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Keywords: COVID-19; Japan; nighttime light
JEL Classification: I14; R11; R14

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How Effective Was the Restaurant Restraining Order against COVID-19? A Nighttime Light Study in Japan[§]

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1. Introduction

Since its outbreak in early 2020, various restrictions, including citywide or nationwide lockdowns, have been imposed on people and businesses to contain the spread of the coronavirus disease 2019 (COVID-19). One typical measure is the closure of schools and workplaces. Peoples' movements have been restricted not only between countries but also between intra-national regions. Public events have been canceled. In addition, restrictions

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have been placed on gatherings according to the number of people. Stay-at-home orders have required people to remain at home with exceptions being made only for daily exercise, grocery shopping, and "essential" trips. Numerous countries have imposed such restrictions to prevent the further spread of COVID-19. These measures have affected economic and social activities.

Japan, among other countries, has introduced various measures to contain the spread of COVID-19, including a declaration of a state of emergency and various restrictive measures. Here, we focused on the effect of the government order to shorten business hours on restaurants in the Greater Tokyo area in Japan. Our focus on the restaurant sector is important because restaurants are considered a major source of spreading COVID-19. Many countries have introduced similar measures. For example, bars in Paris were ordered to close at 10 pm from September 28, 2020 onward.[1] Moreover, the governor of New York announced on November 11, 2020, that restaurants and liquor-serving establishments must remain closed between 10 pm and 5 am.[2] Madeira et al. (2021) have shown that the measures by the governments to contain the pandemic are major sources of concern for entrepreneurs in the restaurant business.

Specifically, we examine how the government order changed restaurants' business operations by measuring the brightness of nighttime light (NTL). We employed two kinds of data for the analysis: the remotely sensed data on NTL at a spatial resolution of 500 m × 500 m and the OpenStreetMap (OSM), which is a free and editable world map powered by high-resolution satellite images. Volunteers worldwide have added spatial information, such as the shapes of roads, buildings, and points of interest (POIs). Using this information, we identified the location of restaurants. Furthermore, we investigated how the NTL of restaurants at a location point in terms of its daily level changed when the order of shortening business hours was given for that location. The shortening order differs by prefecture and date. Our empirical identification relies on these differences. Because the order of shortening business hours requests restaurants to close early, the NTL is expected to decrease if the order is effective at a given location on a given date. We analyzed the NTL from January 2 to June 23, 2020, when the first measure was ordered in Japan.

This study aims to contribute to the growing body of literature on the effects of lockdown orders on business/economic activities during the COVID-19 pandemic. The effect of restrictive measures, such as lockdown orders, on the number of confirmed COVID-19 cases (Ullah and Ajala, 2020; Askitas et al., 2020; Ghosh, 2020), the number of deaths (Conyon et al., 2020), unemployment insurance claims (Kong and Prinz, 2020), international trade (Hayakawa and Mukunoki, 2021), air pollution (e.g., Deb et al., 2020; Dang et al., 2020;

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1 https://www.france24.com/en/20200928-last-call-paris-bars-forced-to-close-early-amid-new-rules-to-stem-covid-19-second-wave

2 https://www.cbsnews.com/news/new-york-covid-cuomo-announcement-bars-restaurants-close-10-pm/

Keola and Hayakawa, 2021), and household spending and macroeconomic expectations (Coibion et al., 2020) have been investigated in previous studies. Furthermore, several scholars have examined the effect of lockdown orders on the NTL (e.g., Bustamante-Calabria et al., 2020; Elvidge et al., 2020; Ghosh et al., 2020; Jechow et al., 2020). These investigations have consistently found that lockdown orders dimmed the NTL in various countries, such as China, India, Germany, and Spain.

Although the present study also explores the effect of one form of lockdown order on the NTL, we examine such an effect at a higher spatial resolution (500 m × 500 m) linked with the location information (i.e., restaurants). Our major findings can be summarized as follows. First, we found that the order of shortening business hours significantly decreased the NTL in areas with many restaurants. This result did not change even when controlling for other types of order, namely, a state of emergency and the closing down of businesses. In addition, a similar finding was obtained in our analysis with a machine learning technique called "causal forest."[3] Second, the business hour shortening order increased the NTL in other areas, such as residential areas. In particular, this increase can be found after the order was lifted. In sum, the order of shortening business hours worked as it reduced the NTL around the restaurant area. Our findings indicate that this government order succeeded in reducing people's sojourn time at restaurants, which is a major source of spreading COVID-19.

Our study provides two types of essential information to policymakers engaged in developing policies against infectious diseases such as COVID-19: the effectiveness of a particular restrictive measure and the economic impacts of the measure on the restaurants. Information on the NTL directly enables one to ascertain whether restaurants are open or closed. Using this information, policymakers can determine the rate of compliance by the restaurants or the effectiveness of the order. The same information may be used to estimate the impacts of restrictive measures on the business performance of the restaurants because business performance largely depends on business hours. One notable benefit of an NTL study is its speed: information on the NTL can be obtained within approximately a week. More accurate information on the compliance rate and economic impacts on the restaurants can be obtained by checking the accounting records of the restaurants, but it takes the government a considerably long time to develop effective policy measures; in the case of emergencies such as the COVID-19 pandemic, rapid responses from the government are crucial.

The remainder of the paper is organized as follows. Section 2 introduces the issue of the COVID-19 pandemic and policy measures against the pandemic in Japan. Moreover, it discusses the significance of this study. Section 3 presents the empirical framework. Section

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[3] There are some studies that apply machine learning techniques to economic issues. For example, Bjorkegren and Grissen (2020) and Glaeser, Hillis, Kominers, and Luca (2016) applied machine learning techniques to various issues such as predicting loan repayment, poverty, and home values.

