Self-Scheduling Labor Supply in the Peer-to-Peer Housing Rental Markets

by

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**Abstract**

Airbnb, as the largest platform of the accommodation-sharing business, is not only offering convenience for tenants but also creating a flexible supply environment for hosts who list their properties on the website. Flexibility on Airbnb enables hosts to decide to open or block business on a random day. This research focuses on the flexible supply, attempting to delineate Airbnb’s accommodation supply curve by studying the blocking behavior of property suppliers. I investigate the blocking behavior of 897 properties that fit the definition of active properties in New York City by examining Airbnb website data. Through the basic data analysis, I find three features of Airbnb’s accommodation supply: First, the majority of properties choose to block more often than open. Second, the willingness to block is almost consistent from month to month. Third, most properties provided on Airbnb are long-term accommodation suppliers despite the high rate of blocking behavior. Through building a probit regression on the status, I predict the probability of blocking for properties every day in 2015. By plotting the reservation profit obtained by multiplying the probability of blocking with the published nightly rate with the number of open days, I find a supply curve with an upward trend.

**Key words:** *Sharing economy, Airbnb, flexibility in supply, accommodation supply*

**JEL Classification:** L1, L81, J22

1. **Introduction**

Sharing economy has become a phenomenon in recent years. Empowered by information and communications technology (ICTs), the peer-to-peer-based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services (Hamari et al. 2016) has gradually permeated into every aspect of people’s daily life. From the ride-sharing, to peer-to-peer lending, and to even talent-sharing, the public welcomes and enjoys the life enriched by companies like Uber, SoFi, and TaskRabbit.

Among numerous services provided by individuals, the accommodations of the sharing economy attracts the largest number of users from all over the world. One of the most prominent participant in the accommodation-sharing business is, of course, Airbnb, an Internet platform where hosts list their residences to potential guests (Xie & Mao 2017). Founded in 2008, Airbnb has been rapidly growing in the past decade. In 2020, the number of listings increased to 7 million spreading over in 100,000 cities in 220 countries and regions where have in total 2.9 million hosts (Steve Deane 2020).

In a nutshell, Airbnb is a platform subsisting on providing an environment for accommodation-sharing business to take place. It could be categorized as a two-sided market, where interaction and transaction take place by bring sellers and buyers “on board” (Rochet & Tirole 2004). The essence of each transaction is both supply and demand sides’ willingness to engage in the trade rather than the platform itself. The sharing economy or the two-sided market, after all, is a peer-to-peer-based activity (Hamari et al. 2016), which grants both sellers and buyers power to freely execute their will. Buyers have always had the power, but, to sellers, the power enabled by the flexibility of supply is realized for the first time in transactions. For example, in the ride-sharing economy, Uber drivers have the high autonomy to choose to provide and decline service anytime they are willing to. Such supply-side flexibility catalyzed the rapid growth of peer-to-peer platforms and becomes a significant hallmark of sharing economy (Zervas et al. 2017).

This research aims to study the supply-side flexibility in the Airbnb case. To be more specific, I would like to acquire a supply curve of accommodation in the Airbnb market. Nevertheless, with such flexibility in the supply end of the accommodation-sharing market, it is not easy to gain an insight into the supply directly because every individual property owner’s everyday decision regarding the status of their properties affects the supply. On Airbnb, a property is manifested with three potential statuses in a day: Available (A), Rented (R), and Blocking (B). A indicates that the property is not occupied yet and available for a reservation; R indicates that the property is already rented; and B indicates that the property is not open for business for the day. Evidently, both A and R are indicated that the host is engaging in the trade. Given that they essentially represent a unified status of opening, in this paper, the discussion of the status would only differentiate the opening and blocking behavior. This research is designed to find the supply curve through the study of the blocking behavior.

To understand the blocking behavior, it is necessary to understand the incentive that leads hosts to make the decision of blocking their properties on every night. Given the Uber driver choosing to work only when the reservation wage is lower than the expected earnings (Chen et al. 2019), it is reasonable to assume that the flexibility of providing accommodation is also driven by the time variation in a host’s reservation profit on a specific night. By definition, reservation wage is the minimum rate at which a worker would be willing to work (“Reservation wage,” n.d.). Similarly, the reservation profit is the minimum rate at which a host would be willing to not block his/her property on Airbnb. Thus, the reservation profit can be acquired by calculating the product of the average daily rate and the probability of blocking on a night. The average daily rate is provided by Airbnb as known information, while the probability of blocking is unknown. As a result, to obtain the probability of blocking is the first major task assigned to this research.

