

# COVID-19, state of emergency, and housing market

Delgado Narro, Ausugto Ricardo and Katafuchi, Yuya

Faculty of Political Science and Economics, Waseda University, Research Institute for Humanity and Nature

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## COVID-19, state of emergency, and housing market

Augusto Delgado †
Yuya Katafuchi ‡
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#### Abstract

This study analyzes how the declaration of a state of emergency stemming from COVID-19 affected long-term consumer behavior, i.e., real estate purchasing activity. For our analysis, we define the earliest event that a state of emergency was declared as a treatment and monthly macro data on the real estate market at the county level as an outcome, and construct a panel dataset with various covariates. Using the dataset, we estimated the treatment effect using a difference-in-differences model and found the following; first, the emergency declarations issued by a government do not appear to have affected long-term consumption behavior. Second, this lack of effect remains after excluding various control variables or using a continuous treatment variable.

**Keywords:** COVID-19, State of emergency, Housing market

**JEL classification**: I15, I18, R31

Address: 1-104 Totsukamachi, Shinjuku-ku, Tokyo, 169-8050, Japan.

Email: delgado.auri@gmail.com

<sup>‡</sup>Research Institute for Humanity and Nature

Address: 457-4 Motoyama, Kamigamo, Kita-ku, Kyoto 603-8047 Japan

Email: yuya.katafuchi@gmail.com

<sup>&</sup>lt;sup>†</sup>Corresponding author. Faculty of Political Science and Economics, Waseda University

#### 1 Introduction

The pandemic of COVID-19 has undoubtedly affected the world's economies to different degrees and in different ways. Japan, of course, has not been spared this negative shock. By January 2020, Japan had already confirmed its first case in Kanagawa Prefecture and subsequently by arrivals from Europe and the United States. As measures to mitigate the spread of the virus, the Japanese government ordered the temporary closure of schools and later the postponement of the Olympic Games. As the situation worsened, on April 7th, the government imposed a state of emergency in the prefectures of Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka. On April 16th, at the request of the other prefectures, the state of emergency was extended to the rest of the country for an indefinite period. The state of emergency ended on May 14 in 39 of the 47 prefectures, representing 54% of the population; however, the prefectures of Tokyo, Osaka, Kyoto, Hyogo, Hokkaido, Chiba, Kanagawa, and Saitama. On May 21st, the state of emergency ended for Osaka, Kyoto, and Hyogo prefectures. Finally, on May 25th, the state of emergency was lifted for the whole country.

COVID-19 being a recent negative shock, all impacts on the economy are not yet fully evident. The first short-term consequences can be seen in the changing consumption patterns, with changes in the forms of work and the temporary closure of several companies, shops, and restaurants, the population has reduced its consumption of transportation, visits to restaurants, and internal and external tourism has been compromised. However, due to the novelty of the events, the effect on long-term sectors is still not entirely clear. One such sector is real estate. Within the sector, we have buyers who are probably thinking of postponing the purchase of real estate until the economic outlook becomes clearer. This is because purchasing decisions depend on the long-term expectations of the economy. On the other hand, in the case of people who rent apartments, they are affected by short-term expectations because the dynamism and the current employment situation determine those decisions. In the case of Japan, even though the economy has been strongly affected, domestic labor dynamism seems

to have remained relatively stable.

In view of this situation of COVID-19, the Japanese government has intervened in the policy of declaring a state of emergency. This declaration of a state of emergency is aimed at controlling the infection by asking the public to refrain from going-out unnecessarily and to refrain from operating in the business community, especially in the service sector. This policy intervention has no penalties for individuals or legal entities that act in ignorance of the request of declaration, i.e., it is non-legally binding policy intervention. Based on this vague legal basis, the period of time for declaring a state of emergency varies from prefecture to prefecture. The criteria used to determine the period of issuance depend on the infection situation in each prefecture. In the seven relatively urban prefectures where significant numbers of people were infected, namely Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka prefectures, a state of emergency was declared on April 7, 2020, ahead of the other 40 prefectures. Therefore, it is likely that the prefectures with these early interventions are more likely to be more significantly affected by COVID-19 than the other 40 prefectures. This study analyzes how COVID-19 has affected the housing market by using differences in the criteria used to determine the duration of such interventions.

In this sense, this research analyzes the effect of emergency state on real estate dynamics in Japan as part of the long-term consumption decisions affected by the pandemic (COVID-19). In particular, we analyze the effect of COVID-19 on new housing construction using as proxies the number of new homes, the total new areas built, and the estimated cost of new housing construction. To this end, in addition to endogenous variables, we used the establishment of the state of emergency as the intervention that allows us to differentiate the effects caused by the pandemic more clearly.