4 shows and discusses the estimation results. Finally, Section 5 concludes the paper.

2. Background and Significance of the Study

This section presents the background of the study and discusses its significance. Let us first give an overview of COVID-19 damages and policy measures to prevent its spread in Japan. The first case in Japan was detected on January 16, 2020, of a person who suffered from a fever in Wuhan, China, on January 3 and returned to Japan on January 6. Subsequently, the number of cases and deaths gradually increased until the end of March (Figure 1). By the end of March, a relatively large number of cases per population have been recorded in urban areas, including Tokyo, Hokkaido, and Osaka, as shown in the left panel of Figure 2. In April, however, those numbers experienced an explosive rise. The number of newly confirmed cases became 691 on April 11, whereas the number of deaths reached 29 on April 21. These two numbers started to gradually decrease from May. As shown in the right panel of Figure 3, numerous cases per population have been recorded in Tokyo, Ishikawa, and Toyama from April to June. The latter two prefectures are situated in rural areas but had the spread of COVID-19 in hospitals and nursing homes.

=== Figures 1 & 2 ===

The decrease of COVID-19 damages after April was realized through various policy measures by the central and local governments. The first strong measure was a state of emergency declared by the local government in Hokkaido on February 28. It was simply to request people not to go out, which continued until March 19. Later, as mentioned earlier, the number of cases explosively rose in Japan. Thus, the central government declared a state of emergency in seven prefectures (Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka) on April 7, which was later extended to the entirety of Japan on April 16. This emergency measure was lifted from prefectures with fewer cases and ended across Japan on May 25. This emergency measure authorized the restriction of people’s movement and business activities. However, such a restriction is request-based, and its violation does not pose a severe legal punishment. This order is expected to appeal to people’s morals to maintain public health by restraining behavior that may spread the virus.

For the concrete measures, there are two kinds of the order declared by local governments. One is the order to close down businesses. This order requests that amusement facilities, sports facilities, theaters, meeting facilities, and exhibition facilities be closed down. The other order is to request restaurants to shorten their business hours (e.g., until 8 pm). The start and end dates differ across prefectures. The dates for the prefectures examined later are shown in Table 1. These spatial and temporal data of policy measures related to COVID-19 are compiled by the Ministry of Agriculture, Forestry, and Fisheries of Japan. For example, in Tokyo, both the orders of closing down and shortening business hours started on April 11 and ended on June 18. In Ibaraki, the order of closing down began on April 18 and ended on June 7, whereas that of shortening business hours started on April 22 and ended on May 17. The effective period of these orders is determined by prefectures based on the situation of COVID-19 infection. Once again, these orders are request-based and do not have strong penalties.

=== Table 1 ===

Let us turn to discuss the significance of this study. The imposition of restrictive measures caused several controversial issues. One issue concerns the economic impacts of restrictive measures. Businesses that were ordered to close or shorten business hours naturally suffered from a decline in their revenue and profits. Not only business owners but also employees can lose their jobs or experience a decline in their income in such cases. For restaurants, considering the interindustry effects of restrictive measures is essential. The wholesalers engaged in food and beverage businesses would experience a decline in sales. In addition to these "backward" interindustry linkage effects, the "forward linkage" effect must be taken into account. One such example is the taxi business. People visiting restaurants and particularly those having imbibed alcohol tend to use taxis to return home. Therefore, the taxi business slowed down when restaurants close their business or close early.

The preceding discussions on the economic impacts of restrictive measures boil down to the issue of public health and economic performance. Many observers assume a trade-off relationship between them. Some observers argued that restrictive measures are necessary to protect people's health and lives even at the cost of economic slowdown. By contrast, other critics state that the cost of restrictive measures would not be limited to economic activities but would extend to people's mental and physical health. In line with the latter argument, the number of suicides has been reported to increase during severe economic situations, as people lose jobs or experience a substantial cut in their incomes.

Notably, both of the aforementioned arguments assume a trade-off relationship between the protection of public health and the maintenance of economic activity. This assumption is valid in the short run but not in the medium to long run. One may argue that to achieve economic growth in the medium to long run, strict restrictions on people's mobility through restrictive measures, such as a complete closure of the restaurants, are necessary. Economic recovery would, arguably, be strong and sustainable if the COVID-19 pandemic is strictly under control. These discussions point to an observation that the short-run economic cost of strong restrictive measures will be surpassed by medium- to long-run economic benefits. To develop an optimal policy to deal with the COVID-19 pandemic, identifying the impacts of restrictive measures on economic activities and public health-related matters is essential.

Another issue concerning restrictive measures is their effectiveness. Because these measures are implemented on a request basis in Japan, one cannot assume that all restaurants will comply with the request. Restaurants that belong to business associations are likely to comply with the order. Furthermore, restaurants that expect to receive a sufficient amount of financial assistance from the government would certainly comply with the request. Examining the effectiveness of restrictive measures is necessary in developing effective policies for dealing with the COVID-19 pandemic.

We have discussed two issues related to the restrictive measures, one on the relationship between public health and economic performance and the other on their effectiveness or compliance by the restaurants. Our study will provide useful information on these issues. Let us consider how the information obtained from our research can be used to deal with these two issues in reverse order, beginning with the second issue.

Estimating the impact of restrictive measures on the NTL, our study reveals the extent of compliance by the restaurants. If the NTL declines significantly during the days subject to the restrictive measures, the compliance rate can be considered high, indicating that the measures are effective; conversely, if the NTL does not change during the period of restrictive measures, the compliance rate is low, indicating the ineffectiveness of the policy. An accurate compliance rate may be obtained by examining the data on the business records of the restaurants; however, it takes time to obtain such data. A quick evaluation using the information of the NTL is considerably useful in emergency situations such as that caused by the COVID-19 pandemic when a quick formulation of the policies is extremely important. This observation brings us to realize the usefulness of our analysis for the first issue, that is, the impacts of restrictive measures on economic performance.

