Effects of Abnormal Weather Conditions on the Performance of Hotel Firms

Abstract

Weather is one of the critical factors that influence tourists' destination choices and activities. Apart from ambient temperature anomaly, rain anomaly is also an important factor considered by tourists when they plan and modify their vacation and holiday trips. This study confirms the important role of abnormal weather conditions in explaining hotel performance, such as occupancy, average daily rate, and revenue per available room. Moreover, operational performance indicators are observed to exhibit dynamic patterns in response to abnormal weather conditions in accordance with different types/classes of hotels. Evidence indicates that tourists prefer to stay at full-service hotels with complete facilities rather than at hotels with limited facilities and services during an abnormally heavy rain situation. Therefore, the findings of this research suggest a useful determinant (i.e., weather changes) of revenue management practices for hotel firms to maximize their operating performance.

Keywords: ambient temperature anomaly; rain anomaly; occupancy rate; ADR; RevPAR

1. Introduction

Weather is a critical factor that determines the destination choices and activities of tourists. Tourists actively seek information regarding temperature, precipitation, wind, humidity, and abnormal weather conditions, particularly before and even during their trip (Becken, 2013; Hamilton, Maddison, & Tol, 2005; Scott, Hall, & Gössling, 2019). Changes in ambient temperature are among the most important information for tourists in their decision-making process (Fisichelli *et al.*, 2015; Matzarakis, 2006; Rosselló-Nadal, 2014). On the one hand, international and domestic tourists make necessary adjustments to their travel plans, including their choice of hotels, length of stay, transportation mode, and choice of activities in certain destinations, by considering weather conditions. On the other hand, hotel firms constantly change room prices until the last minute on the basis of daily and weekly room occupancy rates (Guizzardi, Pons, & Ranieri, 2019). Approximately 50%–60% of travelers tend to book their hotels within 2 weeks before their date of arrival (Falk & Vieru, 2019; Jang *et al.*, 2019), and approximately 48% of hotels change their room prices more than five times within the last 7 days prior to check-in (Mohammed, Guillet, & Law, 2019). Such spontaneous travel behavior has been augmented by the advancement of mobile technology that enables travelers to search for environment information at any time and place (Wang, Park, & Fesenmaier, 2012).

In the aforementioned contexts, the influence of weather changes on revenue management practices in the hospitality industry has become an interesting topic among researchers and policy makers (Amelung, Nicholls, & Viner, 2007; Becken, 2013; Berrittella, Bigano, Roson, & Tol, 2006; Scott & Lemieux, 2010). Several scholars have demonstrated that the hospitality industry is sensitive to changes in weather, and they have emphasized the increasing risks of extreme weather events (Hamilton et al., 2005; Weaver, 2011). Environmental factors are indispensable considerations for tourists when they plan their vacation or holiday trip activities. For example, "76% of Italian tourists usually consult weather forecasts when organizing their holiday" (Zirulia, 2016). An exceptional weather condition itself is already an irreplaceable tourism resource for a country or destination (Amelung *et al.*, 2007; Matzarakis, 2006).

The vulnerability of the tourism industry to weather changes has continuously increased in recent decades. Thus, an accurate assessment of the effect of weather changes is essential to enable the hospitality and tourism industries to avoid conceivable drawbacks. However, most previous studies have focused on country-level weather changes and their effect on tourists' destination choices (Amelung *et al.*, 2007; Burke, Hsiang, & Miguel, 2015; Lise & Tol, 2002). In particular, most literary works have examined the influence of macrolevel weather changes (e.g., country-level weather changes) on country-level tourist arrivals; in general, these works have confirmed substantial negative or positive effects of weather changes on tourism (Bujosa, Riera, & Torres, 2015; Hall *et al.*, 2015; Scott, Hall, & Stefan, 2012).

Evidence consistently indicates the potential merits of using weather information, such as macrolevel tourist forecasting. However, little research has linked recent weather information, including ambient temperature and precipitation amount, with property-level performance in the hospitality industry or explained how hospitality firms can apply weather change information to their daily operations. Although many hotel rooms are booked in advance, only a few customers book very early (approximately 20% of customers book earlier than a month before arrival) (Falk & Vieru, 2019; Jang, Chen, & Miao, 2019). Moreover, these customers can frequently modify their hotel bookings near the days of their actual arrival even after making a reservation (Rosselló-Nadal, 2014). In addition, most hotels do not charge any cancellation fees even if consumers send notice of their decisions within a few weeks before their arrival date. Kimes (1989) reported that tourists frequently change their length of stay while staying in a hotel. In this regard, online travel agencies offer extended stay options in their booking system to accommodate increasing demands, such as "add-a-night (Priceline)" or "add to your stay (Hotwire)" (Tepper, 2015).

Furthermore, the importance of walk-in customers cannot be disregarded in hotel operations because they constitute a sizeable proportion of revenue (Aydin & Birbil, 2018). The preceding discussion implies that consumers can cancel their hotel bookings and/or change their length of stay without any restrictions because of changes in environmental elements (i.e., weather conditions). Such behavior directly affects hotel performance. In addition, previous findings have been mainly based on statistical models that have not fully controlled the seasonality of tourism activities, namely, biographical seasonality (i.e., summer versus winter) and functional seasonality (i.e., vacations and holidays). Given these limitations, empirical findings are ill-timed and hardly applicable to the hotel industry. Accordingly, the current study aims to fill the research gap and provide several practical business implications (i.e., how hotel firms can use information on abnormal weather conditions to improve their operating performance). With the aim to achieve its objectives, this study intends to control the seasonality of tourism activities by using the abnormality of monthly ambient temperature and monthly precipitation amount collected from the National Oceanic and Atmospheric Administration (NOAA). Furthermore, the extant literature on hospitality has suggested that different hotel classes not only exhibit distinct operating characteristics, such as differences in investment and operating strategies, organizational behavior, operating efficiency, and target markets (O'Neill, Hanson, & Mattila, 2008), but also develop different consumers' expectations of their services (Assaf & Tsionas, 2018). In this regard, the current study examines the influence of monthly weather conditions on the operating performance of different hotel segments (i.e., luxury versus economy hotels and full-service versus limited-service hotels) to explore industry-specific factors and enhance the robustness of the implications.

2. Literature Review

2.1. Weather Changes in Hospitality and Tourism

Tourism is highly sensitive to weather, which affects the success or failure of tourist destinations (Scott, Gössling, & Hall, 2012). Weather can play the role of a facilitator or an inhibitor for travelers participating in activities at their destinations with implications on their psychological needs. Weather conditions act as push or pull factors in travel planning. Travelers tend to avoid unfavorable weather conditions in their places of residence (push motivations) and search for favorable weather conditions at their prospective holiday destinations (pull motivations) (Amelung *et al.*, 2007). The importance of the weather issue has been recognized; thus, the extant literature has discussed its effect on three areas: travel behavior, destination demand, and development of a tourism climate index (Rosselló-Nadal, 2014; Scott, Hall, & Gössling, 2019).

Understanding travelers' responses to weather changes is critical not only for predicting potential changes in tourism demand brought by geographic and seasonal shifts but also for evaluating how such shifts increase or decrease the competitiveness of certain tourism markets (Gössling *et al.*, 2012). In particular, weather changes can influence destination selection, trip timing, travel experiences, and satisfaction (Gössling *et al.*, 2012). Becken and Wilson (2013) found that approximately 40% of international tourists tend to revise their trip timing, with half of them changing their intended activity at their destination, in response to weather changes. The number of travelers who choose domestic overnight stays tends to increase with the increase of average sunshine and temperature (Falk, 2014). As a type of climate change, global warming leads to a reduction in ski season duration and the loss of skiing areas at certain places, affecting the destination choices of travelers who are particularly interested in winter sports (Bujosa *et al.*, 2015). Travelers tend to change destinations from where they used to visit to other places that allow them to enjoy natural resources.

