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An Empirical Analysis of US Hotels Including Free Breakfast with Room Rent

The likelihood of a US hotel including free breakfast with its rent is empirically measured as a function of hotel star rating, capacity, and rack rate. We used mixed-effects logistic regression to analyze the choices made by 1607 US hotels regarding whether to offer or not offer free breakfast with their room rent. Our analysis reveals that the probability of a hotel including free breakfast with its rent decreases with an increase in the star rating, decreases with an increase in hotel capacity, and decreases with an increase in the rack rate. These results have practical implications for hotel strategy.

Keywords: *hotels; rent; free breakfast; logistic regression; mixed effects; rating; capacity; rack rate;*

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1. Introduction

Hotels are a critical part of the travel and tourism industry and the service economy, especially in the United States. According to market research portal, Statista and the 2019 US Travel and Hospitality Outlook by Deloitte, the revenue in the US hotels industry is expected to hit US$9.85 Billion in 2020, with an expected CAGR of 5-6% over 2020-2023. In fact, the average revenue per user (ARPU) is approximately US$629.78 (Statista.com; Deloitte.com). In the hotel industry, offering free breakfast with the room is a popular strategy adopted by an increasing number of hotels. For example, hotels such as Best Western, Canopy by Hilton, Comfort Inn, Embassy Suites, Fairfield Inn and Suites, Hampton Inn, Holiday inn, La Quinta Inn, and Wingate by Wyndham all offer their guests free breakfast (TripAdvisor.com; Creditcards.com). However, not all hotels offer guests free breakfast, as indicated in our survey. We surveyed a large variety of 1607 hotels situated in 34 cities in the United States of America and recorded whether or not they offered free breakfast with their room rent. We observed that 761 hotels (i.e., 47.4% hotels) included free breakfast, while the remaining 846 hotels (i.e., 52.6% hotels) excluded breakfast from room rent. This dichotomous distribution of choices among hotels prompts a deeper investigation regarding the likelihood of hotels including free breakfast. On what factors does the likelihood of a hotel offering free breakfast depend? What is the profile of hotels more likely to include free breakfast, and how does their profile differ from those excluding free breakfast from room rent? This paper partially answers these questions.

In order to formally analyze the likelihood of a hotel including free breakfast with rent, we analyze a mixed-logit regression model, estimated using data derived from hotels renting rooms on the popular www.hotels.com portal. We focus empirical attention on how three important hotel attributes factors – (i) star rating, (ii) capacity (i.e., number of rooms), and (iii) rack rate – influence this likelihood. Our regression analysis leads to the following three insights:

(i) The probability of including free breakfast with rent decreases with an increase in hotel star rating.
(ii) The probability of including free breakfast with rent decreases with an increase in hotel capacity.
(iii) The probability of including free breakfast with rent decreases with an increase in hotel rack rate.

2. Literature Review

Many lodging operations offer a complimentary breakfast as a sales tool. Our research is closely related to Nicolau and Sellers (2012), who study the zero price effect in tourism, extending the research by Shampanier, Mazar, and Ariely (2007). Here, a free product can become so extraordinarily attractive that another much more preferred alternative is foregone by consumers. This insight holds critical managerial implications for multicomponent tourism products because fixing a zero price for a specific component (e.g., breakfast) included in a product (e.g., hotel room plus breakfast) can abnormally raise the demand for the product.
In related research, Monty and Skidmore (2003) evaluate consumer willingness to pay for specific characteristics of free breakfast with the room, applying the hedonic price technique to the bed and breakfast market.

Acknowledging that a hotel is a complex, experience-based product, Xiang and Usyal (2015) use text analytics to determine what leads to guest satisfaction. They analyze online customer reviews for hotels and report that the word 'Breakfast' appears with a frequency of 2.9 times per hotel and is the 9th most frequently occurring word among the top 80 primary words. Lee et al. (2017) identify which bundle of breakfast items is most preferred by travelers. Their findings suggest that managers should keep fruit bowls, waffles, scrambled eggs, and coffee on their menus.

Mixed-Logit Regression: We estimate the probability of offering free breakfast using the well-known mixed logistic regression model (McFadden and Train, 2000; Andrews et al., 2002; Ben-Akiva et al., 2002; Hensher and Greene, 2003; Hess and Polak, 2005; Fiebig et al., 2010). We model the probability of a hotel including free breakfast with rent as a function of the star rating, capacity, rack rate, spatial characteristics across different cities, and seasonality across ten dates. We use the mixed logit model since it is known to overcome some crucial limitations of the classical logit model. In particular, it allows us to model random variation and possible correlation in unobserved factors over time and across spatial locations. It also allows us to relax the strong assumption of the Independence of Irrelevant Alternatives (IIA) present in the classical logit model. Moreover, this model framework is flexible enough to reasonably approximate many random utility models (McFadden & Train, 2000). One limitation of mixed-effect models is that they tend to be computer resource intensive. However, given recent advances in computing power, simulation algorithms, and computer packages, it has become feasible to run them (Alfnes, 2004; Espino et al., 2008). Although the mixed logit model can be derived under a variety of behavioral specifications (Train, 2003), the most commonly used version is the random coefficient version of the model, and the same version is used in this paper.

