ORIGINAL RESEARCH ARTICLE

Estimating the Treatment Effect of Japan's Go To Travel Campaign

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ABSTRACT
The COVID-19 pandemic has had a significant impact on the Japanese economy with the tourism industry being one of the hardest hit. In response, the Japanese government has introduced a national economic policy to revitalize tourism industry, called the Go To Travel campaign. Even though the government has committed significant funds, 539.9 billion yen, for the campaign, there is still a lack of research on the effectiveness of the policy. This study quantitatively assesses whether the policy increased the occupancy rate for tourism accommodation using difference-in-differences analysis. The analyses demonstrate that, by type and size of accommodation, the policy successfully increased the occupancy rate by over 30% in most cases. The results provide insights for both policymakers and academia in that the policy was highly effective in uplifting tourism demand and successfully increased the occupancy rate.

KEYWORDS
COVID-19; Go To Travel Campaign; Difference-in-Difference; Economic Policy; Tourism Industry

1. Introduction

The COVID-19 pandemic has caused much destruction to the global economy. In Japan, to curb the number of patients, the government announced the first state of emergency on April 7, 2020 for major prefectures, such as Tokyo and Kanagawa, and expanded these voluntary measures nationwide on April 16, leading to an immediate contraction of economic activities. Tourism, a key industry in Japan, has been one of the hardest hit and may be the last to recover. It accounted for 9.6% of total employment and 2.0% of total GDP in Japan in 2017, with domestic tourism sales comprising 80% of total tourism revenue [18]. However, as Figure 1 shows, there was a steep decline in the number of overnight trips in April and May, which corresponds to the period of the state of emergency. According to the Japan Tourism Agency, there were 45.7% to 81.6% fewer overnight tourists in April–June 2020 than in the same period in the previous year [15, 16, 17].

[Figure 1 about here.]

In response to the economic contraction caused by the pandemic, the Japanese government introduced the 'Go To Travel' campaign, a measure to revitalize the tourism industry by providing discounts on accommodation expenses and coupons that can be used at the destinations [11]. It is one of the major economic policies the Japanese government introduced in response to the pandemic devastation, and includes a COVID-19 special fixed benefit payment of 100,000 yen. Despite its importance, no study has yet been undertaken on the effectiveness of the policy. To fill this research gap, this study seeks to quantitatively assess the effectiveness of the Go To Travel campaign using a difference-in-differences approach.

2. Background

The first stage of the Go To Travel campaign began on July 22, 2020, providing a 35% discount of all travel-related fees for up to 14,000 yen per night for overnight trips for all domestic tourists [11]. The second stage of the campaign started on September 1, providing an additional 15% cash-back coupon for all travel-related fees in addition to the 35% discount on trip fees, with the maximum discount raised to 20,000 yen per night for overnight trips [11]. However, Tokyo was initially excluded from the scheme owing to concerns about the spread of COVID-19 in the city, but was included from October 1, 2020 [14].

According to the Japan Tourism Agency, the Go To Travel campaign was used for at least 8.78 million overnight stays and the sum of discount was estimated to be approximately 539.9 billion yen [13]. The average discount per overnight stay was 4,649 yen while the total cost per overnight stay was 13,282 yen [13]. These results provide a convincing case that the campaign was effective in uplifting the tourism industry at least to some extent. Moreover, according to Japan Tourism Agency, the Go To Travel was used mainly for hotels in the lower price range [12]. This study seeks to generate insights for policymakers and scholars by providing an estimate of the percentage increase in occupancy rate in a counterfactual framework employing the basic statistics on the Go To Travel campaign provided by the Japanese government. In other words, the study provides an estimate of the change in occupancy rate resulting from the campaign compared to the counterfactual setting of no campaign.

3. Data

The study uses the Statistical Survey on Overnight travel of Japan Tourism Agency for hotel occupancy rate data from January 2015 until December 2020. The data are available since 2007 and provide detailed information on overnight travel, including hotel occupancy rate based on hotel type and number of employees in each prefecture. In this study, I used data for ryokan (traditional Japanese inn), resort hotels, business hotels, city hotels, and lodging for analysis. Moreover, to categorize hotels of different size, we used hotels with 0–9 employees, 10–29 employees, 30–99 employees, and 100 or more employees. Since 2010, the data for all accommodation establishments with more than 10 employees have been collected; the sample of accommodation establishments with 5–9 employees and 0–4 employees accounts for one-third and one-ninth of of total establishments in Japan, respectively. Moreover, we employ climate-related data, such as temperature, from the Japan Meteorological Agency, which provides detailed data on Japanese climate conditions. All data used in this study are collected at the prefecture level from 2015 until the end of 2020.

4. Model Specification

To estimate the causal effect of the campaign on occupancy rate, we adopted the difference-in-differences method, which is a popular framework for analyzing treatment effects for observational data. This method is an ideal approach considering the panel structure of the data and the variations in the periods in which the campaign was implemented. The difference-in-differences approach provides an ideal setting for the estimation for causal effects, as we can control for fixed effects and time effects that seem to be present in the data. In fact, as Figures 2 and 3 show, there is a significant fixed effect and seasonality (time effect) present in the occupancy rate. This is indeed intuitive, because prefectures have very different time-invariant characteristics, which can cause substantial differences in the average occupancy rate. For instance, such prefectures as Tokyo and Hokkaido have coastal areas while others do not. This may make Tokyo and Hokkaido more popular during the season when water entertainment such as hot springs and water sports are more popular. Moreover, some prefectures, such as Tokyo, have an international airport and extensive public transportation system, which makes it easier for travelers to visit. This may result in a higher average occupancy rate in Tokyo owing to its accessibility for both domestic and international travelers. These time-invariant characteristics as well as time-varying characteristics, such as weather, seem to influence the occupancy rates collectively. It is essential to consider fixed effects as well as time effects for the analysis and therefore, the difference-in-differences method provides a good framework for analysis.

[Figure 2 about here.]

[Figure 3 about here.]

4.1. Difference-in-Differences

In this subsection, we explain the identification of difference-in-differences, a popular method that has been used in many studies for causal effect estimation of observational data. This is because the difference-in-differences method allows us to eliminate potential bias between the control group and treatment group. This makes it a popular method especially in the social sciences, which often uses observational data whereby researchers do not conduct experiments themselves. One well-known study using the difference-in-differences method is that of Card and Krueger, who studied the effect of minimum wage change in the US by using observational data in New Jersey and Pennsylvania [8]. They took advantage of the fact that while New Jersey and Pennsylvania are neighboring states and seem to show similar pre-treatment 'trends' in employment, the only difference between the two is the treatment assignment, which is the change in minimum wage [8]. In other words, difference-in-differences relies on both the treatment group and control group having a similar 'trend' during pre-treatment periods. In the paragraphs that follow, we sought to explain the difference-in-differences method in detail as well as how the method fits our research.