Moreover, the extent to which weather affects travel behavior varies with the nature/location of destinations (McKercher, Shoval, Park, & Kahani, 2015) and individual characteristics (Scott, Gössling, & de Freitas, 2008; Steiger, Abegg, & Jänicke, 2016). Several scholars have evaluated how weather affects tourist behavior, mostly in nonurban destinations (Scott *et al.*, 2008). By contrast, McKercher *et al.* (2015) investigated the effect of weather on travel mobility at urban tourism destinations (e.g., Hong Kong). They suggested its limited influence compared with that in other studies that explored nature-based destinations. However, weather perceptions, including the effects of air quality, heat, and humidity on personal comfort, affect destination satisfaction. Among weather indicators, temperature is apparently highly important for travelers visiting urban destinations, sunshine is relatively much important to tourists who are visiting beaches, and rain is critical for people who are visiting mountains (Scott *et al.*, 2008). The authors also found that sunshine and temperature are the most important factors that determine satisfaction for campers, whereas heavy rains (more than 16 mm/h) and strong winds (41–90 km/h) influence campers' decisions to leave earlier than planned (Hewer, Scott, & Gough, 2015). Wilkins, de Urioste-Stone, Weiskittel, and Gabe (2018) analyzed the influence of weather on various types of overnight accommodations. They also determined that travelers who use tents to camp are most heavily affected by weather, followed by those who camp in recreational vehicles, those who stay in hotels/motels, and those who lodge with friends. The relevant literature indicates that weather is an important situational factor that affects pretrip (destination choice and trip timing) and during-trip activities through planned and impulsive decision-making processes

(Becken & Wilson, 2007, 2013). On the one hand, good weather can enable tourists to accomplish their planned travel activities; on the other hand, unfavorable weather can be an obstruction, prompting travelers to develop adaptation strategies by changing their plans and finding alternatives (Denstadli, Jacobsen, & Lohmann, 2011).

Several tourism studies have empirically demonstrated the relationships between weather (particularly weather indicators, including temperature, precipitation, sunshine, and wind) and destination demand (Rosselló-Nadal, 2014). In particular, British outbound tourism exhibits a negative growth in the following year as temperature rises, whereas the demand for domestic holiday trips increases (Rosselló-Nadal, Riera-Font, & Cárdenas, 2011). Eugenio-Martin and Campos-Soria (2010) investigated 16 countries in the European Union for 12 months and obtained similar findings. The climate index is positively correlated with the probability that travelers will go on domestic trips but presents a negative association with the probability of international trips. Climate change also reshapes the seasonality of destinations. For example, golf courses in the Great Lakes Region are expected to extend the average golf season by 10 days to 51 days as the temperature increases (Scott & Jones, 2007). With regard to winter activities, the number of visitors who purchase ski lift tickets is statistically related to weather indicators, such as maximum and minimum temperatures, snow depth, and wind chill. Rosselló and Waqas (2016) explored Google trend data as a proxy index for indicating destination demand that includes diverse international markets. The results indicated the effect of weather factors (i.e., temperature, rainfall, and wind speed during a day) on explaining short-term variability in travel demand (i.e., number of search queries for a certain destination).

Becken (2013) attempted to quantify the effects of weather on tourism demand and activity levels at a destination and then link weather effects with seasonality. She identified a relationship between temperature and monthly overnight stays at a given destination but reported that rain does not explain the intra-annual variability of tourism. In conclusion, seasonality varies with temperature. Activity-level analysis determined that the number of travelers who visit local visitor centers is negatively correlated with wind run and positively associated with rainfall amount. This finding is consistent with that of Meyer and Dewar (1999). Apart from the estimation of the direct relationship between weather changes and destination arrivals, an attempt was also made to identify an optimal temperature (21 °C) for tourists in Organization for Economic Co-operation and Development countries in their choice of travel destination by considering the different origins of tourists and their activity-seeking behaviors (Lise & Tol, 2002). The study suggested that the preferences for certain weather conditions at tourist destinations differ according to varying demographic features, such as age and income. These aforementioned studies imply a shift in the attractiveness of destinations and seasonality, given that certain destinations are expected to have more climate resources for tourism than others (Scott, McBoyle, & Schwartzentruber, 2004).

Another school of literature has proposed a climate index and suggested additional indicators to encompass weather effects comprehensively. In general, the tourism climate index has been used to understand how alterations in climatic conditions, such as a consequence of global climate change, affect the relative attractiveness of certain destinations and tourist arrivals at these destinations (Becken, 2013). Building upon an initial approach for creating a tourism climate index (Mieczkowski, 1985), Amelung *et al.* (2007) developed a tourism climatic index rating system that links a numeric index with the comfort level for tourism activities. The authors also presented changes in destination attractiveness along with climate change. In particular, the peak seasons at Mediterranean destinations are expected to shift from summer to current off-peak periods, and the destinations at high latitudes tend to have longer summer seasons than the current durations. Morgan *et al.* (2000) proposed a climate index for beach/coastal tourism based on travelers' preferences (e.g., thermal sensation, sea temperature, and other climatic attributes, types of travel, and location of destinations). Matzarakis (2006) criticized the previous literature on developing regular climate indices, stating that they mostly considered air temperature and humidity. He suggested including thermal comfort or thermal stress conditions. Hence, Matzarakis (2006) proposed a climate index that shows discrete levels of physiologically equivalent temperatures based on human thermal sensitivity and physiological stress. Scott *et al.* (2019) suggested a climate change vulnerability index for tourism, integrating information from various sources that may influence the tourism sector. This index contains 27 indicators that reflect a wide range of domestic and transnational effects of climate change on the tourism sectors of 181 countries.

Several studies have recently explored the relationship of weather changes to guest bookings and staying behaviors in accommodations. Chen and Link (2014) estimated the effect of weather by considering temperature, number of rainy days, hours of sunshine, and number of typhoon days on hotel demand. They assessed the moderating effect of room rates with weather change on the average number of hotel guests in Taiwan. Falk (2015) analyzed the effect of weather conditions on overnight tourist stays in nine provinces of Austria. The research showed that sunshine duration and temperatures positively influence domestic overnight stays in the same month for most provinces except for the country's capital (Vienna). However, the study of Falk (2015) focused on summer rather than exploring the four seasons. Similarly, Bausch, Gartner, and Humpe (2021) investigated not only tourist arrivals but also their length of stay at accommodations. Although Bausch (2021) collected daily demand and weather-related (e.g., temperature, humidity, cloud cover, air, and vapor pressure) data, an analytical approach was not proposed to estimate the effect of weather changes on guest behaviors. Instead, the results presented the mean differences in accommodation performance in accordance with variations in weather conditions.

Given the research gap in the existing literature, the current study examines the effect of abnormal weather conditions on hotel performance by using a large and consistent set of weather and accommodation data. Accordingly, this study explores factors that affect operational performance in accommodations, with weather change as one of the external factors.

2.2. Factors Affecting Operational Performance in Accommodations

Several hospitality scholars have identified factors that affect hotel performance (Jeffrey, Barden, Buckley, & Hubbard, 2002). These influential elements can be classified into two types: internal and external. Internal factors reflect attributes associated with hotel properties, including management practices, owner's leadership, and knowledge sharing, along with hotel facilities, including its location. In terms of management practices, marketing and channel strategies are key influencers that drive hotels' occupancy performance (Lei, Nicolau, & Wang, 2019; de Pelsmacker, van Tilburg, & Holthof, 2018). Strategic marketing and channel initiatives target different markets. They are designed not only to maintain current consumers and encourage their repeat visits but also to expand additional market segments. As a key element in revenue management practices that provide different rates based on customer values, booking windows, and available capacity (Jones, 1999), dynamic pricing considerably influences hotel performance to manage fixed capacity (Abrate, Fraquelli, & Viglia, 2012). In addition to management practices, hotel facilities also affect hotel performance. For example, Lee and Jang (2012) suggested the importance of hotel locations and found that hotel rates decrease as the distance of hotels from the city center increases. Hotels tend to generate a premium rate of US$18.39 per kilometer of proximity to the city center (Lee & Jang, 2012).

