Original Article

The impact of travel subsidy on individual accommodations under COVID-19 pandemic:
Analyzing changes of plans listed on an online travel service

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Abstract
This study clarified the impact of subsidy from the Japanese government to revitalize the tourism industry, which has been negatively affected by COVID-19. Unlike previous studies, this analysis was performed on an accommodation basis rather than on a regional basis. We quantified the reservation status of each accommodation in Japan using the number of reservationable plans at the Online Travel Agency, finding that the number of reservations for many accommodations in 2020 decreased significantly from the previous year due to the influence of COVID-19. On the other hand, the number of accommodations with decreased numbers of reservations was limited during the period when all travels were covered by the subsidy. Moreover, binomial logistic regression analysis with reduced reservations as the dependent variable showed that consumers tended to select higher-priced accommodations during the COVID-19 pandemic with or without subsidy. In addition, it was suggested that during the period covered by the subsidy, consumers select accommodations to maximize both the discount amount and the discount rate.

Keywords
online travel agency, big data, COVID-19, travel subsidy, accommodation

1. Introduction

Since 2020, the spread of COVID-19 has affected all industries around the world, particularly the tourism industry. Since tourism is a leisure activity that requires the movement of a large number of people, it is subject to regulation as an unnecessary and urgent action highly likely to spread infections. Overall, as tourism is expected to have a high economic spillover effect due to the large number of related industries, imposition of such regulations will have a widespread negative impact. Therefore, countries with larger tourism sectors are adopting more aggressive economic stimulus measures to mitigate the effects of the pandemic and revitalize the slumping economy [Khalid et al., 2021; Okafor et al., 2022]. In Japan in particular, tourism was promoted by a large-scale government-led campaign (GTC) after the summer of 2020 in consideration of the infection situation.

GTC is a nationwide travel subsidy provided by the Japanese government that discounts travel expenses such as accommodation expenses by 35 %. However, since the upper limit of the subsidy is 14,000 yen per person per night, the discount rate will be less than 35 % if the subsidy exceeds 40,000 yen per person per night; on the other hand, the discount can be used without limit during the period. This campaign started at the end of July, but only travel to and from Tokyo were targeted from October.

It is rare for the above-mentioned large-scale tourism support measures to be implemented universally, and it is necessary to examine the impact of the measures in detail for future improvement. Matsuura and Saito [2022] also point out the necessity of verifying the impact of this subsidy, arguing that such subsidy at the time of pandemic may not have a favorable impact depending on the situation. By verifying the impacts on a smaller geographical scale, it is possible to clarify the targets and factors that have been affected, and to specifically consider points for improvement. However, since Japan's official tourism statistics (accommodation travel statistics survey) are compiled on a prefectural basis, the areas that can be analyzed at the city level are limited [Okamoto et al., 2020]. Furthermore, it is not possible to analyze individual accommodations. In Matsuura and Saito [2022] using data of a service for paying members, the analysis unit is the prefecture, and individual accommodations are not analyzed.

Therefore, in this study, we use OTA (Online Travel Agency) data to analyze how the reservation status of individual accommodations changed due to COVID-19 and related subsidy measures. OTA data allow an analysis for individual accommodations, which is not possible with existing statistics, as well as an analysis considering the characteristics of accommodation such as price and number of rooms. In this study, we will clarify how the reservation status of each accommodation changed due to the subsidy using the above OTA data. Next, we will clarify the characteristics of the accommodations that are likely to be selected by consumers in the COVID-19 pandemic, and identify changes due to the subsidy.

This study is the first to examine the actual situation of subsidy by the government for each accommodation. In addition, clarifying the characteristics of inns more frequently selected during COVID-19 has highly practical value. Also, since research on OTA data has mainly involved word-of-mouth analysis and that on changes in reservations is limited, this study shows new ways to utilize OTA data. Furthermore, it contributes to the theory of consumer behavior by clarifying how consumer choices change with a uniform large discount.