A probit regression with panel data is the approach in this paper to find the probability of blocking for a specific property on a specific day. This paper defines a status of “active” as being not blocked at least one day in a month, and refers to properties that have been active in 4 out of 12 months in a year as “active properties.” The probit regression model is built based on examining the data set that contains 897 active properties in New York City. The dependent variable of the regression is a binary variable with 0 representing opening and 1 representing blocking, and independent variables are everyday prices and fixed attributes of each property. After building the regression, it is plausible to predict the probability of blocking for each property on each night. By taking the average of blocking probability in a year for a property, the general probability of blocking on a random night for that property is determined, so is the reservation profit.

For each level of reservation profit, there is a certain number of opening properties. With price and quantity, the supply of accommodation on Airbnb is found. Hence, the supply curve of property describing the relationship between the reservation profit and the opening level on Airbnb platform is established. Further research can proceed based on the result so far. Due to the time constraint, this research stops after calibrating the supply curve.

This paper proceeds as follows. Section 2 reviews literature on Airbnb, sharing economy, and supply flexibility. Section 3 introduces the data. Section 4 displays salient features of the accommodation supply in the Airbnb market. Section 5 demonstrates the methodology of the probit regression with panel data and the approach to plot the supply curve. Section 6 demonstrates results of the regression and supply curve. Section 7 provides a conclusion and summary of all findings.

1. **Literature Review**

The ultimate objective of this research is to obtain insights of the accommodation supply in the Airbnb market. Researchers have been discussing this topic from different approaches. Yang and Mao (2019) investigated the impact of external factors including the local hotel market demand and supply and housing market demand and supply on the Airbnb accommodation supply based supply data from 28 major cities in the U.S. Among several factors, they found that tight regulation polices would significantly reduce the Airbnb unit supply. Regarding the relationship between regulation and supply, Uzunca and Borlenghi (2019) did a more in-depth discussion. They compared the strictness of rules and laws in 59 cities in the U.S. with the short-term accommodation offerings. Contrary to Yang and Mao’s finding, they claimed that the stricter the regulation is, the higher the supply would be in those platforms. This counter-intuitive conclusion, as they explained, resulted from the diminished legal uncertainty and clearer guidelines provided by regulations. No matter what the relationship between regulation and accommodation supply is, the regulation and law pointing at sharing economy market is always a major element that impacts the entire market, particularly in the supply end.

In this research, I would like to inquire into the supply on Airbnb from the perspective of the property owner’s willingness of providing the accommodation service, which, as far as I know, is an innovative approach to study the accommodation-sharing economy. Property owners’ willingness is directly reflected from the blocking behavior, everyday decision about opening or blocking business. Flexibility in supply is a salient feature of sharing economy. Despite the lack of investigation on the flexibility of supply in the accommodation -sharing market, researchers have studied this feature in other sharing economy.

Chen et al. (2019) discussed the flexibility of the labor supply in the Uber case. They mainly proved that the flexibility is economically beneficial for drivers by examining nearly two hundred thousand Uber drivers with high frequency labor supply and wage data. Specifically, they stated that drivers can generate more than twice surplus than they could in less flexible work arrangement. The reservation wage in Chen et al. (2019) is a brilliant concept to explain the driver’s willingness of providing the labor. That is, drivers would be willing to work only if the their own reservation wages are lower than the prevailing expected wage. I apply the similar concept, reservation profit, to this study as an major factor that explains the property owner’s willingness of providing the accommodation. In Airbnb case, property owner would be willing to provide the accommodation only if their reservation profit is lower than the expected revenue. In this research, I do not probe into the ultimate surplus that a property owner can obtain from the flexible supply mechanism because I simply do not have the data of the true revenue of each matching in the transaction. Instead, I aim to discover the probability of opening and blocking for a specific property with the help of reservation profit.