External factors represent environmental elements that directly or indirectly influence hotel operations and performance; they include seasonality, online reviews, and crises/national disasters. Koenig and Bischoff (2004) suggested a strong correlation between pronounced seasonality in tourism demand and hotel occupancy. They emphasized a major strategic issue in extending peak seasons by developing events at the destination and designing dynamic travel packages. Several studies have empirically assessed the effect of online consumer reviews on hotel performance. Yang, Park, and Hu (2018) summarized the existing literature on online reviews and performance and empirically tested their relationships by using a set of meta-analyses. They determined that the valence-based elasticity of online consumer reviews presents a value of 0.99, and their volume-based elasticity indicates a value of 0.56. Similarly, other studies have suggested that a 10% increase in review ratings (valence) for hotel properties enhances online hotel bookings by approximately 5% (Ye, Law, & Gu, 2009).

Studies have also reported the important influence of crises/natural disasters on hotel performance. Chen, Jang, and Kim (2007) demonstrated the negative effect of severe acute respiratory syndrome (SARS) on the tourism industry in general and hotel performance in particular. In addition to the effects of SARS pandemic, the effects of a couple of external shocks, namely, the 9/11 terrorist attacks and the 2008 financial crisis, on the performance of U.S. hotels were tested by Kosová and Enz (2012). Both events exhibited dramatic effects on hotel occupancy, but U.S. hotels quickly recovered within 4 months.

Some studies on hospitality have endeavored to identify diverse internal and external factors that affect hotel performance. However, the attempt to estimate the influence of weather changes as one of the most critical environmental elements has been largely limited. An imperative study of He et al. (2019) assessed the economic gain and loss of hotel properties from weather changes by focusing on weather indicators instead of hotel attributes.

Therefore, the researchers developed empirical models to test how abnormal weather conditions affect the performance of U.S. hotels by considering not only weather indicators but also important hotel features (i.e., types and classes).

The hospitality literature suggests that different classes of hotels represent not only distinct operating characteristics, such as differences in investment and operating strategies, organizational behavior, operating efficiencies, and target markets (O'Neill et al., 2008), but also different consumers' expectations of their services (Assaf & Tsionas, 2018). Consumers tend to consider discrepant importance levels of hotel attributes across different hotel classes (Yang et al., 2018). For example, a high classification level generally leads to a high attribute importance value. For high-tariff A and B hotels (luxury/upper-up and up/upper-middle hotels), staff service quality and room quality are regarded as the two most critical attributes, whereas security and room quality are recognized as the two most salient attributes for medium-tariff hotels (mid/economy hotels) (Choi & Chu, 1999). Moreover, the key determinants that lead to consumer satisfaction and dissatisfaction vary across different types of hotels. Xu and Li (2016) indicated the extent to which the influences of certain hotel attributes, products, and services on customer evaluations vary according to different types of hotels. In particular, the results determined that hotels' core attributes, products, and services, such as location, staff performance, and room quality, play more important roles in hotel customers' perceptions than auxiliary services in full-service hotels compared with in limited-service hotels. Consequently, investigating the effect of abnormal weather conditions on hotel performance by considering different types/classes of hotels is vital to provide profound implications to the hotel industry.

3. Methodology

3.1. Data and Variables

This study used the monthly operating information (occupancy rate and average daily rate [ADR]) and revenue per available room (RevPAR) of property-level hotels in the United States from STR (former Smith Travel Research) reports as dependent variables. These hotels have operated in the country's five largest states—California (CA), New York (NY), Illinois (IL), Florida (FL), and Texas (TX)—in the past decade (from 2008 to 2017). From 2008 to 2017, more than 80% of international visitors to the United States visited one of those five states. The monthly data on county-level ambient temperature and rain (or precipitation) were collected from NOAA. Then, abnormal ambient temperature (difference between the average monthly temperature since 1960 and the current monthly ambient temperature) and abnormal rain (difference between the average monthly precipitation since 1960 and the current monthly precipitation) were used as independent variables to examine the impact of weather changes on hotel firms' operating performance after controlling seasonality. This study winsorized the extreme values (below 1% and above 99%) of important variables, such as monthly ambient temperature, rain (or precipitation), occupancy rate, ADR, and RevPAR, to eliminate the effect of outliers. Finally, 118,662 observations with 1,065 hotel firms were included in the models.

For the control variables, years of operation (Age), hotel size (Size), hotel type (Full), hotel class (Class), hotel location (Location), and hotel place (State) were included in the models. In this study, Size was measured by the number of rooms; Full was the dummy variable, which was 1 for full-service hotels and 0 for limited-service hotels; Class was a categorical variable, which was 1 for luxury, 2 for upper-upscale, 3 for upscale, 4 for upper-midscale, 5 for midscale, and 6 for economy; Location was a categorical variable, which was 1 for urban, 2 for suburban, 3 for airport, 4 for interstate or motorway, 5 for resort, and 6 for small metro or town; and all classifications were based on the definition of STR reports. In addition, State was a categorical variable, which was 1 for CA, 2 for NY, 3 for IL, 4 for FL, and 5 for TX. Each state represented the western (CA), middle (IL), eastern (NY), and southern (FL and TX) regions of the United States. Lastly, the dummy variables of months and years were included in the models to control time effects.

3.2. Models

For statistical analysis, this study used time-fixed (months and years) ordinary linear regression (OLS), two-way (time and firm) random effects (RE), and time-fixed (months and years) generalized estimating equations (GEE). Their inferences were also compared to achieve robust conclusions. Scholars have used the RE or fixed-effects (FE) regression model and the GEE model for repeated (the same qualitative or quantitative responses over time) longitudinal data (Gardiner, Luo, & Roman, 2009).

The dependent variable (Y_{it}) is a natural log of monthly occupancy rate, ADR, and RevPAR in this model. β_0 is the unknown intercept, γ_{it} represents the between-entity error, and ε_{it} represents the within-entity error.

$$Y_{it} = \beta_0 + \beta_1 * \text{Temperature anomaly}_{it} + \beta_2 * \text{Rain anomaly}_{it} + \beta_3 * \text{Age(years of operation)}_{it} + \beta_4 * \text{Size (number of rooms)}_{it} + \beta_5 * \text{Full-service}_{it} + \beta_6 * \text{Class}_{it} + \beta_7 * \text{Location}_{it} + \beta_8 * \text{State}_{it} + \beta_9 * \text{Month dummy}_t + \beta_{10} * \text{Year dummy}_t + \gamma_{it} + \varepsilon_{it}$$

3.3. Model Selection

In the models, the control variables, including Age, Size, Full, Class, Location, and State, were all time invariant. However, they played important roles not only to verify the reliability of the models (i.e., ADR at luxury hotels would always be higher than that at economy hotels) but also to distinguish the implications in different business circumstances (i.e., difference between full-service and limited-service hotels). Therefore, this study applied the RE and GEE models for the repeatedly observed panel data along with the fixed OLS model because time-invariant variables could not be included in the FE model.

In this study, the RE model used the generalized least squares estimator, whereas the GEE model used the weighted least square (quasi-likelihood) estimator (Liang & Zeger, 1986). The RE model assumes that the variation across the observations is random, and the error term is uncorrelated with the independent variables (Greene, 2003). In other words, the inferences would be inconsistent if the observation is not random or if the errors are correlated with the regressors. Meanwhile, the GEE model does not require an unobserved (random) heterogeneity of the observations, and the inferences would be valid even in cases of variance misspecification (Hubbard *et al.*, 2010). However, the RE estimators would be more efficient than the estimators of the GEE model when the assumptions of the RE model are valid (Gardiner *et al.*, 2009). In these contexts, comparing the inferences of each model is valuable to achieve reliable and valid conclusions because weather changes within a county (or state) can be particularly correlated over months or years.