Our paper contributes to the wide spectrum of past research on choice model in the hotel industry context (Kim & Perdue, 2013; Mei & Zhan, 2013; Masiero et al., 2015, 2016; Kim and Park, 2017). In particular, it is noteworthy that the mixed logit estimation approach has been previously successfully used by researchers in Tourism Management (e.g., Albaladego-Pina & Diaz-Delfa, 2009; Choi et al., 2009; Kim and Park, 2017). For example, Choi et al. (2009) study the economic valuation of cultural heritage sites using choice modeling; Albaladego-Pina and Diaz-Delfa (2009) analyze tourist preferences for rural house stays in Spain using discrete choice modeling; while Kim and Park (2017) study the moderating role of context in hotel choice in a mixed-logit framework.

Discrete choice modeling has often been utilized to empirically analyze the relationship between product characteristics and choice in tourism and hospitality domains (Crouch & Louviere, 2000). For example, such models have been frequently used in analyzing the destination choice of tourists (Morley, 1994; Eymann & Ronning, 1997; Seddighi & Theocharous, 2002), while other applications include analyzing restaurant selection (Kim & Geistfeld, 2003; Kim & gu, 2006), recreational choice (Bhat & Gossen, 2004). Consistent with the methodology used in previously published papers, our research also used a mixed-logit model framework to analyze the factors driving the likelihood of US hotels offering free breakfast with room rent.

3. Empirical Analysis of Hotels Including Free Breakfast with Room Rent

The overall objective behind the empirical study presented in this paper is to investigate the likelihood of hotels offering free breakfast. The study evaluates the probability of a hotel including free breakfast in a mixed logit model framework. The goal is to analyze how the (i) star rating, (ii) capacity, (iii) rack rate of a hotel influence and impact its probability of including free breakfast with room rent.

3.1 Data

We collected hotel data from the popular travel portal www.hotels.com. Our dataset consists of a total of $I = 1603$ unique hotels located in $J = 34$ major cities across the United States, such as Chicago, New York, Los Angeles, Houston, Pheonix, and Boston. The dataset includes (i) the name of the hotel; (ii) the city in which it is located; (iii) the star rating on a 5-point scale; (iv) the capacity, i.e., maximum number of available rooms; (v) whether or not the hotel includes free breakfast with its room rent; (vi) the rack rate, which is the "published rate," or "the maximum rent that a property charges for a room. During Nov 1-3, 2017, we recorded

(vii) the rent for a standard double occupancy room for (viii) $T = 10$ dates (Nov 29, 2017 - Dec 8, 2017), as posted on www.hotels.com. After cleaning the data with missing values, this yielded a dataset of $N = 15057$ rows. The meaning of the data columns is summarized in Table 1. Table 2 summarizes the room rent, rack rate, and hotel capacity with respect to the star rating and whether or not free breakfast is included with the rent. Table 2 also includes the correlation matrix between star rating, capacity, and rack rate, and the correlations raise the possibility of multicollinearity in the data. It is important to acknowledge that the data used in this paper is from pre-Covid times (Nov 2017).

Table 1: *Data variables and description.*

i	Index to track a hotel
j	Index to track the city in which hotel i is located, ($1 \leq j \leq J$, where $J = 34$)
t	Index to track the date ($1 \leq t \leq T, where\ T = 10$)
$City_j$	The name of the city in which hotel i is located.
$Date_t$	The date for which hotel rent was recorded, where $Date_t \in (Nov\ 29 - Dec\ 8, 2017)$
$StarRating_{ij}$	The star rating of hotel i, in City j, where $Rating_{ij} \in \{2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0\}$
$Capacity_{ij}$	The capacity (i.e., maximum number of rooms) of hotel i, in $City_j$.
$RackRate_{ijt}$	The rack rate (i.e., maximum rent) for a standard, double occupancy room at hotel i, in $City_j$, for $Date_t$ (measured in USD)
FB_{ijt}	Indicator variable for whether hotel i, in $City_j$ on $Date_t$ bundled free breakfast with rent.