Following the discussion on the usefulness of information on the NTL on the compliance of the restrictive measures by the restaurants, the same information may be used to estimate the impacts of the measures on the economic/business activities of the restaurants. The lower (higher) the NTL is, the more (less) depressed business activities are. Similar to the case of compliance, accurate economic impacts may be assessed when data on the business activities of restaurants become available. However, it takes some time until the necessary data become available. Data of the NTL are helpful in making a quick assessment of the impacts of restrictive measures on the restaurant business.

3. Empirical Framework

This section explains the empirical framework used to examine the impacts of the order of shortening business hours in restaurants on their business operations. As shown in

Figure 2, the extent of COVID-19 damages widely differs by region. The causes of the spread of infection (e.g., the spread in nursing homes) and people's minds would also be different across regions. To control for these differences, we focused on the Greater Tokyo Area, which includes Tokyo and its neighboring prefectures (i.e., Chiba, Gunma, Ibaraki, Kanagawa, Saitama, Shizuoka, Tochigi, and Yamanashi).

We measure the level of business operation/economic activities by the brightness of the NTL. Naturally, shortening business hours at night is expected to decrease the NTL in areas with restaurants. Specifically, we estimate the following equation:

$$\ln NTL_{it} = \alpha_1 \times Short_{it} + \alpha_2 \times Short_{it} \times Restaurant_i + \delta_i + \delta_t + \delta_q + \epsilon_{it}. \quad (1)$$

The dependent variable is a log of the NTL in region *i* in time *t*. The unit is in Watts·cm^{-2}·sr^{-1}. As explained below, the region is defined at a spatial resolution of 500 m × 500 m, while the time is defined at a daily level from January 2 to June 23, 2020. These regional unit and time coverage were chosen based on the data availability.

Short is a dummy variable that takes a value of one if the shortening order is effective in region *i* in time *t*. Its coefficient indicates the average effect of the shortening order on the NTL. However, this order targets business hours of restaurants, not all business activities. Therefore, we introduced the interaction term of *Short* with *Restaurant*, which is the number of restaurants in region *i*. The coefficient for this interaction term indicates the additional effect on the NTL in the area with restaurants. We controlled for region fixed effects (δ_i) and time fixed effects (δ_t). The precision of NTL depends on various elements. As explained below, the difference in the data quality is controlled by indicator variables on the data quality (δ_q). ϵ_{it} is a disturbance term. We estimated this equation using the ordinary least squares method.

We obtained the data from three sources. First, we employed satellite data, which are derived from VNP46A2, a product of the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS). VNP46A2 is compiled as part of NASA's Black Marble science product development effort. It generates analysis-ready high-quality nighttime data from NPP-VIIRS's day–night band (DNB). Although another product of Black Marble, VNP46A1, is downloadable near real time, we used VNP46A2, which is usually available for download within about a week because it adjusts the effect of daily moonlight. The spatial resolution of VNP46A2 is approximately 500 m × 500 m, whereas a temporal resolution is daily. The VNP46A2 data include two types of data on the NTL, including DNB_BRDF-Corrected_NTL and Gap_Filled_DNB_BRDF-Corrected_NTL. The latter corrects missing data using the latest high-quality retrieval, which is useful for analysis with longer temporal units of analysis (i.e., weekly or monthly). Since our analysis is conducted daily, we used the former data.

Additionally, the VNP46A2 data include the variables of snow_flag and mandatory_quality_flag. The former indicates the existence of snow in a particular cell.

Since most of our study points do not have snow during the study period, we focused on locations without any snow for consistency across locations. The latter variable includes quality scores based on day/night, land/water background, cloud mask quality, cloud detection results, confidence indicator, and shadow detected, among others. Specifically, there are four categories: zero, one, two, and missing. A higher number indicates a higher quality.[4] We created indicator variables on the data quality (δ_q) using this information.

Second, the location with restaurants is identified using the OSM. It is a free and editable world map created by volunteers tracing high-resolution satellite images and/or inputting other types of spatial data. OSM was built from scratch and is continuously maintained and expanded by volunteers. Spatial information includes shapes of roads, buildings, and POIs. The POIs include various categories, such as restaurants, amusement facilities, sports facilities, and theaters. We restricted the study regions to those where at least one category of the POIs is tagged. The POIs used herein were downloaded from www.slipo.eu (SLIPO), which is a result of the European Union's Horizon 2020 research and innovation program. SLIPO continuously extracts POIs from OSM and provides them in an easy-to-use CSV format. Because it includes the longitude and latitude of each POI, we used the information on restaurants and counted the number of restaurants in each cell.[5] The data were downloaded from SLIPO in April 2021.

Third, we used the spatial and temporal information of policy orders related to COVID-19 (Table 1). It is compiled by the Ministry of Agriculture, Forestry, and Fisheries of Japan, as of June 23, 2020. Therefore, we restricted the study period to the one until then. This period covers the first wave of COVID-19 infection in Japan (Figure 1). People's behavior may change over time because they get used to the pandemic situation. For example, people may not hesitate to go out during the second wave compared with the first wave. Thus, our focus on the first wave would reflect the behavior of people who have never experienced this level of pandemic.

Two empirical issues should be noted. First, a crucial limitation concerning our NTL data is that the NTL is captured primarily from 11 pm to 12 am. Thus, if the regular closing time in a restaurant is 9 pm, the amount of NTL that we examined may not change even after lifting the order of shortening business hours.[6] In short, this limitation may underestimate our coefficient. Second, in our framework, the possibility of reverse causality might be a concern. The order of shortening business hours may tend to be declared in regions with an increase of NTL because COVID-19 is likely to spread in such regions. If

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[4] Our estimation results remain unchanged even after excluding observations where the quality information is missing.

