management*. 22. 797-813.

Elgonemy, A. (2000). The pricing of lodging stocks: A reality check*. Cornell Hotel and Restaurant Administration Quarterly*. 41. 18-28.

Falk, M., & Hagsten, E. (2015). E-Commerce trends and impacts across europe. *International Journal of Production Economics*. 170. 357-369.

Fang, Z., Phang. C., Andrews, M., & Luo. X. (2014). Mobile targeting. *Management Science*, Vol. 60, No. 7, 1738-1756, June 2014

Fotis, J., Buhalis, D., & Rossides, N. (2012). Social media use and impact during the holiday travel planning process. *Information and Communication Technologies in Tourism*.

Filieri, R., McLeay, F., Tsui, B., & Lin, Z. (2018). Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services. *Information & Management*.

Gretzel, U., & Yoo, K. (2008). Use and impact of online travel reviews. *Information and Communication Technologies in Tourism,* 2008. 35-46.

Gupta, S., & Kim, H. (2004). Virtual community: Concepts, implications, and future research directions. *In Proceedings of the Tenth Americas Conference on Information Systems*, 2679-2687.

Jeacle, I., & Carter, C. (2011). In TripAdvisor we trust: rankings, calculative regimes, and abstract systems. *Accounting Organizations and Society*.

Katz E., & Lazarsfeld P, F. (1966). *Personal influence: The part played by people in the flow of mass communications.* Transaction Publishers.

Lazar, J., & Feng, J. H., & Hochheiser, H. (2010). *Research methods in human-computer interaction.* Wiley Publishing.

Lee, H., Law, R., & Murphy, J. (2011). Helpful reviewers in TripAdvisor, online travel community. *Journal of Travel & Tourism Marketing*. 28. 675-688.

Lesser, D. H. (1992). Property-tax valuation of lodging properties. *Cornell Hotel and Restaurant Administration Quarterly*, 33(1), 73–81.

Litvin, S., Goldsmith, R., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism Management. *Tourism Management*. 29. 458-468.

Melnik, M., and Alm, J. (2002). Does a seller's e-commerce reputation matter? Evidence from ebay auctions. Journal of Industrial Economics.

Miller, B. (2019). Chicago hotel industry enjoys a good 2018.

https://www.bizjournals.com/chicago/news/2019/01/23/chicago-hotel-industry-enjoys-a-good-2018.html

Nilsson, M., Harris, P., and Kett, R. (2002). Valuing hotels as business entities. *Journal of Leisure Property,* 2 (1), 17 – 28.

O'Connor, P., & Murphy, J. (2008). Hotel yield management practices across multiple electronic distribution channels. *Journal of IT & Tourism*.

Resnick, P. & Zeckhauser, R. (2002). Trust among strangers in internet transactions: Empirical analysis of eBay's reputation system. *Advances in Applied Microeconomics*, Vol. 11, 127-157.

Resnick, P., Zeckhauser, R., Swanson, J., & Lockwood, K. (2006). The value of reputation on eBay: A controlled experiment. *Experimental Economics*, 9(2):79–101.

Rushmore, S. (1975). How much is your place worth? A case study in hotel-motel valuation. *Cornell Hotel and Restaurant Administration Quarterly*, 16 (1), 38 – 48.

Rushmore, S. (1992). Seven current hotel-valuation techniques. *Cornell Hotel and Restaurant Administration Quarterly*, 33(4), 49–56.

Rushmore, S. (1992b). The valuation of distressed hotels. *Cornell Hotel and Restaurant Administration Quarterly*, 33 (5), 61 – 71.

Ruggero, S. (2010). Hotel performance: state of the art. *International Journal of Contemporary Hospitality Management*.

Sikich, F. (1993). Business valuations: from the accountant's perspective. *The Bottomline*. 8 (2), 14 – 18.

Sizing Worldwide Tourism Spending (or "GTP") & TripAdvisor's Economic Impact. (2017). https://www.tourismeconomics.com/case-studies/sizing-worldwide-tourism-spending-or-gtp-tripadvisors-economic-impact/

Smith, A., Fischer, E., & Yongjian, C. (2012). How does brand-related user-generated content differ across YouTube, Facebook, and Twitter?. *Journal of Interactive Marketing*, 26. 102–113.

Stefanelli, J. M. (1982). Buying or selling a restaurant: how to set the price. *Cornell Hotel and Restaurant Administration quarterly*, 23 (3), 80 – 92

Tanaka, J. (1980). *The san hunter-gatherers of the kalahari: A study in ecological anthropology* University of Tokyo Press.