1. **Data**

This research probes into blocking behaviors of properties in New York City in 2015. There are two original data sets downloaded from the Airbnb official website. Data set 1 records properties’ nightly price[[1]](#footnote-0) and everyday status of R (rented), A (available), or B (blocked) from January 1 to December 31 in 2015, and data set 2 records attributes of individual property, including published nightly rate[[2]](#footnote-1), number of reviews, number of photos, whether the property is rented as an entire home (Entire Home), the occupancy rate in the last 12 months (Occupancy Rate LTM), whether the property is a super host (Superhost), minimum number of staying nights (Minimum Stay), the maximum number of guest (Maximum Guest), whether the property is rented for business (Business), and the number of bedrooms (Bedrooms) during the same period. For the analysis, I look into blocking behavior properties from month to month and define a property to be active in a month if the property has at least one day in the month that is not blocked. To study the whole year’s blocking behavior of a property, the paper refers to properties that have been active in 4 out of 12 months as “active properties.” After applying the active property filter to two data sets and merging them, the final data set consists of 327405 statuses and fixed attributes of 897 properties in New York City.

Status data in data set 1 provides insights into the accommodation supply of Airbnb, which will be further discussed in the next section. This section will introduce the summary statistics of the nightly price in data set 1 and variables in data set 2 that consists of the blocking behavior regression.

Table 1: Summary statistics of attributes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Mean | Std. Dev. | Min | Max |
| Nightly Price ($) | 184.26 | 148.79 | 10 | 9995 |
| Published Nightly Rate ($) | 221.34 | 348.39 | 45 | 8372 |
| Number of Reviews | 31.82 | 38.32 | 0 | 248 |
| Number of Photos | 13.95 | 9.63 | 0 | 132 |
| Occupancy Rate LTM | 0.65 | 0.24 | 0.04 | 1 |
| Minimum Stay | 3.10 | 4.22 | 1 | 31 |
| Maximum Guests | 2.86 | 1.65 | 1 | 14 |
| Bedrooms | 1.09 | 0.71 | 0 | 7 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Binary Variable | Mean | Std. Dev. | Min | Max |
| Entire Home | 0.65 | 0.48 | 0 | 1 |
| Superhost | 0.09 | 0.28 | 0 | 1 |
| Business | 0.15 | 0.35 | 0 | 1 |

1. **Stylized Facts of the Accommodation Supply on Airbnb**

Table 2: Distribution of Average Monthly Blockings

|  |  |
| --- | --- |
| Average Monthly Blocking | Distribution |
| [0, 4] | 4.68% |
| (4, 8] | 6.69% |
| (8, 12] | 6.91% |
| (12, 16] | 9.48% |
| (16, 20] | 12.60% |
| (20, 24] | 18.51% |
| (24, 28] | 18.17% |
| 28 + | 22.97% |

Table 3: Transition matrix of blocking in continuous months

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **T** | [0, 4] | (4, 8] | (8, 12] | (12, 16] | (16, 20] | (20, 24] | (24, 28] | 28 + |
| [0, 4] | 48.65% | 12.45% | 7.95% | 3.86% | 3.33% | 2.41% | 2.48% | 2.21% |
| (4, 8] | 32.88% | 14.57% | 13.45% | 7.70% | 4.52% | 3.88% | 2.80% | 3.54% |
| (8, 12] | 26.83% | 13.33% | 13.59% | 9.25% | 6.96% | 4.23% | 5.53% | 3.60% |
| (12, 16] | 17.76% | 10.05% | 8.94% | 11.09% | 9.63% | 8.10% | 8.42% | 9.34% |
| (16, 20] | 13.25% | 8.92% | 9.96% | 10.04% | 8.97% | 7.92% | 9.66% | 14.63% |
| (20, 24] | 7.94% | 3.76% | 5.80% | 9.58% | 10.37% | 11.47% | 13.09% | 20.68% |
| (24, 28] | 6.76% | 2.20% | 3.23% | 4.43% | 5.61% | 8.64% | 19.26% | 33.22% |
| 28 + | 1.51% | 0.97% | 1.60% | 1.71% | 2.34% | 3.86% | 12.73% | 50.28% |

|  |
| --- |
|  |

Table 2 displays the distribution of average monthly blocking for properties in the data set. To be more concise, the average monthly number of blocking days is divided into 8 number intervals, as displayed in the first column of Table 1. Only 4.68% properties block less or equal to 4 days per month, and 22.97% properties block over 28 days per month. Generally, over 70% of properties block more than half of the time in a month. The majority of properties choosing to block more often than open provide fundamental insight into the flexible supply in the accommodation-sharing market. Property owners are more likely to underlie personal reasons than business reasons when deciding to open or block.