$Rent_{ijt}$	The rent for a standard, double occupancy room at hotel i, in $City_j$, for $Date_t$ (measured in USD)

Table 2: *Summary Statistics of room rent, rack rate, and hotel capacity, with respect to the star rating and whether or not free breakfast is bundled with rent.*

StarRating (S)	*Free Breakfast (F)*	*No. of Hotels*	*% Hotels including Free Breakfast*	*Mean Capacity*	*Mean Rack Rate, in USD*	*Mean Rent in USD*
2.0	No	114	47.2	79.8	$88.82	$71.33
2.0	Yes	123	52.8	76.9	$93.26	$73.69
2.5	No	88	21.4	99.9	$125.25	$98.72
2.5	Yes	314	78.6	97.1	$126.62	$100.52
3.0	No	190	48.0	167.0	$171.58	$127.68
3.0	Yes	204	52.0	119.5	$168.27	$129.68
3.5	No	167	71.6	254.0	$210.91	$156.01
3.5	Yes	68	28.4	166.4	$181.10	$147.61
4.0	No	195	84.1	314.3	$270.76	$204.71
4.0	Yes	37	15.9	250.0	$230.60	$184.12
4.5	No	58	85.1	295.8	$381.08	$278.47
4.5	Yes	10	14.9	323.1	$314.78	$259.46
5.0	No	36	81.3	199.6	$875.15	$623.94
5.0	Yes	8	18.7	195.6	$592.07	$452.79
All	No	846	52.6	209.19	$229.72	$171.32
All	Yes	761	47.4	116.54	$148.70	$117.29
All	All	1607	100.0	164.74	$190.85	$145.40

	StarRating	*Capacity*	*RackRate*
StarRating	1	0.4871***	0.5593***
Capacity	0.4871	1	0.1936***
RackRate	0.5593***	0.1936***	1

3.2 Model

We propose a Generalized Linear Mixed Model (GLMM) to empirically measure the probability of a hotel bundling free breakfast along with the rent. The GLMM is an extension of logistic regression to include fixed and random effects (Gilmore et al. 1985; McCulloch, 1997). They are an extension of the class of generalized linear models in which random effects are added to the linear predictor. This allows the modeling of correlated, possibly nonnormally distributed data with flexible accommodation of covariates (McCulloch and Neuhaus 2005). The general form of the GLMM model, in matrix notation, is

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{Zu} + \boldsymbol{\epsilon} \tag{1}$$

Here, $\boldsymbol{y}$ is an $N \times 1$ column vector of the outcome variable. Our model's outcome variable is binary, indicating whether a hotel includes or excludes free breakfast with its room rent. Specifically, $FreeBreakfast_{ijt} = 1$, if hotel i, located in city j includes free breakfast with its room rent on date t, with $FreeBreakfast_{ijt} = 0$, otherwise.

Also, $\boldsymbol{X}$ is an $N \times f$ matrix of f predictor variables, while $\boldsymbol{\beta}$ is an $f \times 1$ column vector of the fixed-effects regression coefficients. In our model, the fixed-effects include the hotel rating, capacity, rack rate, and the interaction between the rating and capacity. Specifically, $Rating_{ij}$ and $Capacity_{ij}$ represent the star rating and capacity (i.e., no of rooms) for hotel i, located in city j. $RackRate_{ijt}$ represents the rack rate (i.e. maximum rent) for hotel i, located in city j on date t.

It should be noted that $\boldsymbol{Z}$ is the $N \times q$ design matrix for the q random effects, while $\boldsymbol{u}$ is a $q \times 1$ vector of the random effects. In our model, the random effects include the $q = 34$ cities. We model the cities as random effects because we expect that the decision to include free breakfast with rent may be correlated across cities.

Finally, $\boldsymbol{\varepsilon}$ is an $N \times 1$ column vector of the residuals. It is the part of $\boldsymbol{y}$ that is not explained by the model, $\boldsymbol{X\beta} + \boldsymbol{Zu}$. Note that $\boldsymbol{Z}$ is a large, 15057×34 sparse matrix. Since we are only modeling random intercepts, the matrix $\boldsymbol{Z}$ codes which city a given hotel is located in. Also, the random effects are modeled as deviations from the fixed effects $\boldsymbol{\beta}$ and therefore have a mean zero. We assume that $\boldsymbol{u} \sim \boldsymbol{N}\ (\mathbf{0}, \boldsymbol{G})$, where $\boldsymbol{G}$ is the variance-covariance matrix of the random effects. Since we only have a random intercept, $\boldsymbol{G}$ is just a 1×1 matrix, the variance of the random intercept.