2. Related literature

Since 2020, the impact of COVID-19 on the tourism industry has been analyzed using data collected by a variety of methods. The most common is questionnaires. Atadil and Lu [2021] conducted factor analysis and multiple regression analysis using data collected from online questionnaires regarding hotels during the pandemic under the categories Medical Preparedness, Hygiene Control, Health Communication, and Self-Service Technology, showing that the pandemic has strongly affected behavior, and that Hygiene Control is the most important predictor of hotel selection behavior. An analysis using SmartPLS 3 by Li et al. [2020] showed that post-pandemic travel intentions differ among online survey respondents in China depending on their crisis susceptibility. Questionnaires are one of the typical methods for collecting data, but they have limitations due to the difficulty of collecting large-scale samples because of cost, as well as their tendency to generate biased data. It is thus desirable to perform analysis using data collected by several different methods.

Second, social media have been used as a source of data. Zhang et al. [2021] analyzed Weibo posted data, which is mainly used in China, by natural language processing and GIS, and revealed that Chinese consumers' interest in tourism increased during the pandemic. Politis et al. [2021] examined the impact on London public transport users through sentiment analysis of pre-pandemic (2019) and pandemic-era (2020) Twitter tweets. The results showed that on days when restrictions on pandemics were tightened, tweets with negative emotions increased. Mehta et al. [2021] evaluated hotel customer satisfaction during the pandemic period in each country using a TripAdvisor posted review, finding that the United States and Europe met customer expectations, Sri Lanka performed well in Asia, Indonesia maintained customer satisfaction, and India consistently improved satisfaction. They also extracted the 12 topics most discussed by topic model and identified the main reasons for dissatisfaction as being staff, overall service, room, cleanliness, slow booking, and hotel response to pandemic. By using social media data as described above, it is possible to obtain information from all over the world at low cost. On the other hand, data can be collected only from social media users, and among them, only from users who post, so non-user and ROM (Read Only Member) data are not reflected. These points merit closer attention.

In addition, studies using data collected by specific organizations are also being conducted. Fang et al. [2022] analyzed data from the Google's mobility trend database using a fixed effects model to clarify the impact of economic policy on visits to recreational facilities. The results show that economic policy significantly promotes leisure and recreational activities. Furthermore, by category of measures, it was shown that monetary policy has an immediate positive announcement effect, while fiscal policy significantly promotes leisure and recreational activities, although there is a delay in response. Lin and Chen [2021] used data from a Taiwan Tourism Bureau report and panel data estimation methods to show that international tourist hotels with high product varieties and five-star hotels suffered a greater loss in revenue than other types of hotels, while hotels located in scenic areas and international chain hotels were less affected. Anguera-Torrell et al. [2021] collected stock price information from Investing.com and analyzed it by regression methods, showing that economic policy has a positive impact on hotel stock prices.

Matsuura and Saito [2022] analyzed the effects of GTC in Japan, as in our study, to determine the impact of subsidies, including GTC, using data of the "Tourism Forecast Platform," a service for paying members operated by the Japan Travel and Tourism Association. Their study is similar to ours and therefore constitutes important reference information. However, it is difficult to obtain similar information about other regions and other periods because such research is limited to surveys of a specific institution. In addition, Matsuura and Saito [2022] set the departure and arrival points for each prefecture to determine the influence of support measures from the characteristics of the departure and arrival points and the distances between them. On the other hand, our study focuses on the characteristics of individual accommodation to clarify the factors that influence consumer choices. Also, by using OTA instead of information from paid membership services, anyone can access the data for free.

Finally, the following two studies used OTA data, as in our study. Wu et al. [2020] used a Python-based web crawler to collect and analyze daily prices for Hong Kong hotels from various OTAs via Tripadvisor. Their data analysis based on hotel ratings showed that 5-star hotels were relatively unaffected by COVID-19, while 4-star and 4.5-star hotels were most severely affected. Furthermore, analysis at the district level showed quantitatively that the impacts of COVID-19 differed from district to district. However, since their study did not compared these data with those from before the COVID-19 pandemic, it is unclear whether this result is unique to the pandemic. In addition, their study investigates price fluctuations but does not examine the number of reservations or changes in sales, which are important management indicators. Guo et al. [2022] considers the number of reviews posted by Ctrip, a major Chinese OTA, as a proxy for room sales to analyze the factors that affect sales for hotels in major cities in China, indicating that the room sales of hotels with short business years, high quality of amenities and services, and good brand image recovered quickly during a pandemic. Furthermore, a comparison of different city types suggested that hotels in tourist cities recovered faster than hotels in commercial cities, and that the impact of cleanliness review ratings and years of business also differed. The methods and results of their study serve as a reference for ours. However, since it has not been verified whether number of reviews in Japanese OTA can be regarded as adequately indicative of the number of sales in a room, we considered it inappropriate to perform our analysis by the same method. Accordingly, we adopted a different method of analysis that is described in detail in the next section.