[5] Naturally, the coverage of OSM is not perfect. For example, the number of restaurants in Tokyo identified by OSM is 32% of that identified in the economic census in Japan for 2016. However, the census data are available only at a city-level, which is too broad for our study.

[6] During the normal period without the shortening order, the restaurants, whose regular closing time is 10 pm, are likely to keep the lights on until around 11 pm to clean and prepare for the next day.

this relationship exists, our estimates will be biased. To reduce the bias resulting from this reverse causality, we restricted the regions studied herein. Specifically, we focused on regions within one kilometer from the boundary of any prefectures. Such border regions belong to the same commercial zone even if they are located in different prefectures. Thus, the difference in the existence of the business-hour shortening order within a commercial zone is merely because of the difference in prefectures, which may or may not be subject to the order.

Before reporting our results, we reviewed the NTL in the Greater Tokyo Area (Figure 3). The areas with a considerably high (blue and red) level of NTL can be observed around major train stations, such as Shinjuku, Shibuya, and Tokyo. The high (green) level of NTL is found around these stations and further stretches a long way between Tokyo and Asakusa stations. Substantially high and high levels of NTL were observed in March and April. As the number of cases started to rise sharply in mid-March (Figure 1) and remained high in early April, emergency measures, such as closure and shortening business hours orders, were introduced from mid-April to May–June (Table 1). These measures may cause the NTL to become substantially dimmed.

=== Figure 3 ===

4. Empirical Results

This section reports our estimation results of equation (1). We clustered standard errors by region. Column (I) in Table 2 reports the results excluding the interaction term to see the average effect only. Contrary to our expectations, the coefficient for *Short* is positively estimated albeit nonsignificant. Thus, the order of shortening restaurants' business hours does not necessarily decrease the NTL on average. In column (II), we introduced an interaction term with the number of restaurants. The coefficient for the noninteracted variable of *Short* is again estimated to be insignificant, whereas its interaction term with restaurants has a significantly negative coefficient. The latter result implies that the increase of NTL by the shortening order is significantly smaller in the restaurant areas compared with other places. The maximum number of restaurants in our study sample is 100. Thus, the order results in *decreasing* the NTL in regions with numerous restaurants (e.g., more than 20).

=== Table 2 ===

Furthermore, we extended our model. Since our study covered the period after the shortening order was lifted, we can divide the entire period into three subperiods, (1) preorder, (2) during order, and (3) postorder periods, and we compared restaurant operation between subperiods 1 and 3. The restaurant owners' behavior might be different between the two periods. Even after lifting the order, they may hesitate to return opening hours to normal. Moreover, as a reaction to the restricted operation by the order, they may run their business more actively after lifting the order than before the order. Peoples' minds and behavior might differ before and after experiencing the order. They may be more willing to eat and drink outside after the order is lifted. To examine the effect of the order on the NTL in the postorder period, we introduced a dummy variable *After*, which takes a value of one if the concerned period corresponds to the period after the order is lifted. Additionally, we added an interaction term between *After* and *Restaurant*.

The results are shown in columns (III) and (IV). Although the results for *Short* turn out to be significantly positive, the coefficient for *After* is estimated to be significantly positive. Thus, on average, the NTL increases during not only the order period but also the post-order period, compared with the preorder period. This result for the postorder period makes the results for *Short* in columns (I) and (II) insignificant, because *Short* in those two columns compares the period under the Short order and the period covering both preorder and postorder periods. The significantly positive result for *Short* may be because the order of shortening business hours encouraged people to go home earlier than usual. Thus, more NTL might be emitted from their dwelling houses. Furthermore, the coefficient for *After* is slightly larger than the coefficient for *Short*. This result may indicate not only that some people go home earlier but also that some people move around various places at night after drinking in restaurants. The interaction term of *Short* with *Restaurant* again has a significantly negative coefficient. However, because of the absence of the order, the interaction term between *After* and *Restaurant* has an insignificant coefficient, indicating the reinstitution of normal business hours at restaurants after lifting the order.

We conducted four kinds of robustness checks. First, we further controlled for other orders. Specifically, we introduced dummy variables of the state of emergency (*Emergency*) and the order of closing down business (*Close*). The effective duration of these two orders differs by prefectures and dates. As mentioned in Section 2, the state of emergency is only to give local governments the authority to restrict people and businesses. The actual restriction is ordered through the closing down of businesses by the local government. These orders may discourage people from going out at night. The results are presented in Table 3. The coefficients for the two new variables are insignificantly estimated. Thus, these two orders do not have significant effects on the NTL. The insignificant result may be reasonable, particularly in the state of emergency if it does not change people's minds and behavior. The results for *Short*-related variables are unchanged compared with those in Table 2. Its interaction term with the number of restaurants is significantly negative.

=== Table 3 ===

Second, we restrict the study regions to those where a single category of POIs is identified. Thus far, our analysis used information about the regions that may have multiple kinds of POIs (e.g., restaurants, amusement facilities, sports facilities, and theaters). If the order of shortening business hours not only has a direct effect on the restaurant business but also has an indirect effect on other types of business, regions with multiple kinds of POIs will receive mixed effects. For example, because of the early closing of restaurants, people move to parks and enjoy drinking there while bringing some lightning devices. To avoid mixing various effects, we focused on regions with a single category of POIs. The results are shown in Table 4. The results are unchanged in terms of sign and significance. However, the difference in the absolute magnitude of the coefficients between *Short* and its interaction term decreases dramatically, compared with that in Tables 2 and 3. For example, column (II) indicates that the order of shortening business hours *decreases* the NTL significantly in regions with at least one restaurant because the absolute magnitude of the coefficient is (marginally) larger in the interaction term than in *Short*. This decrease becomes larger in regions with more restaurants.