Let p_{ijt} represent the probability of hotel *i*, in city *j*, date *t*, bundling free breakfast along with its rent. Then, the log-odds ratio of bundling free breakfast with rent is $y_{ijt} = log\left(\frac{p_{ijt}}{1-p_{ijt}}\right)$.

We are interested in the influence of hotel rating, hotel capacity, and the rack rate on a hotel's decision to bundle free breakfast with rent. We adopt the logistic regression framework to model this relationship as follows.

$$\begin{aligned} y_{ijt} = log\left(\frac{p_{ijt}}{1-p_{ijt}}\right) \\ = \beta_0 + \beta_s Rating_{ij} + \beta_c Capacity_{ij} + \beta_{sc} Rating_{ij} * Capacity_{ij} \\ + \beta_r RackRate_{ijt} + \epsilon \end{aligned} \tag{2}$$

Table 3 gives the output of the mixed logit regression model described above.

Table 3: *Mixed Logit Regression output to estimate the probability of a hotel including free breakfast, as a function of hotel star rating, capacity, and rack rate*

Predictors	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**
(Intercept)	2.8039	0.23238	12.06	< 2e-16 ***
StarRating (S)	-0.70548	0.05472	-12.892	< 2e-16 ***
Capacity (C)	-0.00257	0.00123	-2.088	0.0368 *
RackRate (R)	-0.000335	0.00019	-1.768	0.0771**.**
*StarRating (S) * Capacity (C)*	-0.00072	0.00035	-2.052	0.0401 *

Signif. codes: '***' $p < 0.001$; '**' $p < 0.01$; '*' $p < 0.05$; '.' $p < 0.1$

Random Effects

Groups Name	**Variance**	**Std.Dev.**
City	0.9578	0.9787

Date	0	0
Observations (N)	15,057	
Deviance	16134.4	
Log Likelihood (LL)	-8067.18	
AIC	16148.36	
BIC	16201.7	

Correlation of Fixed Effects

	Intercept	*StarRating*	*Capacity*	*RackRate*
Rating	-0.653			
Capacity	-0.528	0.627		
RackRate	0.063	-0.313	0.076	
*StarRating*Capacity*	0.545	-0.691	-0.981	-0.065

3.3 Results

The mixed logit regression explains how the hotel star rating influences the likelihood of bundling free breakfast.

Result 1: (Effect of Star Rating on the Probability of Bundling Free Breakfast)

The probability of including free breakfast with rent decreases with an increase in hotel star rating.

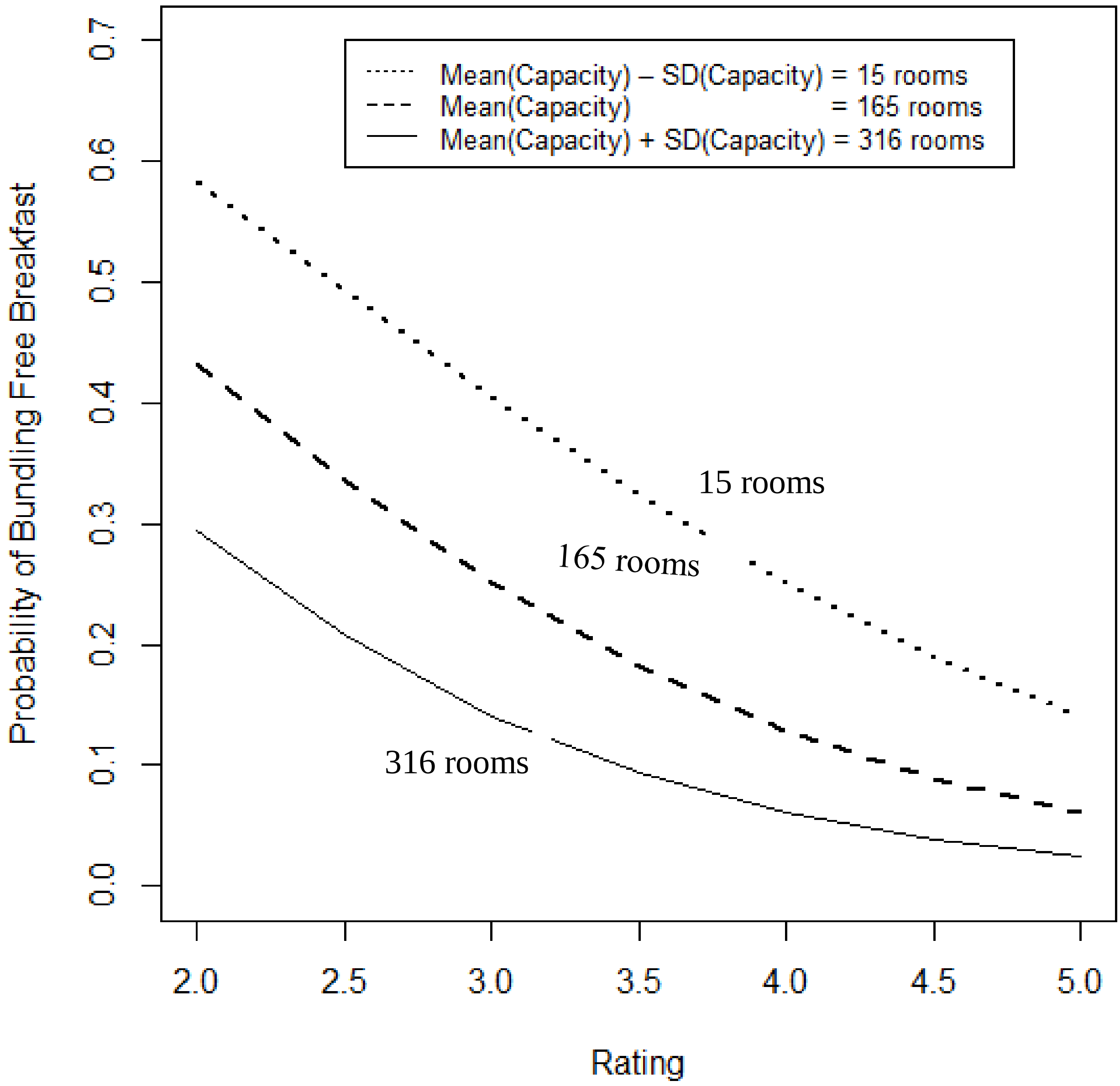
Illustration of Result 1 for Chicago, and New York City, USA: Figure 1 plots Result 1 for the city of Chicago. It depicts the decrease in the probability of Chicago hotels of average capacity (165 rooms), including free breakfast with their rent, as the star rating increases. As a robustness check, Figure 1 also depicts a similar trend for smaller capacity Chicago hotels (15 rooms) and larger capacity Chicago hotels (316 rooms). In fact, as summarized in Table 4, the estimated probabilities of 2, 3, 4, and 5-star hotels in Chicago, including free breakfast with their rent, are 43.2%, 25.0%, 12.8%, and 6%, respectively.