3. Method

3.1 Data and analysis target

As mentioned above, this study analyzed the impacts of GTC using OTA data. The data source was the main OTA of the country to be analyzed, as in a previous study [Guo et al., 2022]. In this study, we selected Jalan [Recruit Lifestyle, n.d], which is one of the most used OTAs in Japan.

In this analysis, we used the number of plans that can be reserved on the day before the accommodation date under the condition of one night per adult in Jalan as the number of unsold items that were not reserved, and compared them in 2019 and 2020. For example, when staying at a certain accommodation on April 1, the number of plans that can be reserved on March 31 is measured, and if this number is larger in 2020 than in 2019, then there are many plans that were not reserved. Therefore, it is considered that the number of reservations is decreasing. In this way, previous studies suggest that the number of remaining plans for the previous day can serve as an index that is inversely proportional to the number of reservations [Suzuki, 2020]. In previous studies, when this number was aggregated for each group such as a region, it was affected by the number and scale of accommodations, so it was necessary to use it as a relative value within the group rather than an absolute value. However, in this study, each accommodation is compared with the previous year, so it is not grouped, allowing a more accurate analysis free of the effects of other accommodations.

The specific analysis target was the number of remaining plans when Saturdays from June to November 2019 and 2020 were set as accommodation days. Furthermore, June to November is divided into every two months, for June and July were periods when GTC was not held, August and September were periods when GTC was held in areas other than Tokyo, and October and November. In the following, we will refer to each period as NGTC (not GTC), LGTC (limited GTC), and GTC. We aggregated and compared the data shown in Table 1 for all three periods. Only Saturday was set as the accommodation day in order to minimize the influence of accommodation for business purposes. The last Saturday in July 2020 was excluded from analysis because the GTC had already started.

Next, the accommodations to be analyzed were selected as follows. As of March 2022, about 20,000 accommodations are registered in Jalan. Of these, only the accommodations whose inventory can be continuously confirmed between June 2019 and November 2020, which are the targets of this study, were targeted, and of those accommodations, we were able to obtain information necessary for analysis such as address and price for 11,679 of them. In this study, these accommodations were analyzed.

Table 1: Example of usage data (Number of remaining plans)

Hotel ID	2019-06-01	2019-06-08	⋯	2020-11-21	2020-11-28
000001	7	10	⋯	20	20
⋮	⋮	⋮	⋯	⋮	⋮
999999	4	5	⋯	2	1

The analysis is divided into two steps. First we classified each accommodation based on the change in the reservation status in 2020 with respect to 2019, and compared the trends in the above three periods. From this, we determined the number of inns where reservations decreased under COVID-19 and the number of inns where reservations increased due to subsidies. In the second step, regression analysis was used to quantify the factors that influenced accommodation reservations, and the trends were compared over the three periods. Details of these methods are described below.

3.2 Classification of accommodations based on reservation status

As mentioned above, we classified the accommodations by assuming that the increase/decrease in the number of remaining plans on the previous day is the increase/decrease in reservations. As a specific method, the mean number of remaining plans was calculated for each of the three periods of NGTC (June/July), LGTC (August/September), and GTC (October/November). The values were then compared between 2019 and 2020 using Welch's t-test, and based on the results, the accommodations to be analyzed were classified into accommodations with significantly increased reservations, accommodation with no significant difference, and accommodation with significantly decreased reservations compared to those before COVID-19. We finally confirmed the distribution of the number of accommodations with increasing/decreasing reservations for each period.