Table 3 displays the probability of changing the blocking numbers of days from one month to the next month for a property. I define Properties located on the low tail of the distribution of blocking as adamant business operators, properties located on the high tail of the distribution as adamant business non-operators, and properties located in the middle of the distribution as sway business operators. Results show that adamant business operators and non-operators are likely to maintain their blocking numbers from one month to the next, whereas sway business operators tend to change their blocking numbers from one bin to adjacent bins. Overall, the willingness to block reflected from the blocking numbers is consistent from one month to another for all properties.

Figure 1：Percentage distribution of total blocking on weekdays

Figure 1 demonstrates the percentage distribution of the total number of blocking on each weekday. While the percentage of blocking is almost evenly distributed from Monday to Thursday, there is a slightly lower percentage of blocking happening on Friday, Saturday, and Sunday. This is a counter-intuitive finding because usually, the business is better on weekends than on weekdays. However, this further corroborates the claim that Airbnb accommodation suppliers often put personal reasons on top of the business reasons when deciding to open or not.

Figure 2: Conditional probability of blocking on n consecutive blocking days

Figure 2 demonstrates the probability of blocking after n consecutive blocking days before a day for a property. The trend implies that the more days a property has been blocking, the less likely it will block for the next day. This finding illustrates that most properties would not continue to block property for a long time. To some extent, it proves that, for most property owners, sharing their properties on Airbnb is a long-term activity, albeit the high probability of blocking.

Tables 2 and 3 and Figures 1 and 2 together reveal three interesting features of the accommodation supply on Airbnb. First, the majority of properties choose to block more often than open in a month. This is a rational finding, which supports the claim that most property owners do not consider providing accommodation for others on Airbnb as their properties’ primary purposes. Second, the willingness to block is almost consistent from month to month. The attitude or thought of listing properties on Airbnb hardly changes for property owners. Third, most properties provided on Airbnb are long-term accommodation suppliers despite the high rate of blocking behavior.

1. **Methodology**
	1. *Blocking Behavior Regression*

This section is designed to analyze how everyday decisions of blocking vary across property owners in New York City. The blocking behavior regression is a probit regression with panel data, including 897 entities and a time series from January 1, 2015 to December 31, 2015. The dependent variable is a binary variable with 0 representing opening and 1 representing blocking. The regression has several independent variables, including everyday prices and fixed attributes of each property.

Table 4: Correlation Matrix of Variables

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Price | Number Reviews | EntireHome | OccupancyRate | Superhost | MinimumStay | MaxGuests | NumberPhotos | Business | Bedrooms |
| Price | 1.0000 |  |  |  |  |  |  |  |  |  |
| Number Reviews | -0.0939 | 1.0000 |  |  |  |  |  |  |  |  |
| Entire Home | 0.3285 | -0.0951 | 1.0000 |  |  |  |  |  |  |  |
| Occupancy Rate | -0.1029 | 0.3266 | -0.0008 | 1.0000 |  |  |  |  |  |  |
| Superhost | -0.0229 | 0.1173 | 0.0030 | 0.0350 | 1.0000 |  |  |  |  |  |
| Minimum Stay | 0.0085 | -0.0418 | 0.0741 | 0.0311 | 0.0114 | 1.0000 |  |  |  |  |
| Max Guests | 0.5158 | -0.0221 | 0.4156 | -0.0387 | -0.0572 | -0.0136 | 1.0000 |  |  |  |
| Number Photos | 0.2620 | 0.1331 | 0.1327 | 0.0017 | 0.1371 | 0.0683 | 0.2524 | 1.0000 |  |  |
| Business | 0.0481 | -0.0238 | 0.0683 | -0.0408 | 0.1230 | -0.0110 | 0.0188 | 0.0407 | 1.0000 |  |
| Bedrooms | 0.4404 | -0.0211 | 0.1055 | -0.0363 | -0.0462 | -0.0094 | 0.6984 | 0.2450 | 0.0333 | 1.0000 |