4. Results

4.1. Descriptive Information

The results showed the strong seasonality of monthly ambient temperature although the monthly precipitation did not show as much clear seasonality as it (Figure 1). To control this conspicuous seasonality of monthly weather changes, this study used the abnormal ambient temperature (difference between average monthly temperature since 1960 and current monthly ambient temperature) and abnormal rain (difference between average monthly precipitation since 1960 and current monthly precipitation) instead of their original values. The additional but significant benefit of using the monthly abnormal ambient temperature and abnormal rain was that the influences of weather changes on hotel performance could be generalized regardless of the locations of the hotel firms (hot or cold areas) and the months of the year (summer or winter). The changes of the monthly abnormal ambient temperature and abnormal rain seemed to become a random walk (Figure 2).

Figure 1. Average monthly ambient temperature and rain from 2008 to 2017

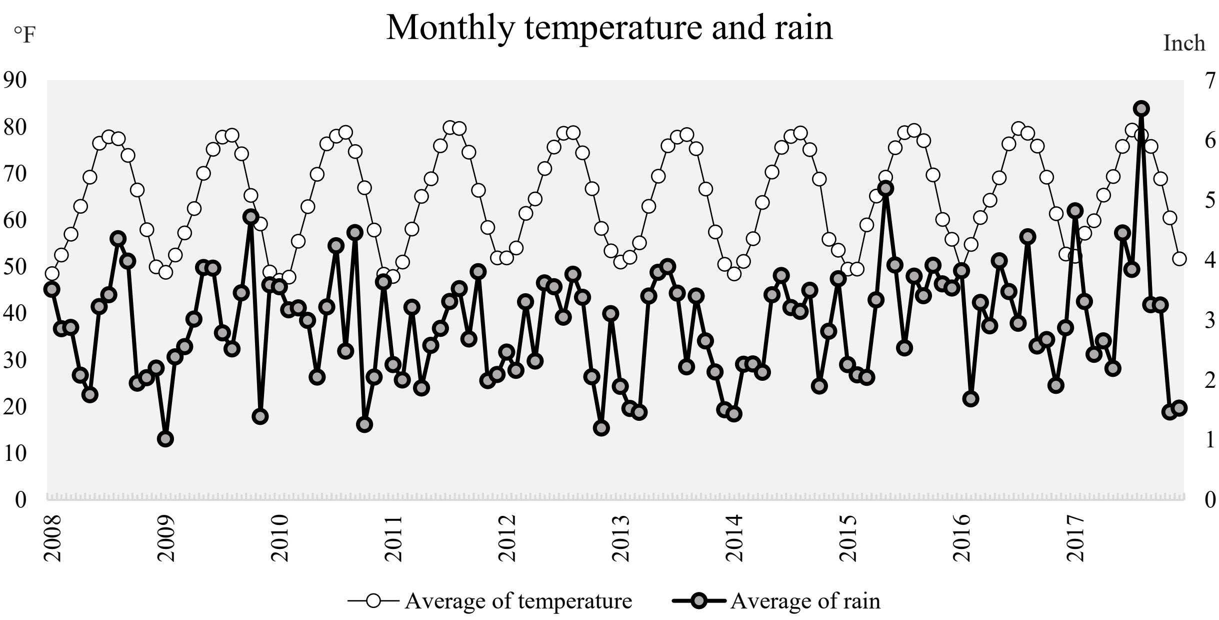
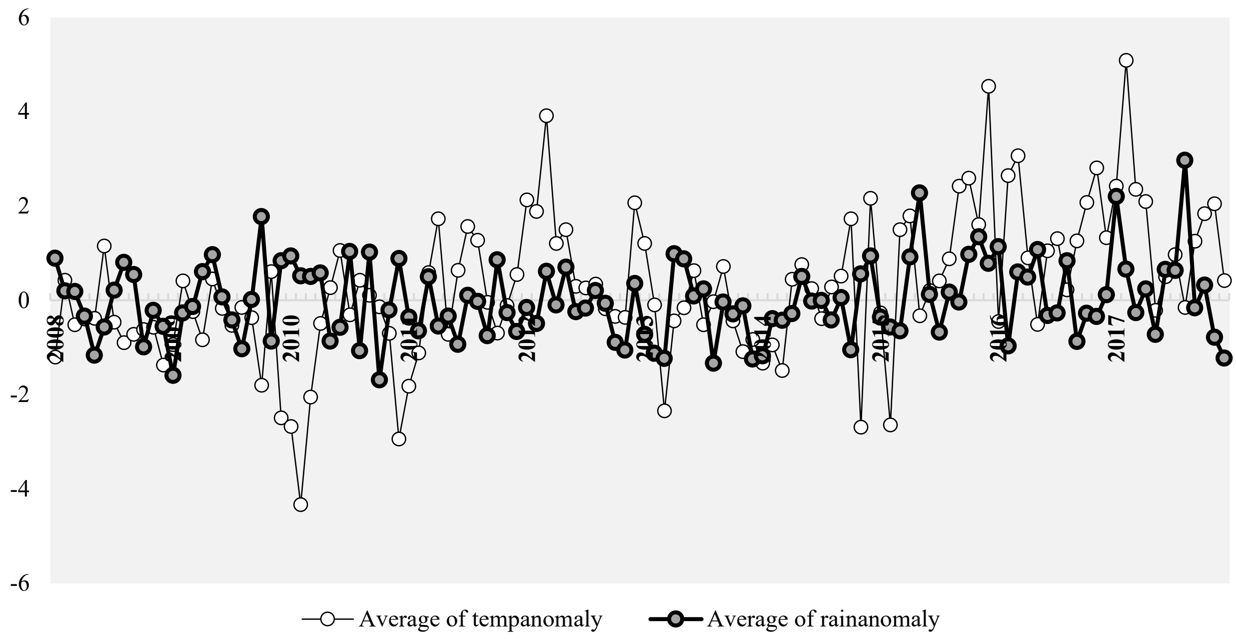


Figure 1. Average monthly ambient temperature anomaly and rain anomaly from 2008 to 2017



The descriptive information indicated the ambient temperature (Temp) went up consistently until July and August but the amount of rain (Rain) did not show such a strong trend although it was higher in hot months (Jun, July, August, and September) than others. However, the temperature anomaly and the rain anomaly did not present such a visible trend or seasonality (e.g., Apr showed the highest temperature anomaly while Feb showed the lowest rain anomaly). The occupancy rate (73.62% on average) was the highest in Jun (77.82%) and July (78.29%) but the lowest in December (64.40%) and January (67.46%). The ADR ($119.22 on average) was the highest in February ($122.99) and March ($123.10) but the lowest in December ($112.67) and August ($116.21). The RevPAR ($89.48 on average) was the highest in March ($95.73) and July ($94.00) but the lowest in December ($73.63) and January ($82.12). Overall, the hotel performance did not present any noticeable seasonality with descriptive information. Besides, this study checked the distribution of the important variables (monthly abnormal ambient temperature, monthly abnormal precipitation, log of occupancy rate, log of ADR, and log of RevPAR) and all variables showed a fairly normal distribution (Supplemental Table 1).