3.3 Analysis of factors influencing reservations

After the classification, a regression model with that classification as the dependent variable was estimated. Models were estimated for each of the three periods: NGTC, LGTC, and GTC. We used a generalized linear mixed model (GLMM) that includes region-specific random effects. Logistic regression analysis was used because the objective variable is categorical. In this study, we used binomial logistic regression analysis because the classification results were classified into two categories, as will be described later. In this analysis, the following variables were used with reference to previous studies (Table 2).

Matsuura and Saito [2022] showed that the number of confirmed cases of COVID-19 has a negative effect on the number of tourists, and a survey conducted by Tripadvisor [2020] shows that the number of cases at the destination is the most important information when deciding the destination. In Japan, the number of COVID-19 cases is generally announced on a prefectural basis, so we assumed that the number of COVID-19 cases on a prefectural basis is also used by consumers when

Table 2: Variable definitions

Variable	Definition
CVD/POP	Number of confirmed COVID-19 cases per period per 1000 residents in the prefecture where the accommodation is located.
PRICE	Standard price required to stay at each accommodation.
JPY40k	Dummy variable for whether Price is over 40,000 yen.
RYOKAN	Dummy variable for whether the type of accommodation is a ryokan.
FPARK	Dummy variable for whether the accommodation has free parking
ROOM	Number of accommodation rooms

selecting a destination. Therefore, we consider CVD/POP to have a negative impact on reservations. These data were downloaded from e-Stat, which is a collection of Japanese government statistics.

Previous studies have shown that high-end, high-quality hotels have been less negatively affected by the pandemic [Wu et al., 2020; Guo et al., 2022], probably because consumers have selected luxury hotels in the belief that they are fully equipped with COVID-19 infection control. In addition, Matsuura and Saito [2022] indicate that GTC may increase the number of overnight stays at high-priced accommodations. During the GTC period, the higher the price of the accommodation, the higher the discount amount, so it is considered that these accommodations were selected. Therefore, we consider that the PRICE has a positive impact on reservations.

The data used in this study do not include the price of each actually reserved plan. Therefore, for each accommodation, we used the median price of the plans posted on OTA during the year before COVID-19 (January 1, 2019, to December 31, 2019) as standard prices for staying at each accommodation. In order to collect more complete plan information, unlike the method of collecting the number of reservations, we collected the prices of plans that can be booked 28 days before each of the 365 days of 2019 as the accommodation day.

As mentioned in the Introduction, the GTC sets the discount rate at 35 % and the maximum discount amount at 14,000 yen, which means that the discount rate decreases with each increase in price above 40,000 yen. Therefore, this paper hypothesizes that while higher prices are more likely to be chosen during the COVID-19 pandemic, consumers tend not to select accommodations with prices over 40,000 yen (JPY40k) during the GTC period in order to maximize profit.

Ryokans are an accommodation type peculiar to Japan that have the image of being able to provide services such as a calm atmosphere, courteous customer service, individual meals in the room, and private baths. Whether the service actually provided matches the image depends on the inn and the plan, but such an image is considered effective under COVID-19. Cai et al. [2021] also state that "Ryokans are more flexible than hotels, have strong anti-risk capabilities, and have received more and more attention from tourists." In addition, in GTC, if a plan is selected that separates accommodation and meals, meal charges are not discounted, so it is likely that inns that offer plans that include meals are more likely to be selected.

In addition, it is thought that ryokans tend to be selected due to the influence of hot springs. Tripadvisor [2020] and NAVITIME [2020] report the survey results that the demand for hot springs is high under COVID-19. However, since most ryokans have hot springs, the problem of multicollinearity occurs. Therefore, in this analysis, hot springs are not included in the variables and only RYOKAN is used. We used the type set by Jalan as the type of accommodation.

Li et al. [2020] point out that the impact of the COVID-19 pandemic has reduced the willingness to use public transportation and increased the willingness to travel by private car. Similarly, in Australia, tourists have shifted from high-risk transportation such as cruise ships and air travel to private, small-scale leisure transportation such as cars and campers [Butler et al., 2021]. A similar tendency has been suggested for Japan [Tripadvisor, 2020], and that inns with parking lots that are easily accessible by private cars are more likely to be selected in order to avoid the use of public transportation during COVID-19. However, accommodations with paid parking lots are located in large cities such as Tokyo and Osaka and in major cities in each prefecture. Therefore, since this does not allow us to focus on factors associated with avoiding crowding, FPARK excluding paid parking lots is considered to have a positive effect on reservations in this study.