The basic model specification of difference-in-differences is as follows.

$$Y_{pt} = \gamma_p + \delta_t + \tau D_{treatment} + \varepsilon_{pt} \tag{1}$$

Moreover, the average treatment effect of interest can be defined as

$$\tau_{DID} := \mathrm{E}\left[y_{pt}^{1} - y_{pt-1}^{1}\right] - \mathrm{E}\left[y_{pt}^{0} - y_{pt-1}^{0}\right] \tag{2}$$

where y_{ps}^{j}, $s = t, t-1$, and $j = 0, 1$. Here, Y_{pt} represents the occupancy rate for prefecture p at time t, γ_p represents prefecture-varying but time-invariant fixed effects, and δ_t represents the time-variant common trend between prefectures. The fixed effects coefficient is important, as it captures prefecture-specific characteristics that are not shared between prefectures. Meanwhile, the time-varying coefficient captures trends and shocks that are common across all the observations, such as economic growth and nationwide shock. The parameter of interest, τ, represents the treatment effect of the Go To Travel campaign. In equation 2, the first term on the right-hand side refers to the difference in occupancy rate before and after the treatment had there been a treatment. The second term on the right-hand side refers to the difference in occupancy rate before and after the treatment period had there not been a treatment. By subtracting the second term, which is also referred to as the common trend, we can carve out the treatment effect of interest, because the only systematic difference between the first term and the second term is the treatment itself, that is, the Go To Travel campaign. Therefore, in the difference-in-differences method, it is crucial to correctly estimate the second term, which is also known as the 'parallel trend'. However, since it is practically impossible to observe the counterfactual occupancy rate of prefectures for which the Go To Travel campaign was introduced, we seek to estimate the term using comparable occupancy data in the past period. In other words, we estimated the common trend by taking advantage of the data on the past monthly occupancy rate from 2015 and the variation in the policy period as outlined in Table 1. In fact, the use of past occupancy rates allowed us to control for the seasonal characteristics of hotel occupancy, which is evident from Figure 3. This is because we can extrapolate the seasonality estimated using the past period into the treatment periods and thereby effectively eliminate the common trend. Moreover, as the Japanese government did not introduce any large-scale tourism policy in the years from 2015 to 2019, it is possible to estimate the common trend correctly to eliminate potential biases and to estimate the treatment effect correctly.

Moreover, to ensure the validity of the estimate, we relaxed the parallel trend assumption by introducing time-varying prefecture-specific trends that are not fully captured by the fixed effects or time effects. By introducing the variable, we can absorb some of the differences in trends between prefectures. Moreover, to ensure that the changes in occupancy rate during the policy periods were not driven by pre-treatment trends or any other shocks during the months corresponding to the Go To Travel policy, we performed placebo tests by creating pseudo-treatment groups in the years preceding 2020 and conducting the same analysis using these groups. If the placebo test shows no significant effect of the pseudo-treatment, it provides evidence that there was no factor other than the treatment itself driving the result of our estimate. In the following subsections, we discuss the variables used in the research in detail.

4.1.1. Estimated Difference-in-Differences

In this subsection, we discuss the baseline difference-in-differences regression and the variables used for the analysis. The baseline difference-in-differences regression is defined as follows.

$$Y_{pt} = \gamma_p + \delta_m D_m + \delta_c D_m D_c + \tau D_{treatment} + \rho X_{pt} + \varepsilon_{pt} \tag{3}$$

X_{pt} represents control covariates, such as temperature and precipitation level of prefecture p, at time t. In this analysis, climate covariates are the percentage difference from its mean, rather than the value itself. D_m is a month dummy variable and D_c is a dummy variable for a COVID-19 year (i.e., 2020). Therefore, δ_m and δ_c corresponding to δ_t in equation (1) are intended to absorb time-varying effects on occupancy rates that are common across all prefectures. The monthly dummy variable takes the value of 1 if the data correspond to any month from January to December and takes a value of 0 otherwise. Likewise, the COVID-19 dummy variable takes a value of 1 if the data are in 2020 and takes a value of 0 otherwise. We regarded the month dummy variable and the COVID-19 year dummy variable as the common trend coefficient, and added them to the model to absorb seasonality of hotel occupancy as well as the effect of COVID-19 on the monthly occupancy rate. Since both Tokyo and other prefectures were impacted by the COVID-19 pandemic and various prevention measures introduced by the government, there does not seem to be any prefecture-specific exogenous shock that may threaten the result of the difference-in-differences analysis. The treatment effect of interest was defined as τ and the corresponding treatment dummy as $D_{treatment}$. The treatment assignment shown in Table 1 required some consideration owing to frequent changes in the policy. As Table A4 in the appendix shows, since the campaign started on July 22, it was not in effect for all of July but only about one-third of the month. Moreover, the campaign was suspended nationwide on December 28, and even earlier in some prefectures, and thus, was in effect for 68% to 90% of the month of December 2020 depending on the policy in the region. Since the data we used in the analysis were monthly observations, the treatment dummy was set as shown in Table 1 to account for these policy changes.

[Table 1 about here.]

In fact, this specification is in line with the literature in which there are differences in treatment even within a treatment group. This is exemplified in the work of [2] studying the effect of changes in the minimum drinking age in the US on alcohol and drug use disorders. The changes in the minimum legal drinking age were caused by changes in state and federal legislation, including the revocation of a federal alcohol prohibition in 1993 that allowed states to freely regulate alcohol and the National Minimum Drinking Age Act of 1984, which required all states to raise the minimum legal drinking age to 21 years [2]. These frequent changes in regulations caused states to have different minimum legal drinking ages at different times [2]. To take advantage of the variations in the minimum legal drinking age policy, the authors assigned the treatment in the range of 0 to 1 depending on the timing and percentage of people between 18 and 20 years of age who were old enough to drink alcohol legally [2]. For instance, around two-thirds of those aged 18 to 20 years could legally drink in a state where the minimum legal drinking age was 19 years [2].

All regressions summarized in the study used a 'within' estimator. Moreover, to test the heteroskedasticity as well as the serial correlation in residual errors, a Breusch–Pegan test [7] and Breusch–Godfrey test [6, 10] were conducted for all estimated regressions. In light of the possible presence of heteroskedasticity and serial correlation, all reported errors are robust standard errors that account for serial correlation as well as heteroskedasticity in the residual errors, following [4].

4.1.2. Estimated Extended Difference-in-Differences

In this subsection, we explain the extended difference-in-differences approach, which accounts for the possible variations in common trends between prefectures. In this model, we added term $\beta D_m D_p$ where D_p is a prefecture dummy. The inclusion of this term can reduce concerns about non-parallel trends across prefectures [1] by capturing the effect of prefecture-level monthly characteristics that are not captured by $\delta D_m D_c$. Prefecture-level characteristics may include such factors as unique climate environment and the hosting of big events in the prefecture. Indeed, this formulation is more likely to give a more robust estimate than the estimate without variables absorbing prefecture-level time effect, as discussed by Angrist and Pischke [1], as we have monthly data of the occupancy rate for 5 years to estimate the pre-treatment trend, which can be extrapolated into the treatment periods. This is a popular methodology to check the identification strategy of the difference-in-differences approach; for example, Besley and Burgess [5] employed it in their study of the effect of changes in industrial regulation on businesses in India. However, as discussed in Angrist and Pischke [1], in the study of Besley and Burgess [5], the inclusion of state-specific trends nullified the estimate of the treatment effect, possibly questioning the result of the analysis. However, in this study, we show that the inclusion of prefecture-specific trends does not eliminate the treatment effect but rather demonstrates the soundness of our difference-in-differences identification.

$$Y_{pt} = \gamma_p + \delta_m D_m + \delta_c D_m D_c + \beta D_m D_p + \tau D_{treatment} + \rho X_{pt} + \varepsilon_{pt} \tag{4}$$

5. Results

5.1. Results by Hotel Type

Table 2 summarizes the result of the extended regression model, which includes prefecture-specific time trends to account for heterogeneous monthly seasonality unique to a prefecture. The result shows that the treatment of interest, Go To Travel, was statistically significant at the 1% level across all types of hotels reported by the Japan tourism industry. Moreover, we can infer that the treatment effect did not vary dramatically across different types of hotels, as there is no significant difference in the coefficient. This result suggests that the introduction of the Go To Travel campaign was indeed significantly effective in uplifting the occupancy rate across all types of hotels.