=== Table 4 ===

Third, we excluded Tokyo from our study. Tokyo prefecture has recorded the largest number of confirmed cases on most days. This trend is natural because Tokyo has the largest population as well. Importantly, neighboring prefectures tend to introduce restrictive orders at a similar timing as Tokyo. This strategy is reasonable because Tokyo people may visit neighboring prefectures and spread coronavirus if restrictive measures are introduced in Tokyo but not in neighboring prefectures. The decision of the orders in neighboring prefectures is somewhat sensitive to the COVID-19 situation in Tokyo. Therefore, our exclusion of Tokyo from the study regions will further reduce the possibility of bias from reverse causality. The results of the estimation are reported in Table 5 and are similar to those in Tables 2 and 3. The interaction term of *Short* has a significantly negative coefficient.

=== Table 5 ===

Last, we checked the robustness of our findings earlier with a machine learning technique called "causal forest." Causal forest is a statistical learning method that applies decision trees that can reproduce any nonlinear relationships by recursively creating branches from independent to dependent variables. We employed the causal forest proposed by Athey and Imbens (2017) to predict the average treatment effects (ATE) of the *Short* order on NTL in regions specified by the number of restaurants. Covariates of decision trees include the number of restaurants, dates, prefectures, and quality flag. Causal forest was developed to draw inference from observational data. The drawback of causal forest or machine learning, in general, is the overfitting, that is, the generated models reproduce any nonlinear relationship, even between nonrelated phenomena, with high accuracy, but perform badly for out-of-sample prediction. Practical applications of machine learning methods, including causal forest, address this drawback by randomly splitting observations into those for model building and testing. A causal forest is, therefore, especially suitable for analyses with numerous observations.

Specifically, we computed the conditional ATE for the regions according to the number of restaurants. To this end, we used the generalized random forest package that provides a function to implement the causal forest in *R* programing language (Athey and colleagues). [7] In addition, subsequent studies have used this package to study heterogeneous treatment effects (Davis and Heller, 2017; Fuster et al., 2020). The result is shown in Figure 4. The level of NTL in the region is predicted to be lower as the number of restaurants increases during the *Short* order period. The ATE of NTL in regions with up to 29 restaurants is positive, indicating that these regions are brighter during the *Short* order period. These results are consistent with the results from the regression analysis. In the analysis we found that the *Short* order increases the NTL in the area with few restaurants, such as residential areas, whereas the *Short* order decreases the NTL in regions with more than 20 restaurants. Causal forest predicts cells with 30 and more restaurants to decrease NTL during the *Short* order period. We concluded that this result supports our main findings with the regression analyses.

=== Figure 4 ===

5. Concluding Remarks

In this study, we examined the effect of the order of shortening business hours of the restaurants, which were considered a major source of spreading COVID-19, on the NTL in regions with restaurants in the Greater Tokyo area. Several local governments in Japan have implemented the order to combat COVID-19. Our results evidenced that the order significantly decreased the NTL in regions with numerous restaurants, indicating the effectiveness of the order. This, in turn, indicates its negative economic/business impacts on restaurants. These findings provide useful information for policymakers who are engaged in developing policies to deal with COVID-19 now and possible infectious diseases in the future.

Before concluding this paper, we would like to highlight the need to improve the

[7] https://cran.r-project.org/web/packages/grf/

accuracy of the research using the NTL in the context of analyzing the impact of policies affecting people's and businesses' behavior. A major benefit of the use of NTL is speed. As we discussed herein, information on NTL can be used to assess the level of business activities. Moreover, this information can be obtained using a short time lag. Thus, a study using the NTL proves considerably useful in developing policies in the case of urgency. However, evaluating the level of accuracy of the research using the NTL is essential. For example, consider the restaurant operations in the present study: we assumed that the closure or operation of restaurant businesses was measured by the NTL. However, the validity of this assumption must be examined once the necessary information on restaurants' operations becomes available. Such an exercise would improve the accuracy and quality of the research employing the NTL.

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Table 1. State of Emergency and the Orders of Closing Down and Shortening Business Hours in Some Prefectures: Start and End Dates

	Emergency		Close		Short	
	Start	End	Start	End	Start	End
Ibaraki	16-Apr	13-May	18-Apr	7-Jun	22-Apr	17-May
Tochigi	16-Apr	13-May	18-Apr	15-May	18-Apr	10-May
Gunma	16-Apr	13-May	18-Apr	29-May	18-Apr	15-May
Saitama	7-Apr	24-May	13-Apr	16-Jun	17-Apr	16-Jun
Chiba	7-Apr	24-May	14-Apr	18-Jun	18-Apr	11-Jun
Tokyo	7-Apr	24-May	11-Apr	18-Jun	11-Apr	18-Jun
Kanagawa	7-Apr	24-May	11-Apr	18-Jun	11-Apr	18-Jun
Yamanashi	16-Apr	13-May	20-Apr	6-May		
Shizuoka	16-Apr	13-May	25-Apr	17-May		

Source: Prepared by the Ministry of Agriculture, Forestry, and Fisheries, Japan.

Table 2. Regression Results

	(I)	(II)	(III)	(IV)
Short	0.015	0.016	0.068***	0.070***
	[0.017]	[0.017]	[0.019]	[0.019]
Short * Restaurant		-0.001***		-0.002***
		[0.000]		[0.000]
After			0.080**	0.083***
			[0.025]	[0.024]
After * Restaurant				-0.004
				[0.003]
Number of observations	342,488	342,488	342,488	342,488
Adjusted R-squared	0.9069	0.9069	0.9069	0.9069

Notes: The estimation results using the OLS method are reported. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by prefectures. In all specifications, we controlled for location fixed effects, time fixed effects, and quality fixed effects.