Various facilities such as a lobby, a restaurant, and a large communal bath are used together with other guests in the accommodation. Under COVID-19, many tourists want to avoid crowds and stay away from others [Tripadvisor, 2020]. Therefore, in order to avoid contact with an unspecified number of people, small-scale accommodations with a small capacity are considered more likely to be selected than large-scale accommodations. In other words, ROOM is considered to have a negative impact on reservations.

Finally, since the characteristics of accommodations are affected by the geographical environment, it is highly likely that accommodations in the same area have similar characteristics. In addition, cities have their own tourism support measures under COVID-19, but there are variations in the population of the target area, the amount of subsidies, and the target period. Therefore, the effect is considered to be different for each city, so in this study the model was estimated including a random effect for each city (City RE).

Tables 3 and 4 show the descriptive statistics and correlation coefficients for the variables used.

4. Results

First, the classification results of the accommodations for each period are shown in Figure 1. About 40 % of the accommodations showed a significant decrease in the number of

Table 3: Variable summary statistics

	Mean	*SD*	Min	Max
CVD/POP_NGTC	0.06	0.07	0.00	0.27
CVD/POP_LGTC	0.16	0.17	0.00	0.71
CVD/POP_GTC	0.23	0.21	0.01	0.65
log (PRICE)	3.98	0.25	3.00	5.41
JPY40k	0.02	0.14	0.00	1.00
RYOKAN	0.27	0.44	0.00	1.00
FPARK	0.61	0.49	0.00	1.00
ROOM	81.64	104.52	1.00	2,384.00

Note: CVD/POP was used according to the analysis period.

Table 4: Correlation between variables

	CVD/POP_ NGTC	CVD/POP_ LGTC	CVD/POP_ GTC	log (PRICE)	JPY40k	RYOKAN	FPARK	ROOM
log (PRICE)	0.091	0.103	0.078	1.000				
JPY40k	0.017	0.039	0.035	0.441	1.000			
RYOKAN	−0.214	−0.224	−0.195	0.198	0.042	1.000		
FPARK	−0.460	−0.378	−0.307	0.082	0.037	0.371	1.000	
ROOM	0.254	0.185	0.181	0.155	0.023	−0.279	−0.376	1.000

Note: The correlation between the three CVD/POPs is omitted because it is not related to the analysis.

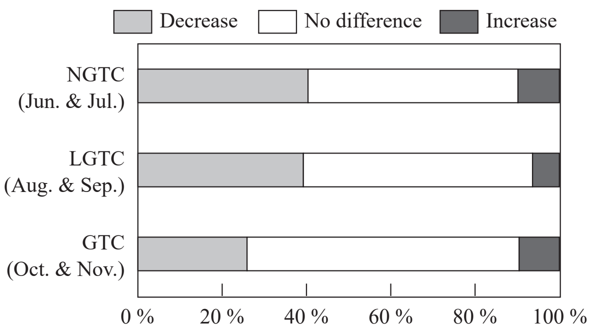

Figure 1: Accommodation classification results by comparing the reservation status with the previous year

reservations compared to the previous year during NGTC and LGTC. On the other hand, the number of accommodations that showed a significant decrease during GTC was less than 30 %. The influence of COVID-19 was large, and the number of accommodations where the number of reservations increased significantly was less than 10 % in all periods, but it is likely that many accommodations were able to maintain the number of reservations during the GTC period by subsidies. Conversely, there were fewer accommodations where the number of reservations has increased during LGTC than NGTC. One factor is that August is when Japanese people travel most and many accommodations had their plans sold out in 2019, so there were many accommodations that could not significantly exceed the previous year.

The classification results showed that only a small number of accommodations had a significant increase in the number of reservations over the previous year (less than 10 %), so these accommodations were combined with those that had no significant difference from the previous year and designated as accommodations without decreased reservations. These accommodations can be regarded as a positive group whose reservations did not decrease under COVID-19. Conversely, the accommodations that showed a significant decrease in the number of reservations from the previous year were classified as the negatively affected group. In this study, we categorize the accommodations binarily into these two groups.