[Table 2 about here.]

5.2. Results by Hotel Size

Table 3 summarizes the result of the extended regression model on hotels with different numbers of employees. It suggests that the Go To Travel campaign was effective in increasing the occupancy rate. Moreover, the estimated treatment effect is generally consistent with the hotel-type regressions for hotel occupancy. We also observe that the coefficient for hotels with 0–9 employees is less than half those for hotels with greater numbers of employees. This may suggest that the effect of the Go To Travel campaign could have been lower for smaller hotels with fewer employees. However, as the summary Table A6 in the appendix shows, the average occupancy rate for hotels with 0–9 employees is about half that for hotels with more employees. Therefore, the resulting difference in coefficient may come from the difference in average occupancy and thus, we are not able to draw a decisive conclusion about whether the treatment effect was indeed smaller for hotels with fewer employees. However, we can say that the campaign was able to significantly uplift the occupancy rate for hotels across all sizes, possibly to a varying degree.

[Table 3 about here.]

5.3. Placebo Test

To assess the validity of the results in the previous subsections, we conducted a placebo test on the treatment coefficient. The placebo test was conducted by assigning 'fake' treatments in each year preceding 2020 for the same months that the Go To Travel campaign was implemented in 2020. Since there were no significant exogenous shocks that could potentially affect hotel occupancy rate in the years for which the placebo test was conducted, we expected there would be no significant positive or negative effect of the pseudo-treatment on hotel occupancy.

As discussed in the subsection explaining the difference-in-difference approach, the placebo test is a popular means to test the validity of the difference-in-differences approach. Another example using the placebo test is the work of Comolli and Bernardi [9], which analyzed the causal effect of the Great Recession on childlessness among white women in the US. The authors conducted a placebo test by conducting a difference-in-differences analysis using two groups of cohorts that were not affected by the Great Recession and showed insignificance of the corresponding coefficient [9]. In other words, the authors showed the robustness of their difference-in-differences method by conducting a placebo test on a pseudo-treatment cohort and a control cohort. By showing that there was no 'treatment effect' on the pseudo-treatment variables, the authors validated the result of their difference-in-differences analysis, because the insignificance of the pseudo-treatment shows that no exogenous variables were driving the result of the true treatment variable of interest.

Following the past literature, we also performed the placebo test to demonstrate the validity of our estimate. The estimated coefficient from Table 4 summarizes the result of our placebo test on ryokan. The placebo tests for other types of hotels are summarized in the appendix and show similar results to those for ryokan. Therefore, for simplicity, we report the result of ryokan as a representation.

Our result indicates that the increase in occupancy rate for ryokan is likely to be causal, as there was no year with a significantly positive coefficient for the pseudo-treatment. Although some placebo treatment coefficient is statistically significant in the summary tables (Tables A10, A11, A12, A13, A14, A15) in the appendix, the sign of the coefficient differs between placebo years and does not indicate the existence of exogenous shocks that may significantly alter the occupancy rate during the months of the campaign.

[Table 4 about here.]

6. Discussion and Conclusion

This study investigated the effectiveness of Japan's Go To Travel campaign in uplifting the occupancy rate for different types and sizes of hotels using the difference-in-differences method. For the estimations, we used monthly occupancy rates for hotels since 2015 and took advantage of data in years preceding 2020 to extrapolate the seasonality and fixed effects that exist in hotel occupancy rates. Moreover, we extended the difference-in-differences method by introducing prefecture-specific trend variables to account for the differences in trends between prefectures to increase the robustness of our analysis. Additionally, we conducted placebo tests to validate the soundness of our identification by assigning a placebo treatment in years preceding 2020. The placebo test provided strong evidence that the analysis results are not driven by an exogenous factor that is not included in our regression.

Our estimate shows that, across all types and sizes of hotels, the Go To Travel campaign had a significantly positive effect in uplifting the occupancy rate. This shows that the policy introduced by the Japanese government was effective to some extent in revitalizing the tourism industry by providing discounts and increasing tourism demand.

However, although the campaign seemed to have served its purpose of increasing tourism demand, there has been a heated debate as to whether its implementation actually increased the number of COVID-19 patients, as discussed by Anzai and Nishiura [3]. In fact, the campaign was partially suspended on December 22, 2020, and then suspended nationwide on December 28, 2020 over concerns about its contribution to the spread of COVID-19. Therefore, further investigation is necessary of the trade-off between the economic benefits of the campaign and the public health danger it could have posed to society.

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Declaration of Interest

The author reports no conflict of interest.