The trend in New York City hotels is qualitatively similar to Chicago. Also summarized in Table 4, the estimated probabilities of 2, 3, 4, and 5-star hotels in New York City, including free breakfast with their rent, are 68.5%, 48.8%, 29.5%, and 15.5%, respectively. These probabilities have been derived from the mixed logit regression output shown in Table 3.

Table 4: *Probability of Chicago and New York City hotels bundling free breakfast with rent (illustrating Result 1)*

City	Hotel Capacity	Star Rating	Probability of bundling Free Breakfast
Chicago	165	2	43.2%
		3	25.0%
		4	12.8%
		5	6.0%
New York	165	2	68.5%
		3	48.8%
		4	29.5%
		5	15.5%

Figure 1: *Probability of hotels in Chicago, USA bundling free breakfast as a function of their star rating for varying levels of hotel capacity.*



The mixed logit regression also describes how the hotel capacity, i.e., the number of available rooms in a hotel, influences the likelihood of including free breakfast, as follows.

Result 2 (Effect of Hotel Capacity on the Probability of Bundling Free Breakfast)

The probability of including free breakfast with rent decreases with an increase in hotel capacity.

The regression output shown in Table 3 also indicates a statistically significant negative interaction between hotel star rating and hotel capacity. This suggests that the probability of bundling free breakfast with hotel rent is the highest for low-capacity, low-star-rated hotels.