Table 4 reveals the correlation between each variable, which indicates that there is no endogeneity problem in the blocking regression. Therefore, the regression model is as the following:

*Statusit*= *β0 + β1 Priceit + β2 Number\_Reviewsi + β3 Number\_Photosi + β4 Entire\_Homei*

*+ β5 Occupancy\_Ratei + β6 Superhosti + β7 Minimum\_Stayi + β8 Max\_Guestsi*

*+ β9 Businessi + β10 Bedroomsi*

where *Priceit* is a time-series variable indicating the nightly price set by property owners for each day regardless of blocking or opening; *Number\_Reviewsi* is a fixed variable indicating the total all timing reviews written by customers who have experienced with the service provided by the property; *Number\_Photosi*is a fixed variable indicating the total number of photos of a property provided by the property owners; *Entire\_Homei*is a fixed dummy variable indicating whether the property is listed on Airbnb as an entire home or not; *Occupancy\_Ratei*is a fixed variable indicating the occupancy rate of a property in the last year; *Superhosti* is a fixed dummy variable indicating whether the property is a superhost[[3]](#footnote-2); *Minimum\_Stayi* is a fixed variable indicating the number of minimum stay nights required by the property owners; *Max\_Guestsi* is a fixed variable indicating the maximum number of guests welcomed by the property owners for a night; *Businessi* is a fixed dummy variable indicating whether the property is rented for business use; *Bedroomsi* is a fixed variable indicating the number of bedrooms in a property.

This regression is not constructed to test how each independent variable will affect the dependent variable, respectively. Instead, it is simply used to predict the probability of blocking for each property every day in 2015.

* 1. *Plotting Supply Curve*

In the data set, the published nightly rate is another fixed attribute of properties set by Airbnb as a suggestion price for each property on each day. Reservation profit, by definition, is the opportunity cost for a property to block. Therefore, in this research, I treat the reservation profit for each property on a day as the product of the published nightly rate and the probability of blocking. By doing this, I acquire the reservation profit for each property on each day.

The supply curve in this research demonstrates the relationship between the reservation profit with the number of open days. After I acquire the reservation profit for each property every day in a year, I can have the year's average reservation profit. I already have the number of open days for a property in the data set. To show a clearer relationship, I calculate the average reservation profit on each level of open days. By plotting the average reservation profit and corresponding open days, I obtain the supply curve of accommodation in the Airbnb market.

* 1. *Robustness Check*

To do the robustness check, I remove the variable of the *Max\_Guestsi* and *Bedroomsi*, which generates a new blocking behavior regression model as the following:

*Statusit*= *β0 + β1 Priceit + β2 Number\_Reviewsi + β3 Number\_Photosi + β4 Entire\_Homei*

*+ β5 Occupancy\_Ratei + β6 Superhosti + β7 Minimum\_Stayi + β8 Businessi*

where all the rest variables are the same as the previous regression model. Results will be presented in the Appendix. Evidently, robustness check results are consistent with the previous.

1. **Results**
	1. *Blocking Behavior Regression*

Table 5: Blocking behavior regression outcomes

|  |  |
| --- | --- |
| VARIABLES | Coefficients |
|  |  |
| Price | 0.001\*\*\* |
|  | (0.000) |
| Number\_Reviews | -0.124\*\*\* |
|  | (0.001) |
| Number\_Photos | -0.004 |
|  | (0.004) |
| Entire\_Home | 0.145 |
|  | (0.091) |
| Occupancy\_Rate | 0.889\*\*\* |
|  | (0.167) |
| Superhost | 0.268\*\* |
|  | (0.134) |
| Minimum\_Stay | 0.018\*\* |
|  | (0.008) |
| Max\_Guests | -0.131\*\*\* |
|  | (0.034) |
| Business | 0.091 |
|  | (0.107) |
| Bedrooms | 0.157\*\* |
|  | (0.073) |
| Constant | 0.874 |
|  | (0.141) |

Table 5 shows the summary statistics of the blocking behavior regression. Through this regression model, I am able to predict the probability of blocking for each property on a random day. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% level, respectively.