A number of literature have analyzed the impact of COVID-19 on economic activity using Japanese data. Kikuchi et al. (2020) analyzes the impact on the labor market in the early weeks of the full-blown outbreak, based on consumer spending data based on credit card transaction history. Watanabe et al. (2020) uses data on credit card payments for the use of goods classified as services to examine the extent of people's self-

restraint behavior in the early stages of infection. Fukui and Kikuchi (2020) analyzes how COVID-19 affects the labor market using micro data from scraping online job information on the internet. However, all of the analyses for Japan were based on the impact of COVID-19 on short-term consumption activity, and no analysis of long-term consumption behavior was conducted.

Several analyses have been made of the emergency declaration triggered by COVID-19 as a treatment. Based on questionnaire survey in Japan, Yamamura and Tsutsui (2020) constructs panel data by following the same respondents twice, once before and once under the declaration of a state of emergency, to analyze individual-level changes in preventive behavior and mental status due to the declaration of a state of emergency. Qian and Yahara (2020) conducted a survey under the declaration of a state of emergency and found that personality and ideology altered mental health status and behaviour towards COVID-19. Based on an internet survey, Yamamoto et al. (2020) shows that for 7 prefectures where the spread of COVID-19 was significant, unforced lockdowns based on the declaration of a state of emergency caused psychological distress. Katafuchi et al. (2020) analyzes that non-legally binding emergency declarations have reduced people's going-out behavior, both through the analysis of a micro-theoretical model that throws in social branding and through an empirical analysis using a daily panel dataset based on the Google Community Mobility Reports. Kobayashi et al. (2020) uses a state-space model based on a susceptible-infected-recovered (SIR) model to predict the evolution of infectious diseases, including the magnitude and timing of the peak of the epidemic after the declaration of a state of emergency in Japan. Using data constructed by an online survey of Japanese small-medium-enterprises, Kawaguchi et al. (2020) finds that in the short term, it reduces both feasible and expected sales of firms. As such, only papers that use the Japanese emergency declaration as an intervention have analyzed the impact on mental condition and behavior using micro-data, or the impact on comprehensive economic activity, have existed in these analyses.

Based on these previous studies, this study contributes to the following points; first, we construct a daily panel dataset for Japan by prefecture that incorporates date data

for emergency declarations, real estate market trends, and various covariates. Second, using this panel dataset, we analyze how non-legally binding decrees affected people's long-term consumption behavior by estimating a difference-in-differences model with the event of the earliest declaration of a state of emergency as the intervention and the real estate market trend as the outcome. The results of the empirical analysis do not confirm the statistical significance of the impact of the issuance of the emergency declaration on people's decision-making in long-term consumption in the real estate market. The statistical insignificance of this effect is also robust in sensitivity analyses that exclude all covariates, and in analyses using continuous treatment variables for emergency declarations.

This paper is divided as follow: section 2 for Data and Methodology; section 3 for presenting the main results and the interpretation of them; finally, section 4 for conclusions.

### 2 Data and Methodology

### 2.1 Data and design

This section introduces a dataset used to identify how policy interventions through non-legally binding emergency declarations have affected long-term consumer behavior, i.e., the real estate market. As a prerequisite, to measure the effectiveness of the interventions in this analysis, we use the situation where the date of the declaration of a state of emergency was issued varies from prefecture to prefecture. Therefore, the following panel datasets are all at the prefectural level.

For the outcomes of the intervention, we use variables that indicate trends in the real estate market. Specifically, we use monthly real estate data by prefecture, all of which are 'Building Starts' reported by the Ministry of Land, Infrastructure, Transport, Japan and Tourism's. We analyze three outcomes from that data set: the number of new housing starts (new\_building\_num), the total floor area of new housing starts (new\_building\_area), and the estimated cost of new housing construction

(new\_building\_cost), natural logarithm. To account for the seasonality of these dependent variables, we use these data as a ratio of the actual monthly data for 2020 divided by the corresponding actual monthly data for 2019.