Table 3. Regression Results: Controlling for Other Orders

	(I)	(II)	(III)	(IV)
Emergency	0.000	0.000	-0.01	-0.01
	[0.043]	[0.043]	[0.047]	[0.047]
Close	-0.022	-0.022	-0.024	-0.023
	[0.023]	[0.023]	[0.022]	[0.022]
Short	0.026	0.028	0.084**	0.085**
	[0.022]	[0.022]	[0.035]	[0.035]
Short * Restaurant		-0.001***		-0.002***
		[0.000]		[0.000]
After			0.084*	0.086**
			[0.036]	[0.035]
After * Restaurant				-0.004
				[0.003]
Number of observations	342,488	342,488	342,488	342,488
Adjusted R-squared	0.9069	0.9069	0.9069	0.9069

Notes: The estimation results using the OLS method are reported. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by prefectures. In all specifications, we controlled for location fixed effects, time fixed effects, and quality fixed effects.

Table 4. Regression Results: Restricting to Regions with Single POI

	(I)	(II)	(III)	(IV)
Short	0.02	0.021	0.067**	0.068**
	[0.024]	[0.025]	[0.025]	[0.025]
Short * Restaurant		-0.022**		-0.023**
		[0.008]		[0.008]
After			0.067*	0.068*
			[0.035]	[0.035]
After * Restaurant				-0.012
				[0.016]
Number of observations	136,486	136,486	136,486	136,486
Adjusted R-squared	0.8909	0.8909	0.8909	0.8909

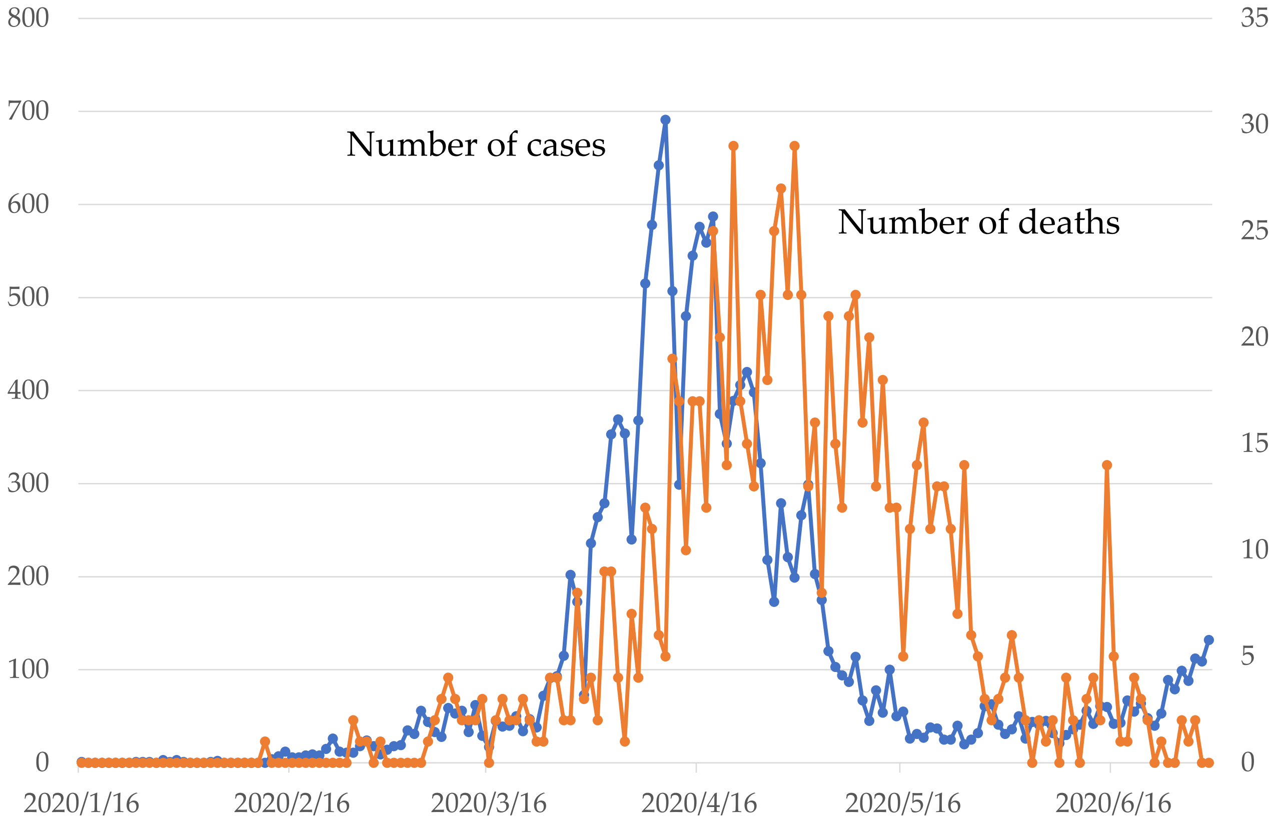
Notes: The estimation results using the OLS method are reported. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by prefectures. In all specifications, we controlled for location fixed effects, time fixed effects, and quality fixed effects.