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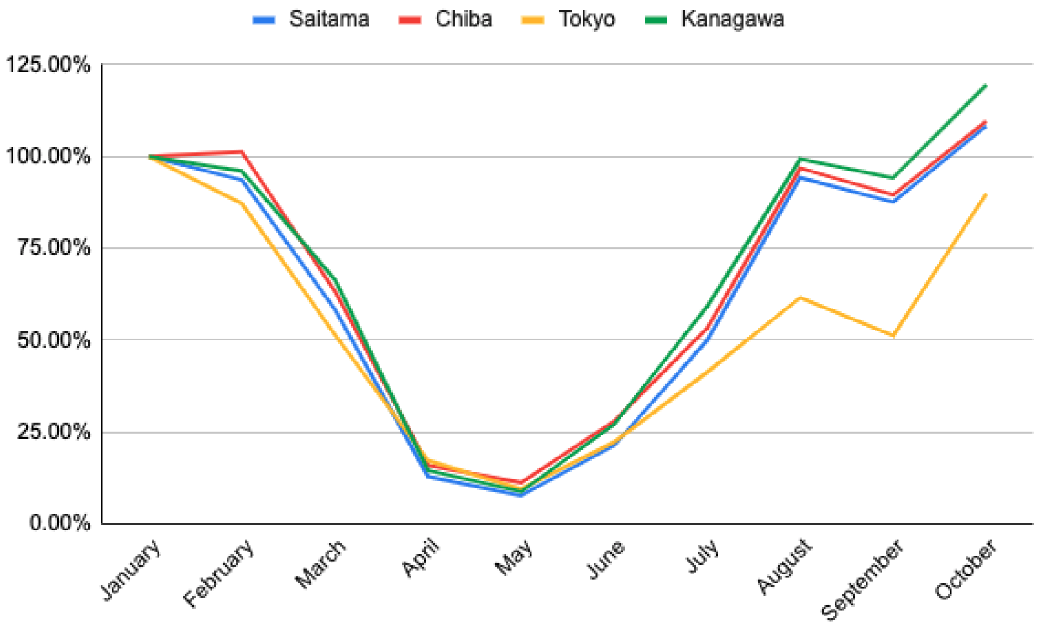
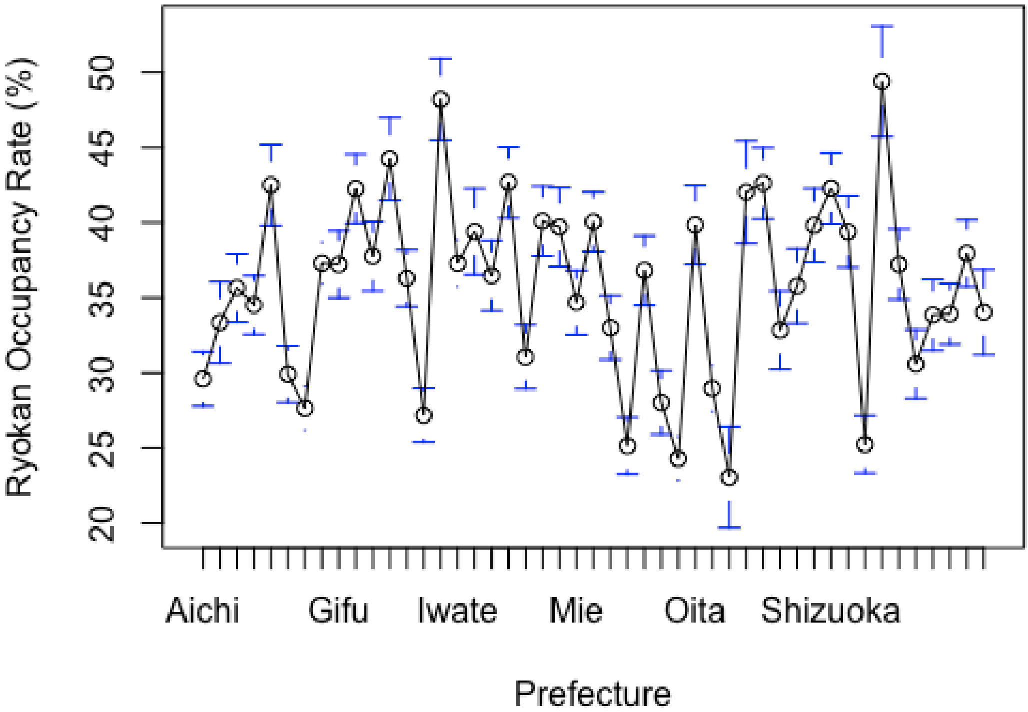


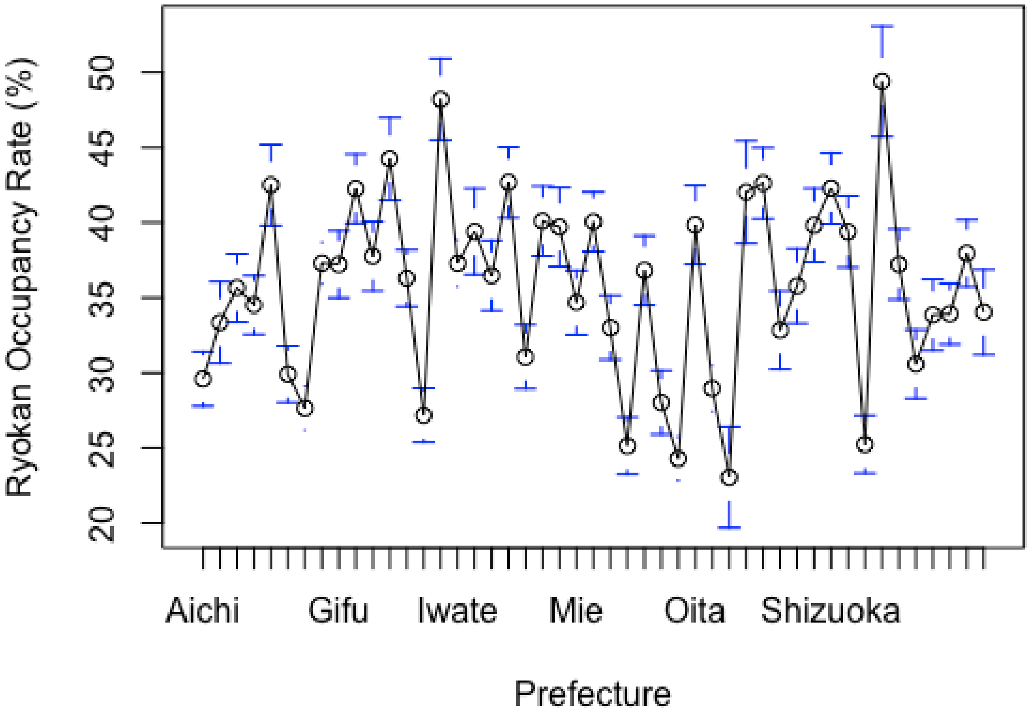
(a) *Notes:* This figure plots the number of travelers based on origin, with January as 100%.

Figure 1. Number of Tourists by Origin



(a) *Notes:* 95% confidence interval.

Figure 2. Average Occupancy Rate for Ryokan by Prefecture



(a) *Notes:* 95% confidence interval.

Figure 3. Average Occupancy Rate for Ryokan by Month

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Table 1. Treatment Assignment

	Hokkaido	**Tokyo**	**Aichi**	**Osaka**	**Others**
July	0.322	0	0.322	0.322	0.322
August	1	0	1	1	1
September	1	0	1	1	1
October	1	1	1	1	1
November	1	1	1	1	1
December	0.677	0.677	0.677	0.677	0.903

Table 2. Extended DID (Robust Standard Errors)

	Dependent variable				
	Ryokan	Resort	Business	City	Lodging
	(1)	(2)	(3)	(4)	(5)
Temp_normalized	-4.715^{*}	-7.156^{***}	-4.872^{***}	-4.364^{***}	-3.017
	(2.459)	(2.251)	(1.494)	(1.658)	(2.694)
Precipitation_normalized	-0.516^{***}	-0.590^{***}	-0.457^{***}	-0.240	-0.586^{***}
	(0.162)	(0.167)	(0.128)	(0.148)	(0.160)
Treatment	35.837^{***}	38.770^{***}	38.425^{***}	41.515^{***}	31.331^{***}
	(3.179)	(6.775)	(4.686)	(6.740)	(5.008)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384
R^2	0.739	0.748	0.853	0.877	0.575
Adjusted R^2	0.686	0.696	0.823	0.852	0.488
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3. DID Extended (Robust Standard Errors)