Secondly, this study uses the declaration of a state of emergency as an intervention. The emergency declaration intervention date-data were obtained from Katafuchi (2020). A summary of this data is shown in Table 1. As can be seen from this table, the date on which the emergency declaration was issued differs from prefecture to prefecture. This study takes advantage of this difference in issuance dates to define the earliest emergency declaration as an intervention. However, as with the outcomes above, monthly data are the most detailed frequency of prefecture-level data available in Japan. Hence, the seven prefectures where a state of emergency was declared on 7 April 2020, namely, Saitama, Chiba, Tokyo, Kanagawa, Osaka, Hyogo and Fukuoka, are defined as the treatment group, and the other prefectures are defined as the control group.

Six variables are used as covariates: (1) the number of births per capita (birth\_per\_population), (2) the number of marriages per capita (marriage\_per\_population), (3) the number of jobs per job seekers (job\_per\_seekers), (4) the consumer price index (cpi\_all\_item), (5) the number of COVID-19 cases per million (positive\_perm), and (6) going-out behavior (mobility). This study considers the fertility rate and the number of marriages as demographic factors that would affect the real estate market. Data were obtained from 'Vital Statistics' by the Ministry of Health, Labour and Welfare, Japan. With respect to the number of jobs per job seekers, we consider the possibility that population shifts in the labor market may affect the real estate market. Data were obtained from 'General job placements', Ministry of Health, Labour and Welfare, Japan. For the consumer price index, we put it into a covariate vector to account for immediate consumption, i.e., the purchasing behavior of goods that are necessities of life, which affects long-term consumption behavior. Data were obtained from the 'Consumer Price Index', Bureau of Statistics, Ministry of Internal Affairs and Communications, Japan. The number of COVID-19 infections reflects changes in infection status at the county level that vary. This trend in the number of people infected could have an impact

on real estate transactions and actual construction through avoidance behavior. This data was calculated by the authors from the daily accumulated number of infected persons in TOYO KEIZAI ONLINE (2020) to the monthly number of infected persons by prefectures. However, since the period of this data is from March 11, 2020, the data before that date were compiled by the author based on a press release by the Ministry of Health, Labor and Welfare, Japan. And finally, we incorporate mobility data into the covariates vector to reflect going-out behavior at the prefectural level. This study consider that such behavior with different trends at the prefectural level influences the behavior to buy a property. This study uses monthly averages of daily data for four categories, i.e., "Retail & recreation", "Grocery & pharmacy", "Parks", and "Workplaces", of data from Google Community Mobility Reports<sup>1</sup>, by prefectures, as a variable to explain the status of going-out behavior.

Finally, we discuss the details of the panel dataset obtained by combining these data. The sample consists of macro data for February, March and April 2020 in 47 prefectures. The overall sample size is therefore  $47 \times 3 = 141$ .

#### 2.2 Methodology

Using the date of issuance of different emergency declarations at the prefectural level, with the earliest emergency declaration as the intervention, this study uses the data described in Section 2.1 to estimate a difference-in-differences (DD) model to analyze the impact of the intervention on the real estate market. Specifically, we estimate the following model:.

$$Y_{it} = \beta_1 \operatorname{March}_t + \beta_2 \operatorname{April}_t + \beta_3 \operatorname{April}_t \times \operatorname{treatment}_i + \mathbf{x}'_{it} \boldsymbol{\gamma} + \alpha_i + \varepsilon_{it}$$
 (1)

for i = 1, ..., 47 and t = 2, 3, 4, where  $Y_{it}$  is outcome of real estate market for ith prefecture and tth month, March<sub>t</sub> is time-dummy for March 2020 and equals 1 if t = 3

<sup>&</sup>lt;sup>1</sup>https://www.google.com/covid19/mobility/, accessed on July 10, 2020

and 0 otherwise, April<sub>t</sub> is post-intervention time-dummy for April 2020 and equals 1 if t=4 and 0 otherwise, treatment<sub>i</sub> is dummy variable for treatment group defined above,  $\mathbf{x}_{it}$  is the covariates vector,  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ , and  $\gamma$  are unknown parameters,  $\alpha_i$  is fixed-effect for i to control the heterogeneity among prefectures other than the covariates, and  $\varepsilon_{it}$  is the stochastic variability. treatment<sub>i</sub> itself can be absorbed in the prefectural fixed-effect  $\alpha_i$  since assignment of treatment is not time-variant.

When estimating a DD model, a parallel trend assumption is often a problem in the debate on the reliability of the results. To confirm this, Figure 1 shows the trend in the outcome, real estate market trend, over the sample period for the control group and the treatment group. All these trends are depicted by within group means in the control and treatment groups. To clarify whether the parallel trend assumption holds or not, if we check the trends (February-March) prior to the issuance of the treatment, i.e., the declaration of an emergency, we find that the new\_building\_num and new\_building\_cost are almost identical, but the new\_building\_area appears to be slightly different trend among groups. Therefore, this study consider that the DD results using new\_building\_area as an outcome should be treated with some caution.