Toh, R., DeKay, C., & Raven, P. (2011). Travel Planning: Searching for and booking hotels on the Internet. *Cornell Hospitality Quarterly*, 52. 388-398.

Torres, E., Singh, D., & Robertson-Ring, A. (2015). Consumer reviews and the creation of booking transaction value: lessons from the hotel industry. *International Journal of Hospitality Management,* 50. 77-83.

US digital ad spending to top $37 Billion in 2012 as market consolidates. (2012, September 12). https://www.emarketer.com/newsroom/index.php/digital-ad-spending-top-37-billion-2012-market-consolidates/

Walsh, C. B., & H. B. Staley. 1993. Considerations in the valuation of hotels. *Appraisal Journal*, 61:348-56.

Wirtz, J., Kimes, S. E., Theng, J. H. P., & Patterson, P. (2003). Revenue management: Resolving potential customer conflicts. http://scholarship.sha.cornell.edu/articles/849

Appendix

Hotel Industry Terms

ADR	*Average Daily Rate. A measure of the average rate paid for rooms sold, calculated by dividing room revenue by rooms sold.*
AAA	*The American Automobile Association is a federation of motor clubs in the United States. Members of AAA can often get discounts on hotel stays. AAA gives members information on more than 27,000 inspected and approved hotels that all meet AAA's standards for cleanliness, comfort, and hospitality.*
Chain Scales	*Chain scale segments are a method by which branded hotels are grouped based on the actual average room rates. Independent hotels, regardless of their average room rates, are included as a separate chain-scale category.*
Franchisor	*A company that sells franchises.*
Franchisee	*An individual or company buying or leasing a franchise.*
FF&E	*Furniture, Fixtures, and Equipment - often referred to as FF&E, these are the hard-good items found in a hotel.*
OTA	*Online Travel Agency, an Internet-based hotel and travel reservations system. Hotels typically provide inventory to*

	OTAs, which sell the rooms in exchange for a commission.
Occupancy	*Occupancy is the percentage of available rooms that were sold during a specified period. Occupancy is calculated by dividing the number of rooms sold by rooms available.*
RevPAR	*Revenue per available room (RevPAR) is the total guest room revenue divided by the total number of available rooms. RevPAR differs from ADR because RevPAR is affected by the amount of unoccupied available rooms, while ADR shows only the average rate of rooms sold.*
Room Revenue	*Total room revenue generated from the sale or rental of rooms.*
USALI	*First published in 1926, the Uniform System of Accounts for the Lodging Industry provides hotel owners, managers and others with operational information pertaining to the lodging industry.*
UGC	*User Generated Reviews*
WOM	*Word of Mouth*
eWOM	*Electronic Word of Mouth*

Regression Tables

ADR/Luxury (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	39.710	43.687		.909	.365					
FALLD	80.172	7.733	.811	10.367	.000	.456	.695	.636	.614	1.627
SPRD	42.535	8.009	.417	5.311	.000	-.106	.444	.326	.610	1.638
SUMD	66.831	7.944	.669	8.413	.000	.221	.617	.516	.594	1.683
TA_Rat	-8.479	9.709	-.071	-.873	.384	.156	-.081	-.054	.572	1.748
TA_LAG1	-5.940	10.876	-.050	-.546	.586	.237	-.051	-.033	.456	2.192
TA_LAG2	9.088	10.568	.076	.860	.392	.263	.080	.053	.481	2.078
TA_LAG3	9.749	10.734	.083	.908	.366	.272	.084	.056	.455	2.199
TA_LAG4	27.693	10.128	.234	2.734	.007	.263	.247	.168	.512	1.954
TA_LAG5	-4.326	9.658	-.039	-.448	.655	.155	-.042	-.027	.500	1.998
TA_LAG6	14.735	8.965	.136	1.644	.103	.137	.152	.101	.552	1.810

a. Dependent Variable: ADR
b. R^2 = .568, F = 15.09, *df* = 125
c. **. Correlations is significant at the 0.01 level (2-tailed)