Supplemental Table 1. Descriptive information

	Temperature	Temperature anomaly	Rain	Rain anomaly	Occupancy rate	ADR	RevPAR	Observation
Jan	52.08	0.09	2.67	0.03	67.46	119.86	82.12	9,301
Feb	53.47	0.51	2.28	-0.39	73.83	122.99	92.40	9,752
Mar	57.93	0.47	2.65	-0.04	76.55	123.10	95.73	10,131
Apr	63.95	0.60	2.58	0.18	75.70	120.70	93.09	10,232
May	69.48	0.09	2.85	-0.02	74.31	120.20	90.86	10,033
Jun	75.92	0.56	3.46	-0.27	77.82	118.45	93.80	10,170
Jul	78.13	0.09	3.40	0.11	78.29	117.89	94.00	9,735
Aug	77.75	0.00	3.33	-0.21	75.96	116.21	90.40	9,233
Sep	74.99	0.50	3.23	-0.10	72.30	117.74	87.37	10,069
Oct	67.50	0.43	2.74	-0.17	75.82	121.95	94.56	10,185
Nov	58.76	0.15	2.06	-0.19	70.42	118.39	84.69	10,226
Dec	52.88	0.55	2.66	-0.07	64.40	112.67	73.63	9,595
Yearly	65.27	0.34	2.82	-0.10	73.62	119.22	89.48	118,662

Note: temperature and rain are based on the county level weather informaton; temperature is fahrenheit; temperature anomaly is the difference between monthly average temperature (1960-2017) and the current month temperature; rain is inch; rain anomaly is the difference between monthly average rain (1960-2017) and the current month rain

4.2. Regression Analysis

As shown in Table 1, surprisingly, most coefficients of variables were quite similar in three different regression models. Especially, both coefficients and standard errors in RE and GEE models were almost identical, which strongly represented the robustness of the models and the findings. In the models, the monthly temperature anomaly did not indicate significant impact on the occupancy rate (0.0002, p-value>0.1 in all three models). Whereas the monthly rain anomaly indicated a significantly positive effect on the occupancy rate in all three regression models (0.0010, p-value<0.01 in OLS, 0.0013, p-value<0.01 in RE, and 0.0013, p-value<0.01 in GEE). In addition, the results presented that the full-service hotels (-0.0755, p-value<0.01) tended to have a lower occupancy rate than the limited-service hotels based on RE and GEE models. Besides, the upper-midscale (4) and midscale (5) hotels (-0.0763 or -0.0762, p-value<0.01 and -0.0679 or -0.0678, p-value<0.01, respectively) had the lower occupancy rate but upper-upscale hotels (2) (0.0337 or 0.0338, p-value<0.01) had the higher occupancy rate than luxury hotels after controlling other variables constant based on RE and GEE models. In the aspects of location, the hotels in urban (1) and airport (3) areas had the higher occupancy rate than others (other locations had a significantly negative coefficients) and the hotels in CA (1) and NY (2) showed the higher occupancy rate than other states (other states had a significantly negative coefficients) after controlling other variables constant based on RE and GEE models.

Table 1. Effect of temperature anomaly and rain anomaly on the occupancy rate

	LogOccupancy		
	OLS	RE	GEE
Temperature anomaly	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)
Rain anomaly	0.0010***	0.0013***	0.0013***
	(0.0002)	(0.0002)	(0.0002)
Age (years of operation)	-0.0000	-0.0001	-0.0001
	(0.0000)	(0.0002)	(0.0002)
Size (number of rooms)	0.0031***	0.0028	0.0028
	(0.0008)	(0.0044)	(0.0044)
Full-service	-0.0753***	-0.0755***	-0.0755***
	(0.0017)	(0.0094)	(0.0094)
Class 2	0.0300***	0.0337***	0.0338***
	(0.0023)	(0.0129)	(0.0128)
3	0.0130***	0.0180	0.0182
	(0.0025)	(0.0142)	(0.0142)
4	-0.0798***	-0.0763***	-0.0762***
	(0.0037)	(0.0171)	(0.0171)
5	-0.0752***	-0.0679***	-0.0678***
	(0.0037)	(0.0218)	(0.0218)
6	0.0050*	0.0067	0.0069
	(0.0030)	(0.0164)	(0.0164)
Location 2	-0.0489***	-0.0526***	-0.0526***
	(0.0014)	(0.0079)	(0.0079)
3	0.0037**	0.0033	0.0034
	(0.0017)	(0.0094)	(0.0095)
4	-0.0401***	-0.0435**	-0.0436**
	(0.0034)	(0.0204)	(0.0204)
5	-0.0473***	-0.0514***	-0.0514***
	(0.0021)	(0.0124)	(0.0124)
6	-0.0749***	-0.0785***	-0.0785***
	(0.0038)	(0.0174)	(0.0174)
State 2	-0.0194***	-0.0161	-0.0159
	(0.0026)	(0.0166)	(0.0167)
3	-0.0767***	-0.0783***	-0.0783***
	(0.0017)	(0.0078)	(0.0078)
4	-0.0265***	-0.0259***	-0.0259***
	(0.0015)	(0.0070)	(0.0077)
5	-0.0964***	-0.0971***	-0.0971***
	(0.0013)	(0.0070)	(0.0070)
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Constant	4.2577***	4.2542***	4.2541***
	(0.0046)	(0.0223)	(0.0223)

Observation	118,662	118,662	118,662
R^2	0.2566	0.3251	N/A

Note: Class represents 1 for luxury, 2 for upper-upscale, 3 for upscale, 4 for upper-midscale, 5 for midscale, and 6 for economy hotels; Location represents 1 for urban, 2 for suburban, 3 for airport, 4 for interstate or motorway, 5 for resort, and 6 for small metro or town; State represents a categorical variable, which is 1 for CA, 2 for NY, 3 for IL, 4 for FL, and 5 for TX; robust standard errors in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

In next analysis (see Table 2), both the monthly temperature anomaly (0.012, p-value<0.01 in RE and 0.012, p-value<0.01 in GEE) and rain anomaly (0.012, p-value<0.01 in RE and 0.012, p-value<0.01 in GEE) indicated a significantly positive relationship with ADR. Like as the previous occupancy models, both coefficients and standard errors in RE and GEE models were almost the same in ADR models and they were not substantially different from those in the OLS model. All models showed the consistent relationship between hotel class and ADR (all coefficients were negative and decreasing as the class number increased since the base was the luxury hotel): the room prices of luxury hotels (1) were highest and followed by upper-upscale (2), upscale (3), upper-midscale (4), midscale (5), and economy (6) in order. In terms of location, room prices were higher in urban (1) and resort (5) areas than others, and hotels in CA (1) had the highest room price (0.1367, p-value<0.01) and hotels in NY (2) had the second highest price after controlling other variables constant.

Table 2. Effect of temperature anomaly and rain anomaly on ADR

	LogADR		
	OLS	RE	GEE
Temperature anomaly	0.0009***	0.0012***	0.0012***
	(0.0003)	(0.0002)	(0.0002)
Rain anomaly	-0.0004	0.0012***	0.0012***
	(0.0003)	(0.0002)	(0.0002)
Age (years of operation)	-0.0006***	-0.0004	-0.0004
	(0.0001)	(0.0006)	(0.0006)
Size (number of rooms)	-0.0094***	-0.0136	-0.0136
	(0.0012)	(0.0105)	(0.0105)
Full-service	-0.0431***	-0.0360*	-0.0360*
	(0.0022)	(0.0196)	(0.0196)
Class 2	-0.3935***	-0.4296***	-0.4297***
	(0.0037)	(0.0341)	(0.0341)

3	-0.6482***	-0.6891***	-0.6892***
	(0.0040)	(0.0357)	(0.0357)
4	-0.9521***	-0.9909***	-0.9910***
	(0.0045)	(0.0401)	(0.0401)
5	-1.1640***	-1.2038***	-1.2039***
	(0.0049)	(0.0434)	(0.0434)
6	-1.3966***	-1.4472***	-1.4473***
	(0.0045)	(0.0402)	(0.0402)
Location	-0.1711***	-0.1694***	-0.1694***
2	(0.0022)	(0.0208)	(0.0208)
3	-0.1466***	-0.1458***	-0.1458***
	(0.0026)	(0.0235)	(0.0235)
4	-0.2683***	-0.2605***	-0.2605***
	(0.0038)	(0.0345)	(0.0345)
5	-0.0173***	-0.0154	-0.0153
	(0.0031)	(0.0277)	(0.0277)
6	-0.1398***	-0.1430***	-0.1430***
	(0.0050)	(0.0423)	(0.0422)
State	0.1386***	0.1367***	0.1367***
2	(0.0042)	(0.0378)	(0.0378)
3	-0.1643***	-0.1741***	-0.1742***
	(0.0022)	(0.0185)	(0.0185)
4	-0.2016***	-0.2049***	-0.2049***
	(0.0020)	(0.0174)	(0.0174)
5	-0.2029***	-0.2126***	-0.2126***
	(0.0017)	(0.0155)	(0.0155)
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Constant	5.7549***	5.7996***	5.7996***
	(0.0067)	(0.0521)	(0.0521)
Observation	118,662	118,662	118,662
R^2	0.7952	0.8505	N/A