Table 5 shows the results of binomial logistic regression analysis using this classification as the dependent variable. The pseudo R2 is calculated by McFadden's method. The coefficient of determination by this method tends to be lower than that of OLS, and is evaluated as a good fit model at about 0.2 to 0.4 [McFadden, 1977]. In the evaluation of the entire model by pseudo R2, the NGTC model shows the worst fit and the GTC model the best. Since this model includes variables that assume the influence of subsidies during GTC, this result is assumed in advance.

Next, the individual coefficients are described. CVD/POP showed significantly negative values in the three periods. PRICE showed a significantly positive value in every period. On the other hand, JPY40k showed a significantly negative value only for GTC. RYOKAN and FPARK showed a significantly positive value in every period. Finally, ROOM showed a significantly negative value in every period.

As shown above, the coefficients are generally significant, but JPY40k is significant for only one period (GTC). The mag-

Table 5: Effect of accommodation characteristics on increases/decreases in the number of reservations

	NGTC (Jun. & Jul.)	LGTC (Aug. & Sep.)	GTC (Oct. & Nov.)
CVD/POP	−0.167**	−0.191***	−0.400***
log(PRICE)	0.379***	0.525***	0.803***
JPY40k	0.063	−0.017	−0.140***
RYOKAN	0.279***	0.237***	0.341**
FPARK	0.305***	0.336***	0.399***
ROOM	−0.152***	−0.127***	−0.075**
City RE	Yes	Yes	Yes
Observations	11,679	11,679	11,679
Pseudo R^2	0.117	0.137	0.233

Notes: All variables are standardized. * Indicates statistical significance at the 5 % level. ** Indicates statistical significance at the 1 % level. *** Indicates statistical significance at the 0.1 % level.

nitude of each coefficient and the interpretation of positive and negative values are discussed in detail in the next section.

5. Discussion

The CVD/POP coefficients suggest that under the COVID-19 pandemic, accommodations in areas with a small number of confirmed COVID-19 cases are more likely to be selected in order to avoid traveling to areas with a large number of confirmed cases. In particular, the coefficient of GTC was higher than for other periods. In other words, although travel to and from Tokyo was covered by the subsidy, it is thought that there was a tendency not to select Tokyo as a destination due to a large number of confirmed cases (CVD/POP is the largest in all regions). Contrariwise, the travel from Tokyo to the rural areas where the number of confirmed cases is small appears to have been promoted.

The log (PRICE) coefficients show that it is easy for consumers to select a high-priced accommodation in Japan, similar to findings for other countries, and since log (PRICE) has the highest coefficient in any period, it has a large influence on reservations. Furthermore, this tendency is more pronounced for LGTC and GTC than NGTC. Therefore, when receiving subsidies, consumers probably make selections that increase the discount amount as much as possible.

On the other hand, JPY40k showed a significantly negative value only for GTC. This result shows that while the standard of 40,000 yen has no particular meaning during periods other than GTC, accommodations whose price exceeds 40,000 yen (the discount rate is not the maximum) are less often selected during GTC, suggesting that GTC subsidy influences consumer selection so as to maximize both the discount amount and discount rate during GTC. These results indicate that accommodations with prices of about 40,000 yen are most positively affected by GTC subsidy. Contrariwise, this measure offers little benefit for accommodations with low prices. As this subsidy is required for high fairness as a public measure, it is thus necessary to improve this subsidy system so that accommodations with low prices be equally selected.

In addition, the RYOKAN coefficient showed a tendency for ryokans to be more likely to be selected than hotels under COVID-19. We hypothesized, that the services peculiar to the inn (such as polite customer service) influenced consumer selection during COVID-19. However, in order to clarify the influential factors in more detail, it is necessary to verify the impact of each service by analyzing the plan unit instead of the accommodation unit.