ADR/Upper UpScale (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	42.897	17.041		2.517	.012					
FALLD	83.551	3.763	.959	22.201	.000	.496	.820	.758	.625	1.601
SPRD	49.790	3.992	.553	12.473	.000	.009	.626	.426	.592	1.690
SUMD	64.158	3.825	.729	16.771	.000	.221	.734	.572	.617	1.621
TA_Rat	-3.477	5.464	-.033	-.636	.525	.028	-.041	-.022	.425	2.353
TA_LAG1	-14.866	5.337	-.142	-2.785	.006	.069	-.177	-.095	.447	2.238
TA_LAG2	1.066	5.066	.011	.210	.834	.151	.014	.007	.444	2.252
TA_LAG3	19.452	5.190	.200	3.748	.000	.229	.235	.128	.409	2.447
TA_LAG4	17.476	5.129	.181	3.407	.001	.188	.214	.116	.414	2.416
TA_LAG5	8.797	5.297	.092	1.661	.098	.142	.106	.057	.382	2.619
TA_LAG6	-5.764	5.074	-.061	-1.136	.257	.109	-.073	-.039	.404	2.474

a. Dependent Variable: ADR
b. R^2 = .719, F = 61.73, *df* = 251
c. **. Correlations is significant at the 0.01 level (2-tailed)

ADR/Upscale (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	-113.949	50.731		-2.246	.027					
FALLD	86.808	7.044	.878	12.324	.000	.419	.759	.653	.553	1.810
SPRD	56.161	7.056	.556	7.959	.000	-.037	.601	.422	.575	1.740
SUMD	83.574	6.655	.827	12.557	.000	.347	.765	.665	.646	1.548
TA_Rat	-.296	7.041	-.002	-.042	.967	.193	-.004	-.002	.839	1.193
TA_LAG1	10.662	6.879	.087	1.550	.124	.244	.145	.082	.886	1.128
TA_LAG2	14.821	6.791	.121	2.183	.031	.181	.202	.116	.908	1.101
TA_LAG3	13.299	6.733	.113	1.975	.051	.050	.183	.105	.857	1.166
TA_LAG4	8.839	6.548	.080	1.350	.180	-.003	.127	.072	.795	1.258
TA_LAG5	7.612	6.138	.071	1.240	.218	.038	.116	.066	.859	1.164
TA_LAG6	.509	6.037	.005	.084	.933	.091	.008	.004	.754	1.325

a. Dependent Variable: ADR
b. R^2 = .686, F = 24.44, *df* = 122
c. **. Correlations is significant at the 0.01 level (2-tailed)

ADR/MidScale Economy (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Sd Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	45.201	7.332		6.165	.000					
FALLD	48.710	3.529	.845	13.802	.000	.364	.790	.653	.598	1.673
SPRD	31.764	3.696	.534	8.594	.000	-.046	.625	.407	.581	1.722
SUMD	52.907	3.446	.909	15.354	.000	.419	.820	.727	.640	1.563
TA_Rat	-5.740	3.396	-.146	-1.690	.094	.212	-.156	-.080	.299	3.347
TA_LAG1	5.328	3.304	.136	1.613	.110	.241	.149	.076	.316	3.168
TA_LAG2	.243	3.178	.006	.077	.939	.249	.007	.004	.332	3.013
TA_LAG3	-.148	3.449	-.004	-.043	.966	.194	-.004	-.002	.276	3.617
TA_LAG4	3.099	3.302	.083	.938	.350	.189	.087	.044	.288	3.472
TA_LAG5	3.529	3.197	.100	1.104	.272	.245	.102	.052	.275	3.643
TA_LAG6	4.727	3.052	.134	1.549	.124	.269	.143	.073	.299	3.346

a. Dependent Variable: ADR
b. R^2 = .742, F = 33.11, *df* = 125
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/Luxury (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Sd Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	-8.235	7.804		-1.055	.294					
FALLD	29.490	1.381	.901	21.347	.000	.359	.894	.706	.614	1.627
SPRD	21.629	1.431	.640	15.116	.000	-.007	.816	.500	.610	1.638
SUMD	33.158	1.419	1.003	23.366	.000	.479	.909	.773	.594	1.683
TA_Rat	1.606	1.734	.040	.926	.357	.263	.086	.031	.572	1.748
TA_LAG1	.798	1.943	.020	.411	.682	.317	.038	.014	.456	2.192
TA_LAG2	3.344	1.888	.084	1.771	.079	.281	.163	.059	.481	2.078
TA_LAG3	1.959	1.918	.050	1.022	.309	.202	.095	.034	.455	2.199
TA_LAG4	6.785	1.809	.173	3.750	.000	.174	.330	.124	.512	1.954
TA_LAG5	-3.153	1.725	-.085	-1.828	.070	.070	-.168	-.060	.500	1.998
TA_LAG6	1.911	1.601	.053	1.194	.235	.008	.111	.039	.552	1.810