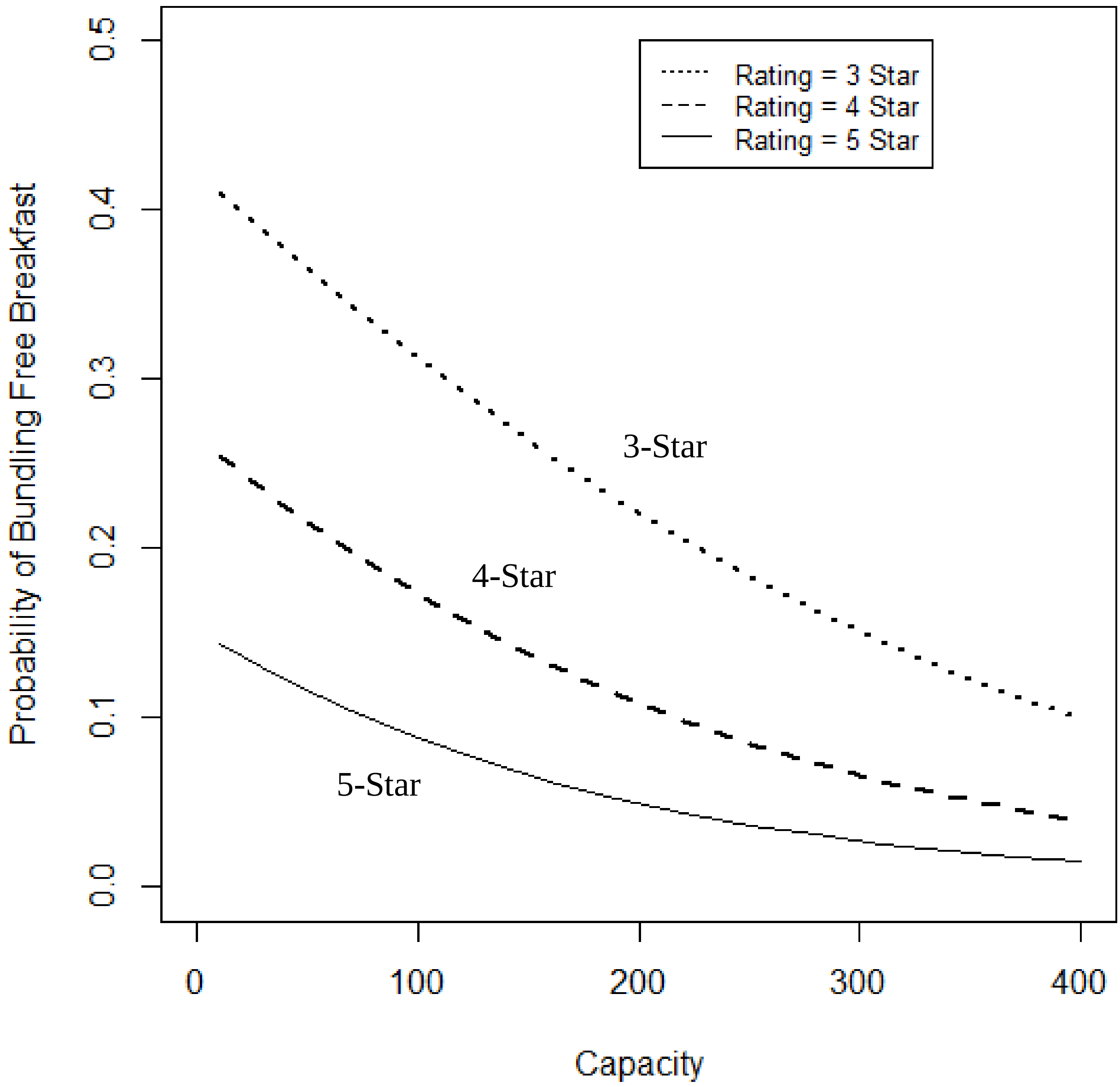
Illustration of Result 2 for Chicago and New York City, USA: Figure 2 depicts the probability of bundling free breakfast with rent in Chicago declines as the hotel capacity increases. As a robustness check, we verify that this trend is true for 3-star, 4-star and 5-star hotels. In fact, as summarized in Table 5, the estimated probabilities of 3-star hotels located in Chicago, having a capacity of 100, 200, and 300 rooms offering free breakfast, are 31%, 22%, and 15%, respectively. Similarly, the estimated probabilities of 5-star hotels located in Chicago, having a capacity of 100, 200, and 300 rooms, respectively, offering free breakfast are 8.7%, 4.9%, and 2.7%, respectively.

Table 5 further indicates that the trend in New York City hotels is qualitatively similar to Chicago, consistent with Result 2.

Table 5: *Probability of Chicago and New York City hotels bundling free breakfast with rent (illustrating Result 2)*

City	Star Rating	Hotel Capacity	Probability of bundling Free Breakfast
Chicago	3	100	31.0%
		200	22.0%
		300	15.0%
	4	100	17.3%
		200	10.8%
		300	6.5%
	5	100	8.7%
		200	4.9%
		300	2.7%
New York City	3	100	56.4%
		200	44.7%
		300	33.5%
	4	100	37.4%
		200	25.7%
		300	16.7%
	5	100	21.5%
		200	12.9%
		300	7.4%

Figure 2: *Probability of hotels in Chicago bundling free breakfast as a function of hotel capacity for 3-star, 4-star, and 5-star rated hotels.*



It is noteworthy that similar trends can be verified for the remaining 32 US cities in our dataset, lending credibility and robustness to Results 1 and 2.