	Dependent variable			
	0–9	10–29	30–99	100–
	(1)	(2)	(3)	(4)
Temp_normalized	−2.391	−4.220***	−4.568***	−4.368***
	(2.613)	(1.279)	(1.375)	(1.612)
Precipitation_normalized	−0.383**	−0.446***	−0.473***	−0.660***
	(0.166)	(0.109)	(0.115)	(0.155)
Treatment	14.010***	39.295***	43.756***	45.417***
	(1.599)	(5.047)	(5.541)	(8.129)
Fixed Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384
R^2	0.513	0.859	0.892	0.884
Adjusted R^2	0.413	0.830	0.869	0.861

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4. Placebo Test for Ryokan

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-4.775^{*}	-4.861^{*}	-5.057^{**}	-5.286^{**}	-4.776^{*}	-4.578^{*}
	(2.491)	(2.503)	(2.506)	(2.144)	(2.462)	(2.523)
Precipitation_normalized	-0.518^{***}	-0.473^{***}	-0.477^{***}	-0.483^{***}	-0.475^{***}	-0.459^{***}
	(0.163)	(0.161)	(0.160)	(0.168)	(0.159)	(0.165)
Treatment	35.837^{***}	0.839	1.147	-0.818	-0.677	-1.172
	(3.179)	(1.133)	(0.700)	(1.036)	(0.914)	(1.066)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix A. Summary of the Japanese Government's Policy and Data

[Table 5 about here.]

[Table 6 about here.]

A.1. Regression Summary by Accommodation Type

[Table 7 about here.]

[Table 8 about here.]

A.2. Regression Summary by Accommodation Size

[Table 9 about here.]

[Table 10 about here.]

A.3. Placebo Test

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List of Tables

Table A1. Summary of State of Emergency and Go To Travel Campaign

Date (2020)	Content	Target Prefecture	Other Information
4/7	State of Emergency	Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka.	
4/16	State of Emergency	Expanded nationwide.	Planned until 5/6.
5/4	State of Emergency	Extension.	Planned until 5/31.
5/14	State of Emergency	Lifted except for Hokkaido, Tokyo, Saitama, Chiba, Kanagawa, Osaka, Kyoto, and Hyogo.	
5/21	State of Emergency	Lifted for Osaka, Kyoto, and Hyogo.	
5/25	State of Emergency	Lifted for Tokyo, Kanagawa, Saitama, Chiba, and Hokkaido.	
7/22	Go To Travel	Initiation of 1st stage (except for Tokyo residents and travel to Tokyo).	35% discount of travel fees.
9/1	Go To Travel	Initiation of 2nd stage (except for Tokyo residents and travel to Tokyo).	35% discount and 15% coupon of travel fees.
10/1	Go To Travel	Tokyo included in the campaign.	
12/22	Go To Travel	Suspension for Hokkaido, Tokyo, Aichi, and Osaka.	Planned until 12/27 2020.
12/28	Go To Travel	Nationwide suspension of the campaign.	Planned until 1/11 2021.

Sources: [19]; [11]

Table A2. Summary Statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Accom_0_9	3,384	30.8	12.3	1.3	22.1	38.8	74.9
Accom_10_29	3,384	61.1	13.4	6.4	54.9	69.9	96.0
Accom_30_99	3,384	64.0	14.5	5.6	58.1	73.5	92.1
Accom_100_	3,384	63.5	18.4	0.0	55.2	76.5	94.3
Ryokan	3,384	35.8	11.6	0.7	28.7	43.4	70.6
Resort_Hotel	3,384	49.3	18.5	0.1	37.9	61.1	97.9
Business_Hotel	3,384	67.8	13.3	10.1	62.6	76.7	93.3
City_Hotel	3,384	66.9	17.1	0.5	60.3	78.7	95.1
Lodging	3,384	21.8	13.8	0.1	11.5	29.6	73.3
Temp_normalized	3,384	1.0	0.5	−0.3	0.6	1.5	1.9
Vapor_normalized	3,384	1.0	0.5	0.2	0.5	1.5	2.4
Precipitation_normalized	3,384	1.0	0.9	0.0	0.4	1.3	8.9
Humidity_normalized	3,384	1.0	0.1	0.6	0.9	1.1	1.3
Treatment	3,384	0.1	0.2	0	0	0	1

Table A3. DID (Robust Standard Errors)

	Dependent variable				
	Ryokan	Resort	Business	City	Lodging
	(1)	(2)	(3)	(4)	(5)
factor(Month)2	3.261***	4.152***	7.324***	7.017***	2.115***
	(0.386)	(0.529)	(0.368)	(0.529)	(0.340)
factor(Month)3	7.429***	10.200***	11.112***	11.778***	5.266***
	(1.325)	(1.499)	(0.911)	(1.116)	(0.852)
factor(Month)4	4.795*	7.875***	7.719***	8.856***	5.660***
	(2.532)	(2.149)	(1.668)	(1.979)	(1.446)
factor(Month)5	6.995**	9.731***	5.956***	6.763***	7.691***
	(3.399)	(2.579)	(2.117)	(2.342)	(1.953)
factor(Month)6	2.291	3.825	3.223	3.362	4.849**
	(3.900)	(2.778)	(2.178)	(2.347)	(2.139)
factor(Month)7	4.796	8.915***	4.510	3.177	11.711***
	(4.812)	(3.363)	(2.748)	(2.833)	(2.661)
factor(Month)8	16.404***	23.467***	9.492***	9.361***	21.930***
	(4.900)	(3.597)	(2.951)	(2.978)	(2.977)
factor(Month)9	6.373	10.560***	6.603***	5.796**	9.749***
	(4.051)	(2.958)	(2.384)	(2.467)	(2.327)
factor(Month)10	8.969***	12.951***	10.723***	11.039***	6.675***
	(2.838)	(2.203)	(1.721)	(1.876)	(1.676)
factor(Month)11	9.936***	11.809***	12.313***	13.401***	5.099***
	(1.918)	(2.043)	(1.233)	(1.529)	(1.170)
factor(Month)12	2.888***	4.522***	5.514***	6.843***	2.002***
	(0.764)	(1.139)	(0.460)	(0.698)	(0.585)
Covid_Year	0.905	1.388	−0.495	−1.841***	0.646
	(0.869)	(1.163)	(0.611)	(0.703)	(0.817)
Temp_normalized	1.414	1.901	5.520***	7.198***	0.171
	(3.459)	(2.736)	(2.043)	(2.049)	(1.950)
Precipitation_normalized	−0.947***	−1.167***	−1.039***	−1.021***	−0.831***
	(0.154)	(0.262)	(0.154)	(0.170)	(0.158)
Treatment	32.247***	36.895***	38.508***	41.665***	33.076***
	(3.060)	(4.886)	(4.015)	(5.606)	(3.710)
factor(Month)2:Covid_Year	−2.512***	−4.315***	−5.087***	−8.536***	−2.022***
	(0.625)	(1.226)	(0.576)	(1.113)	(0.744)
factor(Month)3:Covid_Year	−17.728***	−28.575***	−27.497***	−36.557***	−10.140***
	(0.945)	(2.318)	(1.337)	(1.678)	(1.095)
factor(Month)4:Covid_Year	−30.009***	−45.866***	−43.644***	−54.483***	−16.844***
	(1.592)	(2.433)	(1.624)	(2.028)	(1.633)
factor(Month)5:Covid_Year	−34.583***	−51.453***	−48.694***	−60.919***	−20.814***
	(1.376)	(2.109)	(1.315)	(1.756)	(1.449)
factor(Month)6:Covid_Year	−22.604***	−35.235***	−31.962***	−46.643***	−13.864***
	(1.008)	(2.162)	(1.503)	(1.682)	(1.281)
factor(Month)7:Covid_Year	−24.417***	−38.332***	−38.309***	−48.322***	−25.399***
	(1.870)	(2.655)	(1.698)	(2.330)	(1.727)
factor(Month)8:Covid_Year	−53.487***	−69.700***	−73.962***	−83.651***	−55.063***
	(3.374)	(5.397)	(4.189)	(5.878)	(4.162)
factor(Month)9:Covid_Year	−41.711***	−55.248***	−61.366***	−69.003***	−44.033***
	(3.419)	(5.045)	(4.054)	(5.608)	(4.083)
factor(Month)10:Covid_Year	−37.048***	−48.043***	−58.273***	−62.881***	−43.161***
	(3.257)	(4.373)	(3.577)	(5.154)	(3.676)
factor(Month)11:Covid_Year	−33.883***	−42.629***	−54.708***	−57.971***	−40.813***
	(3.244)	(4.258)	(3.755)	(5.219)	(3.460)
factor(Month)12:Covid_Year	−34.125***	−46.274***	−50.575***	−56.358***	−36.282***
	(3.165)	(4.567)	(3.404)	(4.904)	(3.218)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	No	No	No	No	No
Robust SE	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384
R^2	0.623	0.611	0.800	0.823	0.475
Adjusted R^2	0.615	0.603	0.795	0.819	0.464
Note:					*p<0.1; **p<0.05; ***p<0.01