a. Dependent Variable: Occupancy
b. R^2 = .874, F = 79.90, *df* = 125
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/Upper UpScale (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	14.838	4.398		3.374	.001					
FALLD	30.516	.971	.906	31.423	.000	.305	.897	.716	.625	1.601
SPRD	23.721	1.030	.682	23.028	.000	.061	.829	.525	.592	1.690
SUMD	35.853	.987	1.054	36.319	.000	.496	.920	.828	.617	1.621
TA_Rat	1.909	1.410	.047	1.354	.177	.050	.087	.031	.425	2.353
TA_LAG1	-.619	1.377	-.015	-.449	.654	.124	-.029	-.010	.447	2.238
TA_LAG2	3.106	1.307	.081	2.376	.018	.156	.151	.054	.444	2.252
TA_LAG3	3.942	1.339	.105	2.943	.004	.163	.186	.067	.409	2.447
TA_LAG4	1.368	1.324	.037	1.034	.302	.137	.066	.024	.414	2.416
TA_LAG5	2.003	1.367	.054	1.466	.144	.162	.094	.033	.382	2.619
TA_LAG6	-2.320	1.309	-.063	-1.771	.078	.146	-.113	-.040	.404	2.474

a. Dependent Variable: Occupancy
b. R^2 = .875, F = 168.47, *df* = 251
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/UpScale (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Sd Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	-21.474	11.430		-1.879	.063					
FALLD	22.806	1.587	.771	14.371	.000	.248	.805	.573	.553	1.810
SPRD	20.174	1.590	.668	12.690	.000	.067	.768	.506	.575	1.740
SUMD	29.915	1.499	.990	19.950	.000	.506	.883	.796	.646	1.548
TA_Rat	3.980	1.586	.109	2.509	.014	.266	.231	.100	.839	1.193
TA_LAG1	5.723	1.550	.156	3.692	.000	.276	.329	.147	.886	1.128
TA_LAG2	2.427	1.530	.066	1.587	.115	.125	.148	.063	.908	1.101
TA_LAG3	2.050	1.517	.058	1.351	.179	.008	.127	.054	.857	1.166
TA_LAG4	2.532	1.475	.077	1.716	.089	-.002	.160	.068	.795	1.258
TA_LAG5	2.707	1.383	.084	1.958	.053	.071	.182	.078	.859	1.164
TA_LAG6	-.382	1.360	-.013	-.281	.780	.119	-.027	-.011	.754	1.325

a. Dependent Variable: Occupancy
b. R^2 = .822, F = 51.62, *df* = 122
c. **. Correlations is significant at the 0.01 level (2-tailed)

Occupancy/MidScaleEconomy (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coefficients			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	38.689	3.829		10.105	.000					
FALLD	32.342	1.843	.867	17.548	.000	.281	.853	.670	.598	1.673
SPRD	24.437	1.930	.635	12.661	.000	-.005	.763	.484	.581	1.722
SUMD	39.925	1.799	1.059	22.188	.000	.551	.900	.847	.640	1.563
TA_Rat	-1.538	1.774	-.061	-.867	.388	.054	-.081	-.033	.299	3.347
TA_LAG1	4.345	1.725	.171	2.518	.013	.071	.229	.096	.316	3.168
TA_LAG2	-.388	1.660	-.015	-.234	.816	.072	-.022	-.009	.332	3.013
TA_LAG3	-.395	1.801	-.016	-.220	.827	.005	-.020	-.008	.276	3.617
TA_LAG4	2.057	1.725	.085	1.193	.235	-.015	.111	.046	.288	3.472
TA_LAG5	-2.287	1.670	-.100	-1.370	.173	-.016	-.127	-.052	.275	3.643
TA_LAG6	-.446	1.594	-.020	-.280	.780	.019	-.026	-.011	.299	3.346

a. Dependent Variable: Occupancy
b. R^2 = .832, F = 57.06, *df* = 125
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu /Luxury (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coef			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	-87943726.056	22551809.869		-3.900	.000					
FALLD	61560219.736	3992065.064	.890	15.421	.000	.411	.821	.698	.614	1.627
SPRD	39490944.734	4134602.985	.553	9.551	.000	-.064	.665	.432	.610	1.638
SUMD	62562907.397	4100776.161	.896	15.256	.000	.387	.818	.691	.594	1.683
TA_Rat	159854.659	5012197.803	.002	.032	.975	.234	.003	.001	.572	1.748
TA_LAG1	-3711923.118	5614341.438	-.044	-.661	.510	.289	-.062	-.030	.456	2.192
TA_LAG2	7995801.330	5455314.121	.096	1.466	.145	.292	.135	.066	.481	2.078
TA_LAG3	4283070.922	5541062.694	.052	.773	.441	.253	.072	.035	.455	2.199
TA_LAG4	18818538.443	5228286.254	.228	3.599	.000	.244	.318	.163	.512	1.954
TA_LAG5	-4384971.828	4985474.901	-.056	-.880	.381	.139	-.082	-.040	.500	1.998
TA_LAG6	8966373.969	4627721.242	.118	1.938	.055	.092	.178	.088	.552	1.810