### 3 Results

This section analyzes the impact of non-legally binding emergency declarations on the Japanese housing market based on the data and an econometric model developed in Section 2.

Table 1 shows the detail of the duration of the state of emergency in each prefecture. Column 2 shows the start date of the state of emergency; column 3 shows the end date of the state of emergency; column 4 details the total length of the state of emergency measured in days; finally, column 5 shows the total days of duration of the state of emergency for the month of April, the month in which the quarantine was established. This table shows that most of the prefectures have had a 28-day state of emergency, while the prefectures where the cases of infection increased rapidly have had longer

state of emergency, even reaching 48 days for several prefectures near Tokyo.

On the other hand, Tables 2 and 3 show the descriptive statistics on mean and standard deviation. One thing to note is that the endogenous variables, housing market variables show peaks in March and declines in April in 2020. Secondly, in the case of the population variables of births and marriages, the values remain stable during the third and fourth months. Thirdly, the control variables related to the economic environment, such as the number of persons seeking employment and the CPI, the values have decreased during the months of the sample. Finally, for the variables directly affected by the pandemic, they have undergone important changes as a result of the evolution of the situation in the country.

In Table 4 we observe the results of the estimation of the DD model for the set of three endogenous variables, i.e., new\_building\_num, new\_building\_area and new\_building\_cost, controlled by the covariates but not including the treatment variable. A first clear result observed in the results is that March is a significant month for the behavior of the endogenous variables. On the contrary, the month where state of emergency had effect, April, the level of significance is diluted and leads us to the conclusion that emergency status has no significant effect on endogenous variables. It is necessary to emphasize that these results occur even when we control for exogenous variables. Table 5 gives us similar results even when we incorporate the treatment variable that interacts with the variable April; in other words, April, as the month in which the state of emergency is declared, and the treatment that controls the length of emergency, are not statistically significant thus generating the conclusion that the emergency declaration measures established in Japan have had no impact on the dynamics of the housing market. It is necessary to mention that the observed results are the impacts of emergency declaration on the dynamics of the housing market in the long-term consumption decisions of consumers. This result of zero impact of the emergency state may find reasons in which consumers expect that the current health crisis is a temporary or short-term shock that should not affect their long-term consumption decisions that in many occasions have been determined ex-ante. In Table 6, when the control variables (demographic factor, labor market, consumer price index affecting short-term consumer activity, infection status and going-out activities) are extracted, the results change significantly. The March variable remains significant although its effect is reduced compared to the case with covariates. Secondly, the April variable becomes significant and the interaction variable between the treatment and the April variable, even though it remains non-significant, the sign changed to negative. In this sense, it is important to mention that the model seems to be sensitive to the presence of covariates.

For robustness, we revisit the treatment variable. The definition of the treatment group introduced in Section 2.1 was to be a prefecture in which the earliest emergency declaration was issued. However, it can be confirmed by examining Table 1 that in April, when post-treatment is defined, the number of days of emergency declarations is not zero not only for the treatment group but also for the control group. Therefore, in order to consider the issuance of emergency declarations in these control groups, this study considers a continuous treatment variable. In other words, we take the number of days of emergency declarations in April, which is displayed in Table 1 by emergency\_length\_april, as the treatment (treatment\_length<sub>i</sub>). We thus reiterate the analysis conducted in this section based on the following model:

$$Y_{it} = \beta_1 \operatorname{March}_t + \beta_2 \operatorname{April}_t + \beta_3 \operatorname{April}_t \times \operatorname{treatment\_length}_i + \mathbf{x}'_{it} \boldsymbol{\gamma} + \alpha_i + \varepsilon_{it}.$$
 (2)

The results are shown in Tables 7 and 8. The results show that the coefficients of the treatment variable show a positive sign (negative when covariates are excluded) and none of them are statistically significant, similar to the results from estimation using binary treatment variables. Therefore, the robustness that can be checked by changing the definition of the treatment variable is acknowledged.