Note: Class represents 1 for luxury, 2 for upper-upscale, 3 for upscale, 4 for upper-midscale, 5 for midscale, and 6 for economy hotels; Location represents 1 for urban, 2 for suburban, 3 for airport, 4 for interstate or motorway, 5 for resort, and 6 for small metro or town; State represents a categorical variable, which is 1 for CA, 2 for NY, 3 for IL, 4 for FL, and 5 for TX; robust standard errors in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

The results in Table 3 were consistent with the findings in Table 1 and 2 and re-confirmed the relationship between the monthly weather changes and hotel performance. More specifically, the monthly ambient temperature anomaly influenced ADR positively (0.0012, p-value<0.01) but did not significantly influence the occupancy rate (0.0002, p-value>0.1) whereas the monthly rain anomaly significantly increased both ADR (0.0012, p-value<0.01) and the occupancy rate (0.0013, p-value<0.01). As a result, the relationship between the monthly ambient temperature anomaly and RevPAR (0.0015, p-value<0.01) was significantly positive not substantially different from those in Table 2 (0.0012, p-value<0.01) but the relationship between the monthly rain anomaly and RevPAR (0.0026, p-value<0.01) was significantly positive and substantially larger than those in Table 2 (0.0013, p-value<0.01) and 3 (0.0012, p-value<0.01). In other words, under the abnormally hot ambient temperature, customers were willing to pay higher room prices but might not extend their stay. However, under the abnormally large amounts of rain, customers were not only willing to pay higher room prices but also tended to stay longer or even might attract other customers who initially did not intend to stay at the hotel. In addition, the RevPAR of luxury hotels (1) were highest and followed by upper-upscale (2), upscale (3), upper-midscale (4), midscale (5), and economy (6) in order. In terms of location, hotels in urban (1) area and in NY (0.1215, p-value<0.01 in RE or 0.1216, p-value<0.01 in GEE) had the highest RevPAR after controlling other variables constant.

Table 3. Effect of temperature anomaly and rain anomaly on RevPAR

	LogRevPAR		
	OLS	RE	GEE
Temperature anomaly	0.0012^{***}	0.0015^{***}	0.0015^{***}
	(0.0004)	(0.0003)	(0.0003)
Rain anomaly	0.0006	0.0026^{***}	0.0026^{***}
	(0.0004)	(0.0003)	(0.0003)
Age (years of operation)	-0.0006^{***}	-0.0005	-0.0005
	(0.0001)	(0.0007)	(0.0007)
Size (number of rooms)	-0.0063^{***}	-0.0107	-0.0107
	(0.0016)	(0.0127)	(0.0127)
Full-service	-0.1184^{***}	-0.1114^{***}	-0.1114^{***}
	(0.0031)	(0.0233)	(0.0233)
Class 2	-0.3635^{***}	-0.3948^{***}	-0.3951^{***}
	(0.0048)	(0.0371)	(0.0371)
3	-0.6352^{***}	-0.6696^{***}	-0.6699^{***}
	(0.0052)	(0.0390)	(0.0391)
4	-1.0320^{***}	-1.0659^{***}	-1.0661^{***}
	(0.0060)	(0.0448)	(0.0449)
5	-1.2392^{***}	-1.2702^{***}	-1.2705^{***}
	(0.0068)	(0.0522)	(0.0522)
6	-1.3916^{***}	-1.4391^{***}	-1.4394^{***}
	(0.0059)	(0.0438)	(0.0439)
Location 2	-0.2200^{***}	-0.2225^{***}	-0.2224^{***}
	(0.0030)	(0.0251)	(0.0251)
3	-0.1430^{***}	-0.1425^{***}	-0.1424^{***}
	(0.0035)	(0.0279)	(0.0279)
4	-0.3084^{***}	-0.3044^{***}	-0.3043^{***}
	(0.0054)	(0.0404)	(0.0404)

5	-0.0646***	-0.0669**	-0.0668**
	(0.0043)	(0.0335)	(0.0335)
6	-0.2147***	-0.2219***	-0.2218***
	(0.0072)	(0.0498)	(0.0498)
State	0.1193***	0.1215**	0.1216**
2	(0.0058)	(0.0497)	(0.0497)
3	-0.2410***	-0.2523***	-0.2524***
	(0.0032)	(0.0229)	(0.0229)
4	-0.2281***	-0.2306***	-0.2307***
	(0.0028)	(0.0208)	(0.0208)
5	-0.2993***	-0.3096***	-0.3096***
	(0.0023)	(0.0182)	(0.0182)
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Constant	5.4074***	5.4476***	5.4477***
	(0.0089)	(0.0586)	(0.0586)
Observation	118,662	118,662	118,662
R^2	0.6973	0.8000	N/A

Note: Class represents 1 for luxury, 2 for upper-upscale, 3 for upscale, 4 for upper-midscale, 5 for midscale, and 6 for economy hotels; Location represents 1 for urban, 2 for suburban, 3 for airport, 4 for interstate or motorway, 5 for resort, and 6 for small metro or town; State represents a categorical variable, which is 1 for CA, 2 for NY, 3 for IL, 4 for FL, and 5 for TX; robust standard errors in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

For additional analysis, this study examined the relationship between the monthly weather anomaly and monthly hotel performance in different classes (luxury & upper-upscale vs. up & upper middle vs. middle & economy hotels). Only the results of GEE models were presented in this step since the findings between RE and GEE models were almost identical. As shown in Table 4, the effect of monthly temperature anomaly had an insignificant impact on the occupancy rate (0.0003, p-value>0.1), ADR (0.0003, p-value>0.1), and RevPAR (0.0006, p-value>0.1) of luxury and upper-upscale hotels. However, it had a significant impact on ADR (0.0015, p-value<0.01) and RevPAR (0.0017, p-value<0.01) of up and upper middle hotels as well as on ADR (0.0015, p-value<0.01) and RevPAR (0.0019, p-value<0.01) of middle and economy hotels. On the contrary, the monthly rain anomaly indicated a significant impact on the occupancy rate (0.0015, p-value<0.01), ADR (0.0025, p-value<0.01), and RevPAR (0.0040, p-value<0.01) of luxury and upper-upscale hotels. Furthermore, the effects seemed to be much stronger than those of lower levels of hotels: the coefficients of the occupancy rate (0.0012, p-value<0.01), ADR (0.0009, p-value<0.01), and RevPAR (0.0020, p-value<0.01) of up and upper middle hotels and the coefficients of the occupancy rate (0.0013, p-value<0.01), ADR (0.0007, p-value<0.01), and RevPAR (0.0020, p-value<0.01) of middle and economy hotels. Interestingly, the age of hotels influenced positively hotel performance in luxury and upper-upscale hotels although it showed a negative effect on hotel performance in lower levels of hotels. In terms of location, in both categories, the hotels in urban area, CA, and NY showed the higher performance than other areas, which was consistent with the findings in Table 1, 2, and 3.