* 1. *Predicted Blocking Probability*

Table 6: Summary statistics of predicted blocking probability

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Mean | Std. Dev. | Min | Max |
| Predicted Blocking Probability | 0.668 | 0.113 | 0.00 | 0.988 |

* 1. *Accommodation Supply in Airbnb*

Figure 3: The supply curve of accommodation in the Airbnb market

Figure 3 reveals a positive relationship between the number of open days and the average reservation profit. With one day increased in the number of open days, the average reservation increases by 0.1399 dollars.

1. **Conclusion and Discussion**

By examining the blocking behavior of 897 properties in New York City in 2015, I have three interesting features of accommodation supply in the Airbnb market. First, the majority of properties choose to block more often than open in a month. This finding directly embodies the flexibility in the accommodation supply on Airbnb, which is nothing like the traditional hotel business. Second, the property owner’s willingness to open or block their properties hardly changes through time. It shows that once a property owner decides what, how, and when to do with Airbnb’s properties, the decision will be consistent for a long time. This is quite different from the Uber driver’s willingness to provide labors because the change in the short-term rental market changes less rapidly than the ride-sharing market. Third, most properties provided on Airbnb are long-term accommodation suppliers despite the high rate of blocking behavior. People provide their properties on Airbnb as an optional choice. However, once they enter this business, they will stay in business, although most of them, like the first feature indicates, choose to block more often than open. To some extent, this explains the explosive growth of Airbnb: with increasing customers, the rate of adding new suppliers is higher than the rate of losing existing suppliers. The most profound result in this research is the supply curve illustrating the relationship between the reservation profit with the number of open days in a year. According to figure 3, the number of open days increases with the reservation profit, which means that suppliers are willing to block less if their average reservation profit is higher. This finding is in line with common sense. The higher the reservation profit is, the property owner is less likely to gain more or equal profit from other activities. As a result, to list their property on Airbnb is the best choice for them. The implication is that the accommodation supply on Airbnb can be regulated and controlled by impacting the property owner’s reservation profit.

The limitation of this research is that I only study properties in New York City. Further investigation can focus on cities with less developed hotel business and less population. How property owners consider the accommodation-sharing business in cities different than New York City is worth studying.

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**Appendix**

Appendix Table 1: Robustness check blocking behavior regression outcomes

|  |  |
| --- | --- |
| VARIABLES | Coefficients |
|  |  |
| Price | 0.000\*\*\* |
|  | (0.000) |
| Number\_Reviews | -0.125\*\*\* |
|  | (0.001) |
| Number\_Photos | -0.005 |
|  | (0.004) |
| Entire\_Home | -0.021 |
|  | (0.080) |
| Occupancy\_Rate | 0.914\*\*\* |
|  | (0.169) |
| Superhost | 0.302\*\* |
|  | (0.134) |
| Minimum\_Stay | 0.020\*\* |
|  | (0.008) |
| Business | 0.104 |
|  | (1.08) |
| Constant | 0.968 |
|  | (0.134) |

Appendix Table 2: Robustness check summary statistics of predicted blocking probability

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Mean | Std. Dev. | Min | Max |
| Predicted Blocking Probability | 0.668 | 0.109 | 0.00 | 0.988 |

1. Nightly price is the final listing price displayed on Airbnb set by the landlord. [↑](#footnote-ref-0)
2. Published nightly rate is the default (recommended) listing price set by the Airbnb’s pricing algorithm. [↑](#footnote-ref-1)
3. “Superhosts are experienced hosts who provide a shining example for other hosts, and extraordinary experiences for their guests (Airbnb).” Superhost Requirements on Airbnb:

- Completed at least 10 trips OR completed 3 reservations that total at least 100 nights;

- Maintained a 90% response rate or higher;

- Maintained a 1% percent cancellation rate (1 cancellation per 100 reservations) or lower, with exceptions made for those that fall under our Extenuating Circumstances policy;

- Maintained a 4.8 overall rating (this rating looks at the past 365 days of reviews, based on the date the guest left a review, not the date the guest checked out). [↑](#footnote-ref-2)