Table A4. DID Extended (Robust Standard Errors)

	Dependent variable				
	Ryokan	Resort	Business	City	Lodging
	(1)	(2)	(3)	(4)	(5)
factor(Month)2	2.076***	0.574**	7.028***	6.143***	2.443***
	(0.191)	(0.255)	(0.129)	(0.188)	(0.190)
factor(Month)3	5.914***	10.905***	10.502***	10.628***	7.348***
	(0.766)	(0.822)	(0.522)	(0.564)	(0.861)
factor(Month)4	2.922*	13.627***	14.042***	14.713***	12.425***
	(1.596)	(1.477)	(1.010)	(1.125)	(1.805)
factor(Month)5	5.997**	17.699***	12.724***	12.600***	15.167***
	(2.397)	(2.222)	(1.501)	(1.696)	(2.703)
factor(Month)6	2.062	14.720***	11.500***	11.966***	13.410***
	(2.742)	(2.534)	(1.684)	(1.884)	(3.067)
factor(Month)7	9.248***	19.814***	16.328***	15.351***	17.688***
	(3.436)	(3.203)	(2.119)	(2.343)	(3.824)
factor(Month)8	21.852***	34.188***	18.125***	14.801***	27.806***
	(3.608)	(3.358)	(2.259)	(2.489)	(4.040)
factor(Month)9	4.596	15.434***	13.870***	10.503***	12.720***
	(2.980)	(2.751)	(1.830)	(2.037)	(3.340)
factor(Month)10	3.245	14.188***	14.559***	13.191***	8.240***
	(2.116)	(2.005)	(1.328)	(1.443)	(2.375)
factor(Month)11	5.232***	15.118***	11.909***	11.715***	6.514***
	(1.324)	(1.198)	(0.760)	(0.870)	(1.386)
factor(Month)12	3.385***	8.784***	7.433***	5.790***	5.872***
	(0.566)	(0.572)	(0.364)	(0.469)	(0.591)
Covid_Year	1.727**	2.609**	0.915	−0.288	1.071
	(0.750)	(1.169)	(0.565)	(0.762)	(0.850)
Temp_normalized	−4.715*	−7.156***	−4.872***	−4.364***	−3.017
	(2.459)	(2.251)	(1.494)	(1.658)	(2.694)
Precipitation_normalized	−0.516***	−0.590***	−0.457***	−0.240	−0.586***
	(0.162)	(0.167)	(0.128)	(0.148)	(0.160)
Treatment	35.837***	38.770***	38.425***	41.515***	31.331***
	(3.179)	(6.775)	(4.686)	(6.740)	(5.008)
factor(Month)2:Covid_Year	−2.751***	−4.674***	−5.507***	−8.990***	−2.144***
	(0.643)	(1.229)	(0.581)	(1.097)	(0.749)
factor(Month)3:Covid_Year	−18.236***	−29.327***	−28.362***	−37.516***	−10.404***
	(0.933)	(2.305)	(1.286)	(1.607)	(1.086)
factor(Month)4:Covid_Year	−31.673***	−48.331***	−46.479***	−57.626***	−17.709***
	(1.452)	(2.418)	(1.425)	(1.863)	(1.736)
factor(Month)5:Covid_Year	−35.519***	−52.840***	−50.291***	−62.685***	−21.300***
	(1.387)	(2.134)	(1.253)	(1.719)	(1.510)
factor(Month)6:Covid_Year	−23.006***	−35.816***	−32.610***	−47.395***	−14.079***
	(1.025)	(2.179)	(1.464)	(1.657)	(1.291)
factor(Month)7:Covid_Year	−27.855***	−42.236***	−41.955***	−52.576***	−26.083***
	(1.845)	(3.018)	(1.775)	(2.591)	(2.112)
factor(Month)8:Covid_Year	−56.985***	−71.562***	−73.978***	−83.502***	−53.331***
	(3.593)	(7.266)	(4.924)	(7.056)	(5.372)
factor(Month)9:Covid_Year	−45.616***	−57.682***	−62.000***	−69.605***	−42.522***
	(3.655)	(6.897)	(4.791)	(6.795)	(5.327)
factor(Month)10:Covid_Year	−41.639***	−51.415***	−59.932***	−64.628***	−41.931***
	(3.456)	(6.161)	(4.365)	(6.361)	(4.981)
factor(Month)11:Covid_Year	−37.906***	−45.161***	−55.403***	−58.646***	−39.287***
	(3.406)	(6.135)	(4.474)	(6.399)	(4.772)
factor(Month)12:Covid_Year	−38.396***	−49.570***	−52.406***	−58.306***	−35.306***
	(3.323)	(6.070)	(4.075)	(5.960)	(4.374)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384
R^2	0.739	0.748	0.853	0.877	0.575
Adjusted R^2	0.686	0.696	0.823	0.852	0.488
Note:					*p<0.1; **p<0.05; ***p<0.01

Table A5. DID (Robust Standard Errors)