Lastly, the mixed logit regression also describes how the rack rate of hotels, i.e., the maximum posted rent for hotels, influences the likelihood of including free breakfast.

Result 3 (Effect of Rack Rate on the Probability of Bundling Free Breakfast)

The probability of including free breakfast with rent decreases with an increase in hotel rack rate.

Here, it is important to acknowledge that we were able to find limited evidence to support Result 3. Specifically, we observed a weakly significant relationship between the probability of including free breakfast with rent and the corresponding rack rate ($p < .1$). We acknowledge that the p-value is 0.0771. This suggests that the influence of rack rate on the probability of offering free breakfast is relatively weaker than the corresponding influence of star rating and capacity, characterized in Result 1 and Result 2.

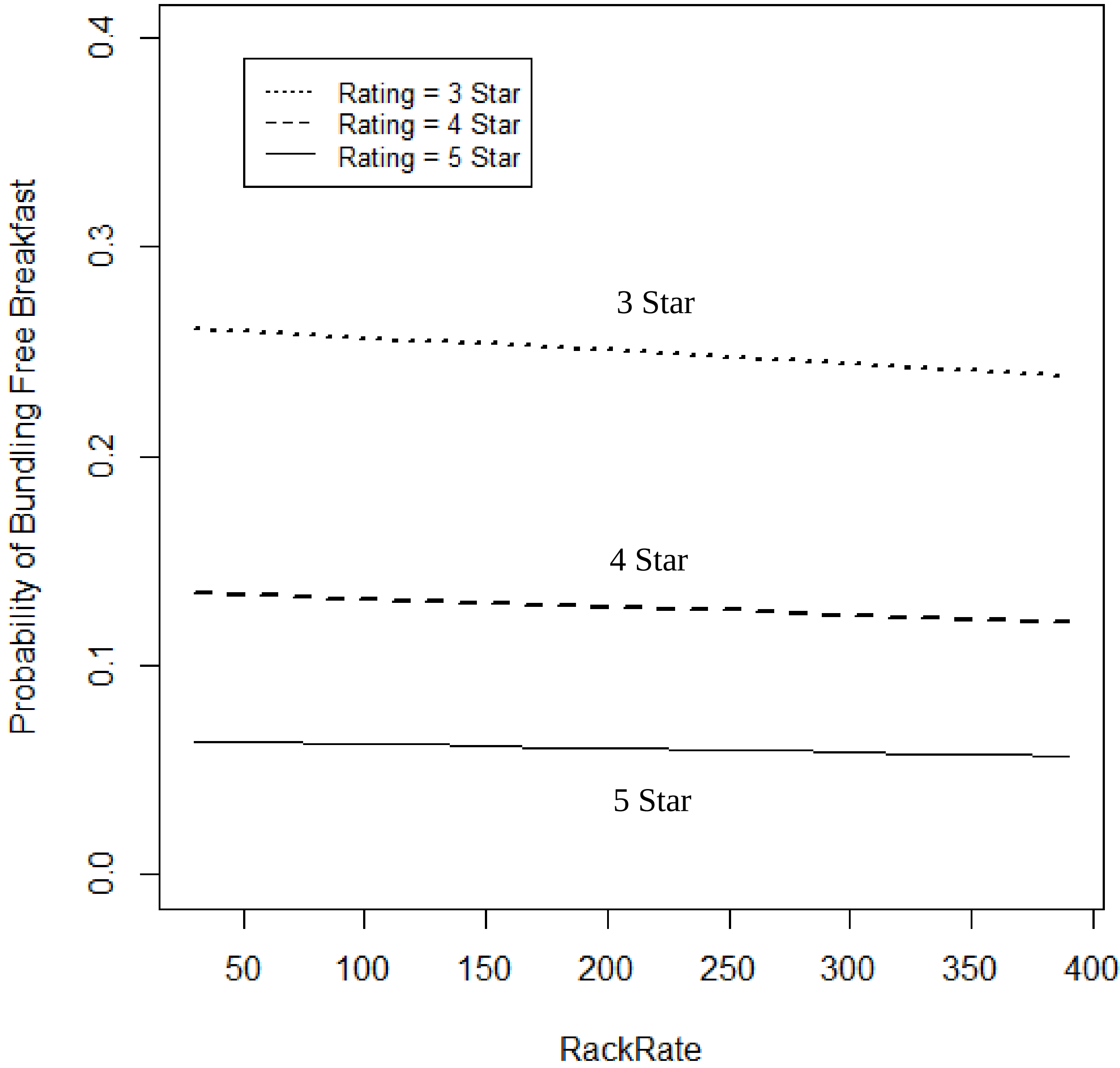
Illustration of Result 3 for Chicago and New York City, USA: Figure 3 illustrates Result 3 for Chicago and New York City. Figure 3 shows that the probability of bundling free breakfast with rent in Chicago declines slightly as the rack rate increases. This trend is true for 3-star, 4-star and 5-star hotels. The trend in New York City hotels is qualitatively similar to Chicago, as summarized in Table 6.