Table 4. Effect of temperature anomaly and rain anomaly on hotel performance by hotel classes

	GEE model								
	LogOccupancy			LogADR			LogRevPAR		
	Luxury& Upper-Up	Up & Upper Middle	Mid & Economy	Luxury& Upper-Up	Up & Upper Middle	Lower Classes	Luxury& Upper-Up	Up & Upper Middle	Mid & Economy
Temperature anomaly	0.0003 (0.0003)	0.0002 (0.003)	0.0004 (0.0004)	0.0003 (0.0003)	0.0015*** (0.0002)	0.0015*** (0.0004)	0.0006 (0.0005)	0.0017*** (0.0004)	0.0019*** (0.0005)
Rain anomaly	0.0015*** (0.0004)	0.0012*** (0.0003)	0.0013*** (0.0004)	0.0025*** (0.0005)	0.0009*** (0.0003)	0.0007* (0.0004)	0.0040*** (0.0007)	0.0020*** (0.0005)	0.0020*** (0.0005)
Age (years of operation)	0.0005** (0.0002)	-0.0015* (0.0006)	-0.0072** (0.0015)	0.0008 (0.0006)	-0.0032* (0.0019)	-0.0076** (0.0030)	0.0012* (0.0007)	-0.0047** (0.0024)	-0.0148*** (0.0033)
Size (number of rooms)	-0.0081 (0.0061)	0.0112* (0.0068)	-0.0019 (0.0156)	-0.0232 (0.0154)	0.0076 (0.0148)	0.0055 (0.0310)	-0.0314* (0.0184)	0.0189 (0.0187)	0.0034 (0.0406)
Full-service	-0.0579*** (0.0199)	-0.0708*** (0.0099)	-0.0924 (0.1157)	0.0362 (0.0573)	-0.0441** (0.0215)	0.5278*** (0.1277)	-0.0218 (0.0573)	-0.1147*** (0.0269)	0.4334*** (0.1061)
Class 2	0.0345*** (0.0118)	N/A	N/A	-0.4142*** (0.0343)	N/A	N/A	-0.4142*** (0.0653)	N/A	N/A
3	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
4	N/A	-0.0790*** (0.0100)	N/A	N/A	-0.2811*** (0.0228)	N/A	N/A	-0.3599*** (0.0281)	N/A
5	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
6	N/A	N/A	0.0193 (0.0156)	N/A	N/A	-0.2785*** (0.0316)	N/A	N/A	-0.2593*** (0.0361)
Location 2	-0.0653*** (0.0138)	-0.0337*** (0.0121)	-0.0430*** (0.0103)	-0.1569*** (0.0373)	-0.1546*** (0.0313)	-0.2059*** (0.0709)	-0.2232*** (0.0431)	-0.1883*** (0.0390)	-0.2489*** (0.0496)
3	0.0161 (0.0151)	0.0146 (0.0148)	0.0020 (0.0146)	-0.2043*** (0.0337)	-0.1364*** (0.0341)	-0.1094* (0.0566)	-0.1885*** (0.0403)	-0.1212*** (0.0424)	-0.1073* (0.0638)
4	N/A	-0.0095 (0.0234)	-0.0243 (0.0230)	N/A	-0.2864*** (0.0433)	-0.1248* (0.0721)	N/A	-0.2959*** (0.0526)	-0.1492** (0.0743)
5	-0.0968*** (0.0166)	0.0416** (0.0206)	-0.0529*** (0.0202)	0.0419 (0.0377)	-0.0211 (0.0557)	-0.1537** (0.0630)	-0.0552 (0.0453)	0.0206 (0.0683)	-0.2067*** (0.0682)
6	-0.1632*** (0.0278)	-0.0371* (0.0204)	-0.0352 (0.0540)	0.1244* (0.0707)	-0.1918*** (0.0463)	-0.2483* (0.1499)	-0.0390 (0.0872)	-0.2288*** (0.0587)	-0.2831* (0.1865)
State 2	0.0159 (0.0266)	-0.0100 (0.0252)	-0.0767** (0.0275)	0.1983*** (0.0650)	0.1420** (0.0582)	0.0938 (0.0709)	0.2145*** (0.0831)	0.1336* (0.0777)	0.0170 (0.0928)
3	-0.0712*** (0.0140)	-0.0851*** (0.0137)	-0.0966*** (0.0104)	-0.0534 (0.0376)	-0.1621*** (0.0306)	-0.3061*** (0.0233)	-0.1245*** (0.0440)	-0.2471*** (0.0395)	-0.4027*** (0.0281)

4	-0.0092 (0.0148)	-0.0511*** (0.0121)	-0.0288*** (0.0105)	-0.1287*** (0.0340)	-0.2570*** (0.0246)	-0.1953*** (0.0328)	-0.1377*** (0.0398)	-0.3081*** (0.0314)	- 0.2241*** (0.0391)
5	-0.1078 (0.0128)	-0.1208*** (0.0114)	-0.0506*** (0.0091)	-0.1454*** (0.0304)	-0.2027*** (0.0236)	-0.3050*** (0.0246)	-0.2528*** (0.0345)	-0.3234*** (0.0299)	- 0.3556*** (0.0282)
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.2868*** (0.0295)	4.2858*** (0.0263)	4.2493*** (0.0426)	5.6762*** (0.0736)	5.0980*** (0.0607)	4.7209*** (0.0934)	5.3574*** (0.0831)	4.7784*** (0.0773)	4.3654*** (0.1137)
Observation	33,520	53,765	31,377	33,520	53,765	31,377	33,520	53,765	31,377

Note: Class represents 1 for luxury, 2 for upper-upscale, 3 for upscale, 4 for upper-midscale, 5 for midscale, and 6 for economy hotels; Location represents 1 for urban, 2 for suburban, 3 for airport, 4 for interstate or motorway, 5 for resort, and 6 for small metro or town; State represents a categorical variable, which is 1 for CA, 2 for NY, 3 for IL, 4 for FL, and 5 for TX; robust standard errors in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Lastly, this study compared the impact of the monthly weather anomaly on monthly hotel performance between full-service hotels and limited-service hotels (see Table 5). The results were consistent with those of different classes in Table 4. Overall, the effect of the monthly temperature anomaly presented an insignificant on the occupancy rate for both limited-service (0.0003, p-value>0.1) and full-service hotels (0.0000, p-value>0.1). However, its impact on ADR was significant for both limited-service (0.0016, p-value<0.01) and full-service hotels (0.0008, p-value<0.01). In addition, monthly temperature anomaly showed a marginally significant impact on RevPAR of full-service hotels (0.0008, p-value<0.01), while a significant impact on RevPAR of limited-service hotels (0.0019, p-value<0.01). Whereas the monthly rain anomaly indicated much stronger effect on the occupancy rate (0.0018, p-value<0.01), ADR (0.0024, p-value<0.01), and RevPAR (0.0042, p-value<0.01) in full-service hotels than those in limited-service hotels (the occupancy rate (0.0011, p-value>0.1), ADR (0.0004, p-value<0.1), and RevPAR (0.0015, p-value<0.01). Therefore, the findings indicated that the performance of full-service hotels tended to be less influenced by the abnormally hot ambient temperature but more influenced by the abnormal amounts of rain than limited-service hotels. In addition, the age of hotels showed a positive influence on overall performance in full-service hotels but it had a negative effect in limited-service hotels. In the aspects of locations, both full- and limited-service hotels in urban area, CA, and NY showed better performance than hotels in other locations when other variables remained constant.