	Dependent variable			
	0–9	10–29	30–99	100–
	(1)	(2)	(3)	(4)
factor(Month)2	3.446***	6.342***	6.173***	5.953***
	(0.401)	(0.365)	(0.410)	(0.502)
factor(Month)3	5.599***	9.995***	10.738***	12.520***
	(0.943)	(0.937)	(1.054)	(1.258)
factor(Month)4	4.811***	6.315***	7.179***	10.227***
	(1.770)	(1.574)	(1.783)	(1.815)
factor(Month)5	6.111**	5.201***	6.037***	10.381***
	(2.401)	(1.904)	(2.188)	(2.046)
factor(Month)6	2.733	1.534	1.546	6.015***
	(2.727)	(1.866)	(2.336)	(2.180)
factor(Month)7	6.719**	3.457	2.774	7.737***
	(3.393)	(2.369)	(2.920)	(2.637)
factor(Month)8	14.879***	10.440***	11.208***	18.948***
	(3.490)	(2.600)	(3.089)	(2.887)
factor(Month)9	6.788**	5.436***	5.176**	10.802***
	(2.949)	(2.085)	(2.491)	(2.229)
factor(Month)10	7.552***	9.174***	10.568***	14.607***
	(2.150)	(1.521)	(1.802)	(1.717)
factor(Month)11	7.548***	10.629***	12.427***	15.051***
	(1.408)	(1.229)	(1.381)	(1.670)
factor(Month)12	2.822***	4.753***	4.937***	6.829***
	(0.608)	(0.464)	(0.594)	(0.906)
Covid_Year	−0.885	−0.605	−0.509	−0.072
	(1.145)	(0.493)	(0.458)	(0.819)
Temp_normalized	1.557	6.113***	6.410***	1.766
	(2.454)	(1.759)	(2.149)	(2.181)
Precipitation_normalized	−0.739***	−0.986***	−1.038***	−1.051***
	(0.170)	(0.128)	(0.128)	(0.215)
Treatment	15.001***	40.358***	44.376***	45.485***
	(1.865)	(4.304)	(4.461)	(6.430)
factor(Month)2:Covid_Year	−2.087***	−4.277***	−5.443***	−7.858***
	(0.807)	(0.653)	(0.667)	(1.139)
factor(Month)3:Covid_Year	−11.353***	−25.258***	−29.897***	−39.084***
	(0.913)	(1.382)	(1.375)	(1.573)
factor(Month)4:Covid_Year	−18.463***	−40.549***	−48.215***	−59.355***
	(1.490)	(1.654)	(1.540)	(1.682)
factor(Month)5:Covid_Year	−23.008***	−45.938***	−54.053***	−64.499***
	(1.387)	(1.363)	(1.136)	(1.549)
factor(Month)6:Covid_Year	−13.793***	−30.161***	−36.927***	−49.057***
	(1.190)	(1.482)	(1.415)	(1.754)
factor(Month)7:Covid_Year	−17.654***	−36.910***	−41.428***	−50.615***
	(1.111)	(1.813)	(1.944)	(2.392)
factor(Month)8:Covid_Year	−35.110***	−74.085***	−80.708***	−87.471***
	(1.686)	(4.560)	(4.804)	(6.790)
factor(Month)9:Covid_Year	−26.675***	−60.253***	−66.620***	−72.097***
	(1.848)	(4.399)	(4.595)	(6.541)
factor(Month)10:Covid_Year	−24.950***	−56.800***	−61.705***	−65.190***
	(1.894)	(3.933)	(3.991)	(5.916)
factor(Month)11:Covid_Year	−23.800***	−53.636***	−57.107***	−57.334***
	(1.959)	(4.060)	(4.082)	(5.963)
factor(Month)12:Covid_Year	−20.936***	−49.795***	−54.632***	−60.289***
	(1.783)	(3.724)	(3.768)	(5.662)
Fixed Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	No	No	No	No
Robust SE	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384
R^2	0.435	0.796	0.823	0.810
Adjusted R^2	0.422	0.791	0.820	0.805
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A6. DID Extended (Robust Standard Errors)

	Dependent variable			
	0–9	10–29	30–99	100–
	(1)	(2)	(3)	(4)
factor(Month)2	0.403*	6.680***	5.777***	3.796***
	(0.206)	(0.127)	(0.134)	(0.223)
factor(Month)3	1.800**	10.175***	10.409***	11.343***
	(0.880)	(0.423)	(0.468)	(0.568)
factor(Month)4	2.730	12.634***	13.590***	15.874***
	(1.802)	(0.804)	(0.894)	(1.047)
factor(Month)5	3.390	11.796***	13.116***	13.255***
	(2.678)	(1.245)	(1.374)	(1.593)
factor(Month)6	0.708	10.552***	11.820***	12.667***
	(3.044)	(1.383)	(1.554)	(1.846)
factor(Month)7	7.789**	15.537***	15.341***	14.551***
	(3.812)	(1.760)	(1.933)	(2.273)
factor(Month)8	13.286***	18.728***	18.155***	16.087***
	(4.018)	(1.899)	(2.062)	(2.389)
factor(Month)9	6.345*	12.988***	11.842***	9.410***
	(3.361)	(1.518)	(1.655)	(1.919)
factor(Month)10	6.383***	12.649***	11.780***	14.077***
	(2.458)	(1.076)	(1.184)	(1.414)
factor(Month)11	5.102***	11.095***	10.689***	10.921***
	(1.414)	(0.670)	(0.703)	(0.869)
factor(Month)12	3.987***	6.604***	6.000***	6.346***
	(0.570)	(0.358)	(0.368)	(0.509)
Covid_Year	−0.364	0.802	0.986**	0.755
	(1.151)	(0.531)	(0.463)	(0.857)
Temp_normalized	−2.391	−4.220***	−4.568***	−4.368***
	(2.613)	(1.279)	(1.375)	(1.612)
Precipitation_normalized	−0.383**	−0.446***	−0.473***	−0.660***
	(0.166)	(0.109)	(0.115)	(0.155)
Treatment	14.010***	39.295***	43.756***	45.417***
	(1.599)	(5.047)	(5.541)	(8.129)
factor(Month)2:Covid_Year	−2.234***	−4.698***	−5.891***	−8.101***
	(0.847)	(0.650)	(0.658)	(1.144)
factor(Month)3:Covid_Year	−11.679***	−26.119***	−30.812***	−39.594***
	(0.927)	(1.337)	(1.306)	(1.559)
factor(Month)4:Covid_Year	−19.528***	−43.372***	−51.214***	−61.024***
	(1.508)	(1.465)	(1.272)	(1.617)
factor(Month)5:Covid_Year	−23.605***	−47.528***	−55.744***	−65.438***
	(1.433)	(1.301)	(1.067)	(1.600)
factor(Month)6:Covid_Year	−14.071***	−30.797***	−37.600***	−49.451***
	(1.192)	(1.448)	(1.381)	(1.790)
factor(Month)7:Covid_Year	−18.953***	−40.167***	−45.034***	−52.837***
	(1.128)	(1.987)	(2.106)	(2.919)
factor(Month)8:Covid_Year	−34.065***	−73.174***	−80.245***	−87.423***
	(1.478)	(5.364)	(5.923)	(8.494)
factor(Month)9:Covid_Year	−25.930***	−59.938***	−66.787***	−72.436***
	(1.708)	(5.201)	(5.709)	(8.240)
factor(Month)10:Covid_Year	−24.580***	−57.482***	−62.941***	−66.137***
	(1.805)	(4.805)	(5.138)	(7.653)
factor(Month)11:Covid_Year	−23.064***	−53.360***	−57.324***	−57.711***
	(1.781)	(4.884)	(5.206)	(7.693)
factor(Month)12:Covid_Year	−20.746***	−50.760***	−56.109***	−61.339***
	(1.671)	(4.473)	(4.767)	(7.180)
Fixed Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384
R^2	0.513	0.859	0.892	0.884
Adjusted R^2	0.413	0.830	0.869	0.861