Table 6: *Probability of Chicago hotels bundling free breakfast with respect to rack rate (illustrating Result 3)*

Hotel Capacity	Star Rating	Rack Rate	Probability of bundling Free Breakfast
165	3	50	25.97%
		100	25.64%
		150	25.32%
		200	25.01%
165	5	250	5.95%

		300	5.85%
		350	5.76%
		400	5.67%

Figure 3: *Probability of hotels located in Chicago, USA bundling free breakfast as a function of rack rate*



4. Discussion

We discuss the marketing implications for practitioners and the research implications arising from this paper.

Marketing implications for practitioners: We begin by discussing how practitioners can use the findings in the paper from a marketing perspective. These marketing implications for practitioners are justified based on the empirical findings in the paper. Our first insight for practitioners is that relatively higher-rated hotels (e.g., five-star hotels) are significantly less likely to include free breakfast with their rent than relatively lower-rated hotels (e.g., three-star hotels). This makes sense. It is well known that five-star rated hotels offer high quality of service and luxury for correspondingly very high rents. Consequently, the consumers staying at such hotels are relatively less price sensitive and are more willing to pay for hotel rooms. Therefore, compared to lower-rated three-star hotels, five-star hotels do not benefit much from offering their consumers free breakfast. In contrast, lower-rated three-star hotels offer lower service quality and are far more of a commodity. They face heavy price competition. The consumers who prefer to stay at such hotels are more price sensitive and are less willing to pay. Therefore, it makes more sense for three-star hotels to tempt their consumers to stay at their hotel by including a freebie such as breakfast as part of the deal.

Our second insight for practitioners is that larger capacity hotels are less likely to include free breakfast with rent compared to relatively lower capacity hotels with fewer rooms. One explanation for this is that when a large number of rooms are involved, the corresponding profit from selling breakfast is a relatively large amount since the profit will be the average margin made on each breakfast multiplied by the number of rooms occupied. This suggests that businesses managing hotels having a large number of rooms should not bundle free breakfast along with room rent.

Our third insight for practitioners is that hotels with larger rack rates are less likely to offer free breakfast with rent than hotels with relatively low rack rates. An explanation is that the rack rates of highly rated hotels, such as five-star hotels, tend to be significantly larger than the rack rates of comparatively lower-rated hotels. Given this positive correlation between star rating and rack rate, and our previous explanation for why higher-rated hotels are less likely to offer free breakfast compared to lower-rated hotels, we expect to see a similar relationship emerge for the rack rate. However, given the magnitude of the findings, it appears that the influence of rack rate is relatively less severe than the influence of star rating and hotel capacity in driving the hotel's decision to include or exclude free breakfast with rent.

Research implications: This paper began with the anecdotal observation that approximately half the hotels in the US market include free breakfast with their rent, while the remaining half exclude free breakfast from room rent. This observation is prima facie quite puzzling with no obvious answer and therefore worthy of deeper analysis and discussion. After all, if one strategy strictly dominated the other strategy, we would observe nearly all hotels following one strategy. Instead, we have a near lack of unanimity on the best strategy – including or excluding free breakfast with rent. Our research contribution lies in using the mixed logit regression analysis framework in exploring this issue and systematically characterizing how hotel star rating, capacity, and hotel room rack rate jointly influence this decision.

5. Research Limitations and Conclusion

This paper has investigated the popular hotel strategy of including free breakfast with room rent, which is an important strategic decision. Our research suffers from several limitations, a few of which are as follows. We confine our attention to the US market. It will be interesting to see how robust our results are in European and Asian markets. Our focus was on the impact of three factors -- hotel star rating, capacity, and rack rate set by hotels, in determining the likelihood of their including free breakfast with rent. We acknowledge that a variety of factors besides these three factors may also influence this decision, and we leave this exploration for future research. For instance, future research could address the impact of other Socioeconomic factors in determining this choice.

It is also important to acknowledge that the data used in this paper is from pre-Covid times (Nov 2017), and it is possible that Covid may have influenced the results and implications presented in this paper.

To summarise, our research has shown that, relatively speaking, three-star hotels having relatively few rooms and relatively low rack rates and relatively low rack rates are the most likely to include free breakfast with rent. On the other extreme, five-star hotels with large capacity and relatively large rack rates are the least likely to include free breakfast with room rents.

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