Table 5. Regression Results: Excluding Tokyo

	(I)	(II)	(III)	(IV)
Short	0.014	0.016	0.076**	0.078**
	[0.020]	[0.020]	[0.023]	[0.023]
Short * Restaurant		-0.001**		-0.001**
		[0.000]		[0.000]
After			0.087**	0.089**
			[0.031]	[0.030]
After * Restaurant				-0.004
				[0.003]
Number of observations	263,276	263,276	263,276	263,276
Adjusted R-squared	0.8955	0.8955	0.8955	0.8955

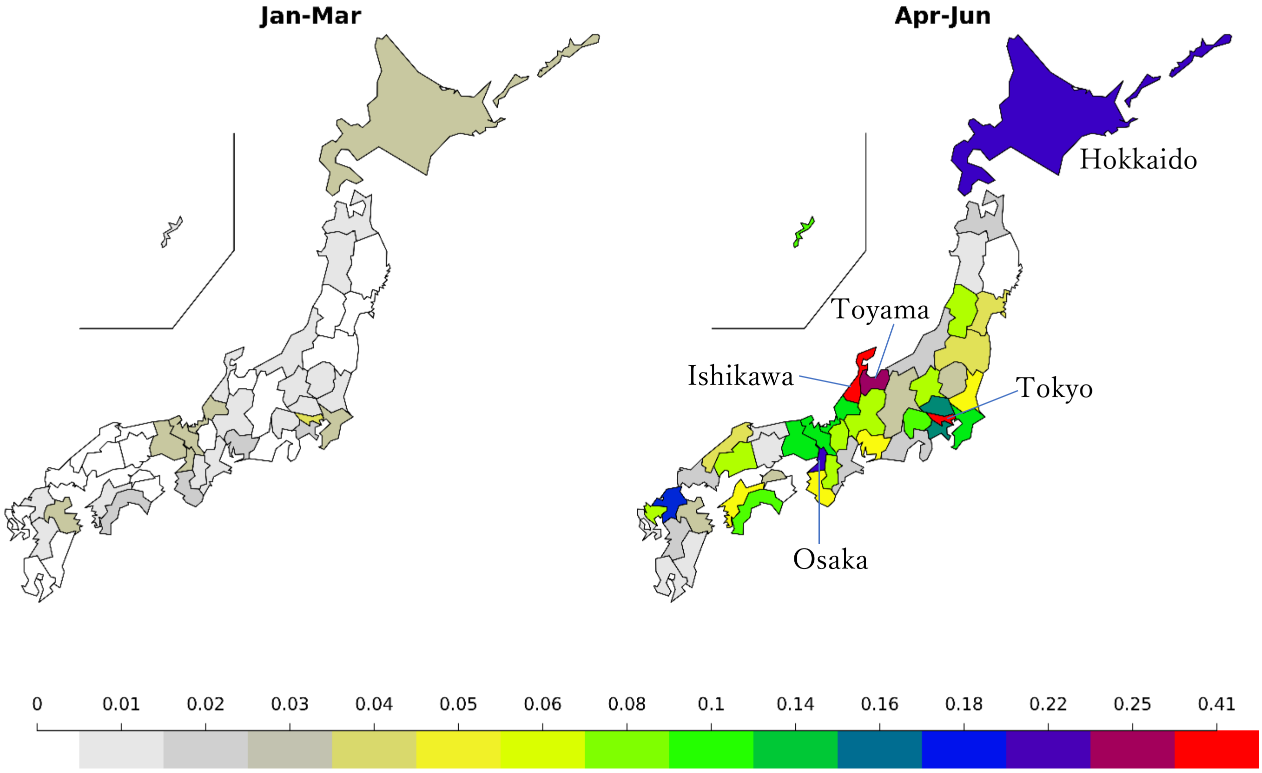
Notes: The estimation results using the OLS method are reported. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by prefectures. In all specifications, we controlled for location fixed effects, time fixed effects, and quality fixed effects.

Figure 1. Numbers of Confirmed Cases (Left Axis) and Deaths (Right Axis)



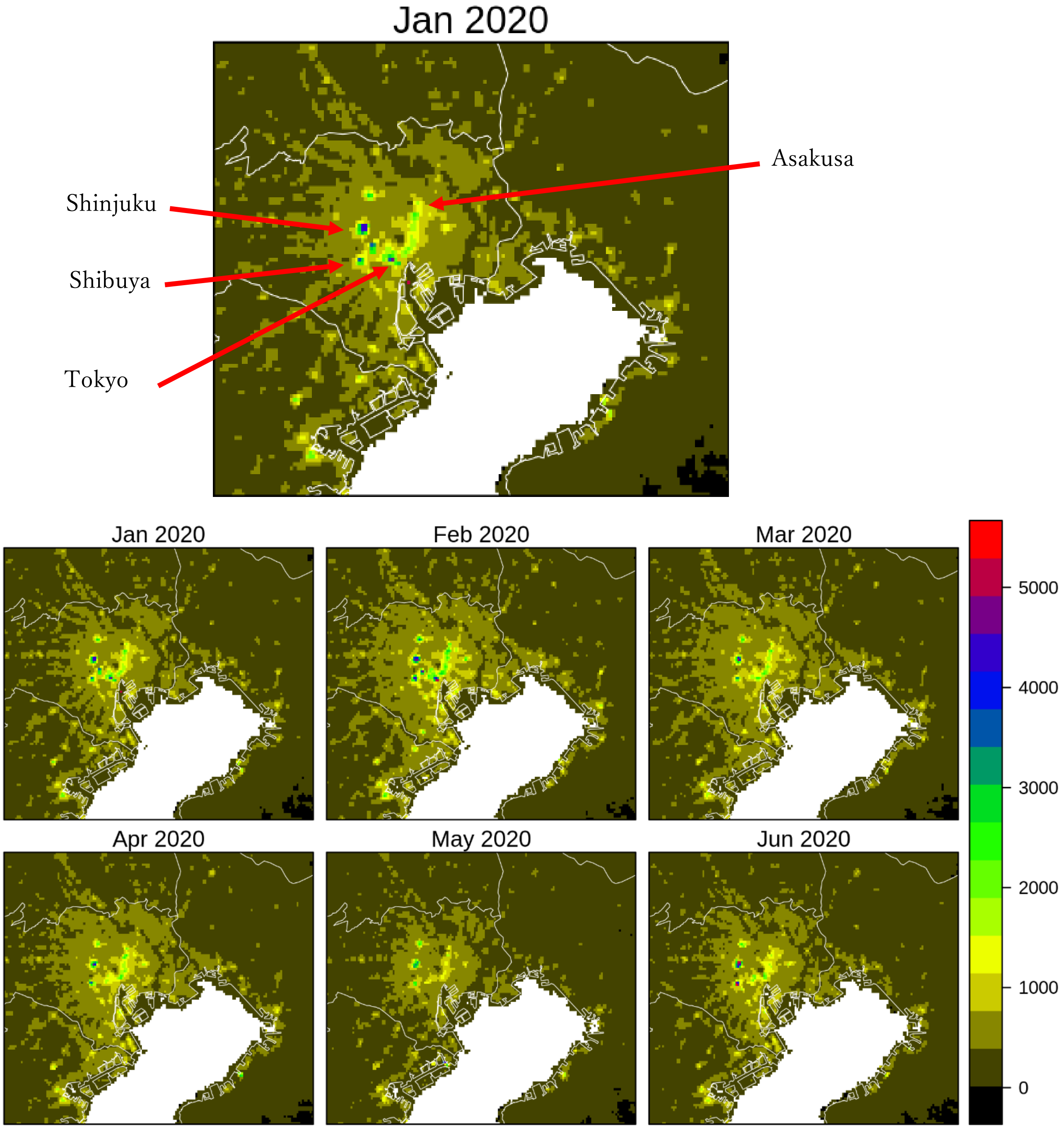
Source: Authors' compilation using the data available on the website of NHK.