Note: *p<0.1; **p<0.05; ***p<0.01

Table A7. Placebo Test for Ryokan

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-4.775^{*}	-4.861^{*}	-5.057^{**}	-5.286^{**}	-4.776^{*}	-4.578^{*}
	(2.491)	(2.503)	(2.506)	(2.144)	(2.462)	(2.523)
Precipitation_normalized	-0.518^{***}	-0.473^{***}	-0.477^{***}	-0.483^{***}	-0.475^{***}	-0.459^{***}
	(0.163)	(0.161)	(0.160)	(0.168)	(0.159)	(0.165)
Treatment	35.837^{***}	0.839	1.147	-0.818	-0.677	-1.172
	(3.179)	(1.133)	(0.700)	(1.036)	(0.914)	(1.066)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A8. Placebo Test for Resort Hotels

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-7.246^{***}	-7.331^{***}	-7.592^{***}	-7.260^{***}	-7.331^{***}	-6.675^{***}
	(2.280)	(2.297)	(2.299)	(2.254)	(2.301)	(2.310)
Precipitation_normalized	-0.592^{***}	-0.543^{***}	-0.549^{***}	-0.541^{***}	-0.542^{***}	-0.512^{***}
	(0.168)	(0.175)	(0.174)	(0.175)	(0.174)	(0.181)
Treatment	38.770^{***}	0.277	1.465	0.125	0.039	-2.818
	(6.775)	(1.411)	(1.184)	(0.935)	(0.984)	(1.716)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01

Table A9. Placebo Test for Business Hotels

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-4.934^{***}	-5.016^{***}	-5.164^{***}	-5.380^{***}	-4.963^{***}	-4.854^{***}
	(1.513)	(1.510)	(1.570)	(1.529)	(1.501)	(1.541)
Precipitation_normalized	-0.459^{***}	-0.410^{***}	-0.413^{***}	-0.419^{***}	-0.411^{***}	-0.402^{***}
	(0.128)	(0.139)	(0.139)	(0.141)	(0.139)	(0.139)
Treatment	38.425^{***}	0.191	0.833	-0.688	-0.465	-0.688
	(4.686)	(0.768)	(0.859)	(0.752)	(0.710)	(1.085)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01

Table A10. Placebo Test for City Hotels

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-4.419^{***}	-4.485^{***}	-4.867^{***}	-4.815^{***}	-4.411^{***}	-4.481^{***}
	(1.679)	(1.684)	(1.687)	(1.687)	(1.676)	(1.706)
Precipitation_normalized	-0.241	-0.186	-0.197	-0.195	-0.191	-0.186
	(0.149)	(0.158)	(0.158)	(0.159)	(0.158)	(0.157)
Treatment	41.515^{***}	-1.365^{*}	2.000^{***}	-0.581	-0.871	-0.105
	(6.740)	(0.817)	(0.710)	(0.638)	(0.738)	(0.870)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01

Table A11. Placebo Test for Simple Lodging

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-3.056	-3.155	-3.585	-3.969	-2.912	-2.594
	(2.728)	(2.722)	(2.736)	(2.615)	(2.747)	(2.780)
Precipitation_normalized	-0.587^{***}	-0.550^{***}	-0.559^{***}	-0.568^{***}	-0.555^{***}	-0.522^{***}
	(0.161)	(0.167)	(0.168)	(0.169)	(0.167)	(0.170)
Treatment	31.331^{***}	2.413	2.564^{*}	-1.592^{*}	-1.935^{**}	-2.278^{**}
	(5.008)	(1.658)	(1.491)	(0.852)	(0.930)	(1.063)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01

Table A12. Placebo Test for Accommodation Establishments with 0–9 Employees

	Dependent variable					
	True			Placebo		
	2020	2019	2018	2017	2016	2015
Temp_normalized	−2.421	−2.469	−2.713	−3.733	−2.153	−2.932
	(2.646)	(2.639)	(2.730)	(2.388)	(2.637)	(2.633)
Precipitation_normalized	−0.384**	−0.368**	−0.373**	−0.398**	−0.378**	−0.389**
	(0.166)	(0.168)	(0.168)	(0.164)	(0.168)	(0.171)
Treatment	14.010***	1.287	1.451	−2.406**	−2.757***	2.082
	(1.599)	(1.980)	(1.456)	(1.093)	(0.970)	(1.709)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01

Table A13. Placebo Test for Accommodation Establishments with 10–29 Employees

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-4.274^{***}	-4.362^{***}	-4.436^{***}	-4.945^{***}	-4.405^{***}	-4.089^{***}
	(1.295)	(1.299)	(1.323)	(1.309)	(1.299)	(1.335)
Precipitation_normalized	-0.447^{***}	-0.397^{***}	-0.399^{***}	-0.411^{***}	-0.395^{***}	-0.384^{***}
	(0.109)	(0.125)	(0.125)	(0.125)	(0.124)	(0.123)
Treatment	39.295^{***}	0.482	0.444	-1.107^{**}	0.462	-1.152^{*}
	(5.047)	(0.693)	(0.530)	(0.453)	(0.511)	(0.700)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01

Table A14. Placebo Test for Accommodation Establishments with 30–99 Employees

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	-4.626^{***}	-4.693^{***}	-5.011^{***}	-5.172^{***}	-4.753^{***}	-4.616^{***}
	(1.392)	(1.391)	(1.398)	(1.453)	(1.407)	(1.464)
Precipitation_normalized	-0.474^{***}	-0.417^{***}	-0.426^{***}	-0.430^{***}	-0.417^{***}	-0.414^{***}
	(0.115)	(0.127)	(0.128)	(0.128)	(0.128)	(0.126)
Treatment	43.756^{***}	-1.606^{**}	1.624^{***}	-0.855^{*}	0.338	-0.435
	(5.541)	(0.644)	(0.503)	(0.500)	(0.546)	(0.819)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table A15. Placebo Test for Accommodation Establishments with More Than 100 Employees

	Dependent variable					
	True	Placebo				
	2020	2019	2018	2017	2016	2015
Temp_normalized	−4.423***	−4.483***	−4.728***	−4.699***	−4.485***	−4.717***
	(1.632)	(1.642)	(1.630)	(1.691)	(1.627)	(1.729)
Precipitation_normalized	−0.662***	−0.601***	−0.610***	−0.609***	−0.605***	−0.614***
	(0.155)	(0.168)	(0.170)	(0.171)	(0.170)	(0.169)
Treatment	45.417***	−2.405***	1.160*	−0.339	−0.305	0.861
	(8.129)	(0.924)	(0.632)	(0.752)	(0.712)	(0.987)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects*Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,384	3,384	3,384	3,384	3,384	3,384

Note: *p<0.1; **p<0.05; ***p<0.01