a. Dependent Variable: MktVal
b. R^2 = .764, F = 37.30, *df* = 125
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu /Upper UpScale (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coef			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
(Constant)	-48053367.835	38204932.958		-1.258	.210					
FALLD	58361701.883	8437091.009	.497	6.917	.000	.216	.407	.393	.625	1.601
SPRD	38782109.445	8949495.544	.320	4.333	.000	.013	.269	.246	.592	1.690
SUMD	54995028.007	8576368.558	.464	6.412	.000	.187	.382	.364	.617	1.621
TA_Rat	379541.697	12249713.568	.003	.031	.975	.042	.002	.002	.425	2.353
TA_LAG1	-7905243.581	11965893.602	-.056	-.661	.509	.064	-.043	-.038	.447	2.238
TA_LAG2	1759436.541	11357524.995	.013	.155	.877	.097	.010	.009	.444	2.252
TA_LAG3	13215770.955	11635976.893	.101	1.136	.257	.134	.073	.065	.409	2.447
TA_LAG4	9636066.117	11499428.807	.074	.838	.403	.115	.054	.048	.414	2.416
TA_LAG5	6403078.938	11875853.765	.050	.539	.590	.107	.035	.031	.382	2.619
TA_LAG6	-2295436.932	11376469.968	-.018	-.202	.840	.095	-.013	-.011	.404	2.474

a. Dependent Variable: MktVal
b. R^2 = .222, F = 6.86, *df* = 251
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu /UpScale (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std Coef			Correlations			Collinearity Statistics	
	B	Std. Error	B	t	Sig.	Zero-order	Partial	Part	Tol.	VIF
(Constant)	-43654566.563	9622497.789		-4.537	.000					
FALLD	17231205.331	1336043.680	.836	12.897	.000	.339	.773	.622	.553	1.810
SPRD	12302971.022	1338410.263	.584	9.192	.000	-.018	.656	.443	.575	1.740
SUMD	19251283.426	1262376.900	.914	15.250	.000	.437	.822	.735	.646	1.548
TA_Rat	791954.758	1335525.739	.031	.593	.554	.223	.056	.029	.839	1.193
TA_LAG1	2486577.512	1304875.680	.098	1.906	.059	.248	.177	.092	.886	1.128
TA_LAG2	2672649.357	1288003.780	.105	2.075	.040	.165	.192	.100	.908	1.101
TA_LAG3	2567991.349	1277163.338	.105	2.011	.047	.055	.187	.097	.857	1.166
TA_LAG4	2107536.867	1241959.083	.092	1.697	.092	.024	.158	.082	.795	1.258
TA_LAG5	2292998.452	1164263.932	.102	1.969	.051	.084	.183	.095	.859	1.164
TA_LAG6	370491.026	1145059.306	.018	.324	.747	.125	.031	.016	.754	1.325

a. Dependent Variable: MktVal
b. R^2 = .740, F = 31.85, *df* = 122
c. **. Correlations is significant at the 0.01 level (2-tailed)

MktVlu /MidScaleEconomy (Model 1)

Coefficients[a]

	Unstandardized Coefficients		Std. Coef			Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tol.	VIF
(Constant)	97919.307	585921.632		.167	.868					
FALLD	4539297.328	282050.432	.845	16.094	.000	.311	.832	.653	.598	1.673
SPRD	3044787.286	295368.910	.549	10.308	.000	-.062	.693	.418	.581	1.722
SUMD	5555879.423	275370.161	1.024	20.176	.000	.534	.883	.819	.640	1.563
TA_Rat	-346914.171	271418.726	-.095	-1.278	.204	.151	-.118	-.052	.299	3.347
TA_LAG1	526446.411	264037.797	.144	1.994	.049	.176	.183	.081	.316	3.168
TA_LAG2	55836.069	253991.209	.015	.220	.826	.192	.020	.009	.332	3.013
TA_LAG3	-181682.554	275609.025	-.051	-.659	.511	.122	-.061	-.027	.276	3.617
TA_LAG4	420208.075	263922.050	.120	1.592	.114	.120	.147	.065	.288	3.472
TA_LAG5	-3741.089	255504.273	-.001	-.015	.988	.139	-.001	-.001	.275	3.643
TA_LAG6	261555.213	243931.895	.080	1.072	.286	.166	.099	.044	.299	3.346

a. Dependent Variable: MktVal