Figure 2. Cases per 1,000 People by Prefecture in 2020



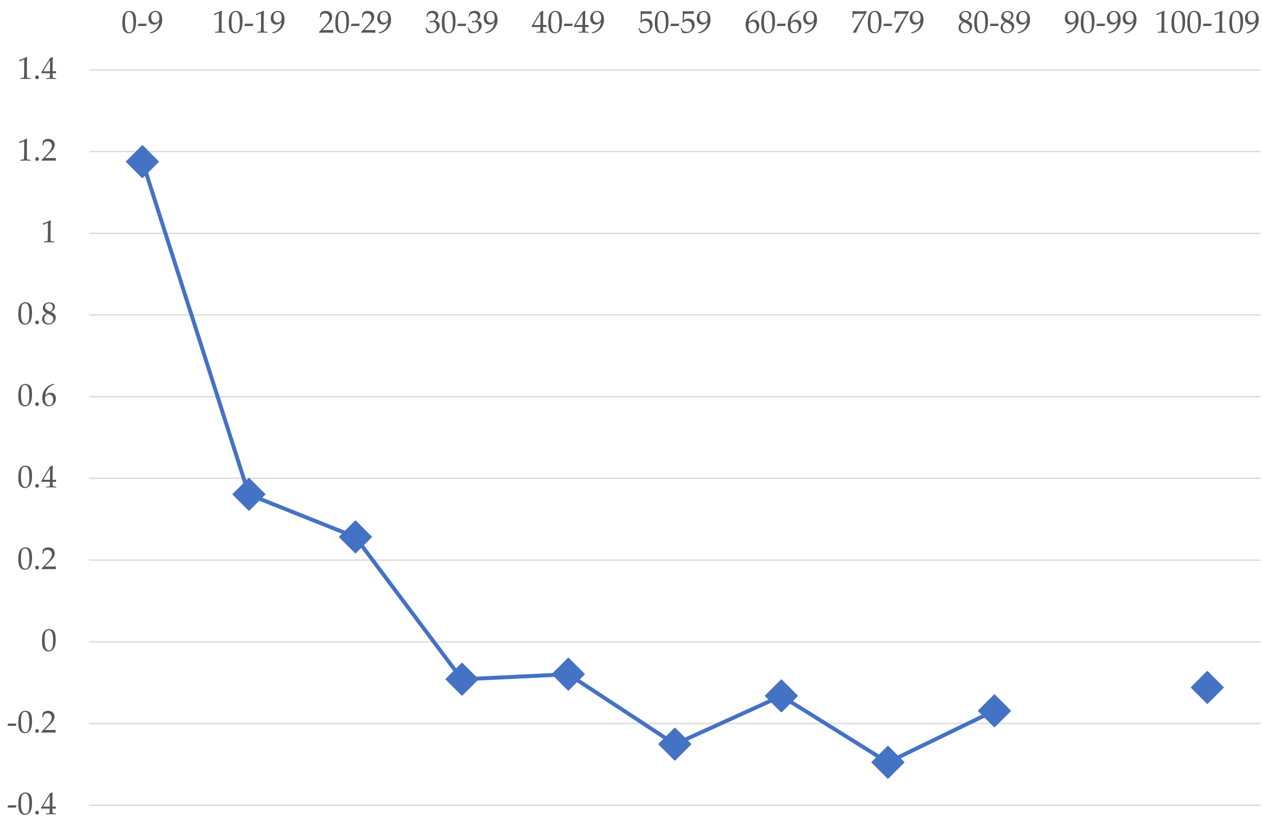
Source: Authors' compilation using the COVID-19 data available on the website of NHK and administrative boundary provided by the Ministry of Land, Information, Transport, and Tourism.

Figure 3. Monthly Average of NTL in the Greater Tokyo Area



Source: Authors' compilation using VNP46A2 nighttime light data and administrative boundary provided by the Ministry of Land, Information, Transport, and Tourism.

Figure 4. Average Treatment Effect by the Number of Restaurants



Source: Authors' computation.