The FPARK coefficient indicates that accommodations with free parking were more likely to be selected in the COVID-19 pandemic, suggesting that travelers may avoid public transportation and travel by private car. As Matsuura and Saito [2022] point out, proximity to the point of departure and destination is also important when traveling by private car. In other words, accommodations located in close proximity to large cities are likely to be selected in the COVID-19 pandemic. In addition to simple distance, accessibility is also important, and distance from highway entrances and exits is likely to have an impact. There is room for further research on these influences. On the other hand, since the Jalan plan used as the source of data in this study does not include package tours, it cannot be ruled out that many of the users of this OTA are private car users who do not need public transportation. Therefore, it is necessary to consider the possibility of bias of the Jalan users for this result.

The ROOM coefficient showed that small-scale accommodations tended to be selected more easily in the COVID-19 pandemic. However, since the value is small compared to other coefficients, the number of rooms is considered to have a smaller influence on reservations than other factors. In other words, consumers are more likely to place greater importance on the facilities and services of the accommodation than on the number of people sharing the facilities. This result suggests that consumer anxiety about contact with others in the COVID-19 pandemic can be controlled by the efforts of accommodations.

6. Conclusion and future work

This study focuses on the current situation in which the tourism industry is negatively affected by the effects of COVID-19, and it bears out that it is necessary to clarify the impacts of the tourism support measures (GTC) implemented by the Japanese government at the accommodation level. This paper uses OTA data to quantify the reservation status of each accommodation and compare them between 2019 and 2020 in order to clarify the impact of the COVID-19 and government subsidy on each accommodation. It was found that the negative impact of the COVID-19 was large, and less than 10 % of the accommodations had significantly more reservations than the previous year. On the other hand, immediately after the end of the state of emergency, about 40 % of the inns had fewer reservations than the previous year, but this value remained below 30 % during the period when Tokyo was included in the GTC subsidy. The results indicate that the subsidy had positively impacted accommodation reservations.

Next, we conducted an analysis to identify the characteristics of accommodations readily selected by consumers under COVID-19 and determine the changes in the characteristics depending on the presence or absence of the subsidy. Binomial logistic regression analysis was performed with the reduction of reservations as the dependent variable and the characteristics of the accommodation as the independent variables, showing that price is the most influential factor regardless of the presence or absence of subsidy, and that the higher the price, the more readily consumers select it. This result supports the hypothesis that high-class accommodations are selected because infection control and hygiene management are important during COVID-19. Comparison of the GTC and NGTC periods showed that GTC has a stronger price influence, and consumers select accommodations with higher discount amounts from the subsidy. On the other hand, since JPY40k was significant only for GTC in the three periods, this suggests that consumers select accommodations so as to maximize not only the discount amount but also the discount rate.

As described above, this study quantitatively showed the impact of the subsidy on an accommodation basis. Since this result cannot be clarified simply by analyzing the number of guests in each region, this study helps reveal the actual situation of the subsidy and its pros and cons. In addition, it is clear that consumers select high-priced accommodations in order to obtain higher discount amounts from this subsidy with a fixed discount rate. Furthermore, consumers tended not to select accommodations above a certain amount so as to maximize the discount rate when there is an upper limit on the discount amount.

Furthermore, it appears that ryokans, which are a form of accommodation peculiar to Japan, tend to be more readily selected by consumers than other accommodations, which should constitute useful reference information for accommodations in all countries aiming to improve facilities and services. However, further research is needed to more accurately understand consumer needs. As mentioned in the previous section, to identify the factors that affect reservations in greater detail, it is necessary to analyze each plan such as the presence or absence of meals. For example, Lin and Chen [2021] state that social distance is especially important for hotels. By analyzing each plan, it is possible to clarify the effects of each element that can help in avoiding contact with other guests, such as guest rooms with open-air baths, meal served in one's room, and independent guest-cottages.

In addition, there is room for research on the impact of the latest technology adopted by each accommodation, as pointed out by Gursoy and Chi [2020], and the difference in reservation status due to the characteristics and popularity of tourism resources located near the accommodation. Clarifying the above will also be useful information when conducting destination marketing. Finally, at the time this paper was written, the GTC subsidy had been suspended for such reasons as an increase in the number of confirmed COVID-19 cases, but early resumption is also being considered. When the subsidy resumes in the future, further analysis should be conducted examining its impact and points for improvement through comparison with the GTC in 2020.

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