Table 5. Effect of temperature anomaly and rain anomaly on hotel performance by hotel types

	GEE model					
	LogOccupancy		LogADR		LogRevPAR	
	Full	Limited	Full	Limited	Full	Limited
Temperature anomaly	0.0000 (0.0003)	0.0003 (0.0003)	0.0008*** (0.0003)	0.0016*** (0.0002)	0.0008* (0.0004)	0.0019*** (0.0036)
Rain anomaly	0.0018*** (0.0003)	0.0011*** (0.0003)	0.0024*** (0.0004)	0.0004* (0.0003)	0.0042*** (0.0006)	0.0015*** (0.0004)
Age (years of operation)	0.0005** (0.0002)	-0.0023*** (0.0006)	0.0008 (0.0006)	-0.0049*** (0.0013)	0.0013* (0.0007)	-0.0071*** (0.0017)
Size (number of rooms)	0.0034 (0.0054)	-0.0089 (0.0078)	-0.0084 (0.0134)	-0.0202 (0.0164)	-0.0051 (0.0160)	-0.0291 (0.0210)
Class 2	0.0315** (0.0125)	0.1676*** (0.0637)	-0.4314*** (0.0350)	-0.2609*** (0.0816)	-0.3990*** (0.0385)	-0.2928 (0.1311)
3	0.0150 (0.0151)	0.0718 (0.0444)	-0.6854*** (0.0388)	-0.6110*** (0.0409)	-0.6693*** (0.0432)	-0.5387*** (0.0682)
4	0.0293 (0.0240)	-0.0315 (0.0442)	-0.9620*** (0.0768)	-0.8781*** (0.0409)	-0.9316*** (0.0771)	-0.9091*** (0.0682)
5	-0.1251*** (0.0388)	-0.0138 (0.0465)	-1.1555*** (0.0944)	-1.1377*** (0.0456)	-1.2800*** (0.1086)	-1.1510*** (0.0741)
6	-0.2047*** (0.0161)	0.0438 (0.0441)	-0.9414*** (0.0413)	-1.3944*** (0.0398)	-1.1448*** (0.0463)	-1.3501*** (0.0665)
Location 2	-0.0641*** (0.0113)	-0.0357*** (0.0113)	-0.1477*** (0.0294)	-0.2073*** (0.0290)	-0.2125*** (0.0354)	-0.2430*** (0.0353)
3	0.0181 (0.0130)	0.0037 (0.0130)	-0.1639*** (0.0296)	-0.1476*** (0.0354)	-0.1458*** (0.0358)	-0.1439*** (0.0425)
4	0.0317 (0.1156)	-0.0279 (0.0158)	-0.2461*** (0.0417)	-0.2732*** (0.0422)	-0.2150 (0.1459)	-0.3011*** (0.0473)
5	-0.0720*** (0.0158)	-0.0121 (0.0174)	0.0302 (0.0347)	-0.0944** (0.0437)	-0.0420 (0.0423)	-0.1065** (0.0522)
6	-0.1174*** (0.0323)	-0.0522*** (0.0194)	0.0040 (0.0790)	-0.2226*** (0.0475)	-0.1138 (0.0848)	-0.2747** (0.0583)
State 2	0.0079 (0.0234)	-0.0302 (0.0242)	0.1568*** (0.0548)	0.1349** (0.0545)	0.1657** (0.0716)	0.1047 (0.0736)
3	-0.0771*** (0.0120)	-0.0798*** (0.0095)	-0.0901*** (0.0289)	-0.2542*** (0.0225)	-0.1669*** (0.0356)	-0.3341*** (0.0280)
4	-0.0051 (0.0126)	-0.0360*** (0.0090)	-0.1378*** (0.0278)	-0.2703*** (0.0216)	-0.1428*** (0.0328)	-0.3063*** (0.0268)
5	-0.1069*** (0.0113)	-0.0864*** (0.0079)	-0.1459*** (0.0252)	-0.2771*** (0.0181)	-0.2525*** (0.0295)	-0.3634*** (0.0218)
Month	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.1782*** (0.0257)	4.2397*** (0.0464)	5.6752*** (0.0646)	5.8631*** (0.0533)	5.2477*** (0.0734)	5.4969*** (0.0790)
Observation	48,547	70,115	48,547	70,115	48,547	70,115

Note: Class represents 1 for luxury, 2 for upper-upscale, 3 for upscale, 4 for upper-midscale, 5 for midscale, and 6 for economy hotels; Location represents 1 for urban, 2 for suburban, 3 for airport, 4 for interstate or motorway, 5 for resort, and

6 for small metro or town; State represents a categorical variable, which is 1 for CA, 2 for NY, 3 for IL, 4 for FL, and 5 for TX; robust standard errors in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

5. Conclusions and Implications

Weather conditions substantially influence tourists' travel plans, including their destination and hotel choices, length of stay, booking cancellations, and activities within the destinations (Zirulia, 2016). Abnormally high ambient temperatures and large amounts of rain can substantially hinder outdoor activities (Scott *et al.*, 2008). Although previous studies confirmed a substantial effect of weather changes on macrolevel tourist arrivals, minimal research has focused on the effects of weather changes on property-level industry performance. According to NOAA, weather forecasts have an accuracy of approximately 80% for a 7-day period and approximately 90% for a 5-day period (NOAA, 2020). In particular, accurate and timely weather information should be readily available, and the majority of hotel bookings are completed within a month or 30 days before the expected check-in (Falk & Vieru, 2019; Jang, Chen, & Miao, 2019; Tse & Poon, 2015). Therefore, this study suggests that weather forecast information should be practically applicable to revenue management practices along with the existing data resources.

The evidence also confirms that tourists are sensitive not only to abnormal ambient temperatures but also to abnormal amounts of rain. This finding is expected because many tourism activities, including sightseeing, shopping, swimming, and outdoor playing, are significantly influenced by weather conditions. However, this finding is unique and meaningful because it statistically proves for the first time that rain information is an important determinant of tourism activities, particularly for hotel-staying behavior. Tourists may want to stay long with the hope of a positive turnaround if weather conditions are unfavorable in certain destinations for short periods. In particular, the occupancy rate does not decrease even with an increase in the room price. Consequently, the significantly positive relationship between weather conditions and hotels' RevPAR implies that many tourists tend to adjust their travel plans based on their destinations' weather situations even during their trip (Aydin & Birbil, 2018; Rosselló-Nadal, 2014; Tepper, 2015). The existing literature has suggested a relationship between weather changes and tourist arrivals in accommodations (Chen & Lin, 2014; Falk, 2015). The current research empirically demonstrates the effects of abnormal weather conditions on room rates (i.e., willingness to pay the rate), and RevPAR is one of the key performance indicators. This finding can be fundamental for revenue management in general and dynamic pricing strategy in particular. Most studies on revenue management have focused on internal issues, such as consumer profiles, types of products/services, inventory, and technological advancement (Kimes, 2011). However, the result of the current research introduces a critical environmental factor (i.e., weather abnormality) into understanding guest behavior and developing operational strategies.

Furthermore, the current study demonstrates that tourists respond differently to various weather conditions. In particular, ambient temperature is not a imperative determinant when choosing high-level or full-service hotels, whereas rain condition is an important factor when selecting such hotels. The results indicate that tourists prefer to stay at superior-quality hotels with various facilities, such as spas, restaurants, and bars, rather than those with limited facilities and services under an abnormally heavy rain situation. This finding makes considerable practical sense and provides hands-on implications. For example, hotels in the United States are suggested to respond dynamically to changes in rain conditions in terms of marketing and revenue management. In particular, hotels that offer full services have high chances of increasing their room rates as the amount of precipitation increases, executing a weather-varying pricing model. The marketing managers of full-service hotels should always monitor weather forecasts for information about precipitation. Developing a proactive promotion and/or advertisement for visitors who tend to stay in the hotel during rainy days is suggested. In these contexts, the current study uniquely contributes to the literature in the aspect of robust model development and to the hotel and tourism industries by suggesting directly applicable revenue management determinants. The hospitality and tourism literature has suggested several internal and external factors that affect hotel performance. Among them, the current research identifies the important role of weather changes in explaining variations in hotel performance. Weather effects are dynamic under different types and classes of hotels.

The present research essentially demonstrates the effects of abnormal weather conditions on hotel performance and their heterogeneous effects across different types/classes of hotels in five states in the United States. Future research is suggested to investigate the issue with various countries and at the state level with various weather indicators (e.g., occurrence of wildfires and hurricanes). This approach will not only generalize the effects of weather changes on hotel performance but also provide a detailed understanding of weather effects by considering the spatial features of hotels, such as properties in beach and airport areas.

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