The results observed in Tables 7 and 8, even when the duration of quarantine is included as a treatment variable, the results do not change much either in marginalization or in significance levels. These results show that, in the first place, the effects of the

month of emergency declaration, April, is sensitive to the incorporation of covariates; in simple words, when we include other characteristics within the model, the effect of emergency statement disappears. Second, long-term decisions, once we incorporate the characteristics of the economy, are not affected by the state of emergency declared by the Japanese government. This possible result, as mentioned above, may be due to the fact that consumers expect the shock to be temporary and therefore their decisions should not be affected. Also, those consumption decisions are generally determined in advance, i.e., possibly much of those decisions were made ex-ante to the onset of the pandemic.

#### 4 Conclusion

The study was motivated by the fact that the economic impact of the spread of COVID-19 on the economy has only revealed the short-term impact on consumption, e.g. on the service sector, and the long-term impact on the sector has not been revealed, and this motivation was used in the empirical analysis to determine the impact of the declaration of a state of emergency on the real estate market. With this motivation, we use the earliest event with a declaration of a state of emergency, which represents a significant spread of infection, as an intervention to determine the impact on the real estate market by an empirical analysis of monthly prefectural-level panel data sets in Japan. The treatment effect estimated by the DD model is not statistically significant for all real estate market outcomes, and this result is similar in the sensitivity analysis where all covariates were not used, as well as in the analysis of a continuous intervention variable, i.e., the period when the emergency was declared, as an intervention variable.

Therefore, the main conclusions of this research can be summarized in two important points. First, the established model is sensitive to the inclusion of covariates. This is important because when the model does not include covariates, the variable that captures the effect of the month in which the state of emergency was decreed, April, would seem to have a relevant and significant effect on consumers' long-term consumption decisions. Thus, once the covariates or control variables are included, the effect of the month in which the state of emergency was declared is diluted. Second, once controlled by covariates, it is observed that the long-term consumption decisions of those consumed (housing market) are not affected by the state of emergency declared by the government, it is not affected by the month in which the state of emergency was declared, nor by the duration of the same that interacts in the form of a treatment variable. This result may be a consequence of the fact that long-term consumption decisions are not affected by temporary or short-term shocks, which is how consumers may be looking at the current situation of COVID-19.

This means that the phenomenon of emergency declarations having no effect on long-term consumer behavior is robust.

One problem that exists with the results of this analysis is that the data are only available at the monthly level for interventions that are issued at the daily level. Although it may be possible to obtain data on people's purchasing activities on a daily basis through credit card usage data and point-of-sale (POS) data, it is difficult to obtain data on forward-looking consumer activity on a short-term basis, as this data represents only short-term consumer activity.

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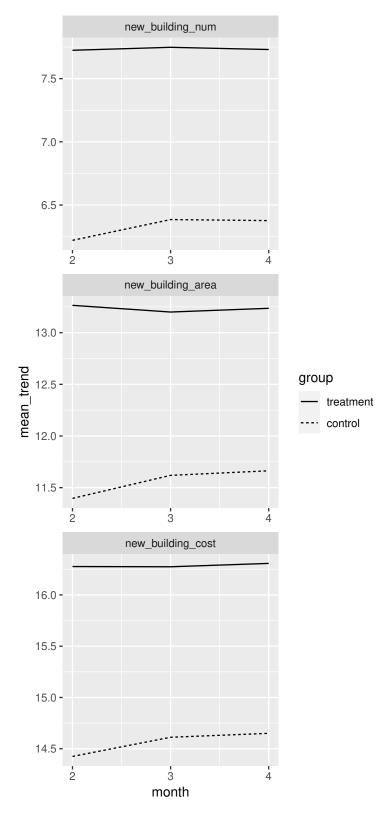


Figure 1: Trends in outcome of real estate market Notes: The figure is made by the authors.

Table 1: Date and length of state of emergency of the prefectures of Japan

| prefecture | emergency_start | emergency_end | emergency_length    | emergency_length_april |
|------------|-----------------|---------------|---------------------|------------------------|
| Hokkaido   | 2020-04-16      | 2020-05-25    | emergency_rength 39 | emergency_rengtn_april |
| Aomori     | 2020-04-16      | 2020-05-25    | 28                  | 15                     |
| Iwate      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Miyagi     | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Akita      |                 | 2020-05-14    | 28                  | 15                     |
|            | 2020-04-16      |               |                     |                        |
| Yamagata   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Fukushima  | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Ibaraki    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Tochigi    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Gunma      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Saitama    | 2020-04-07      | 2020-05-25    | 48                  | 24                     |
| Chiba      | 2020-04-07      | 2020-05-25    | 48                  | 24                     |
| Tokyo      | 2020-04-07      | 2020-05-25    | 48                  | 24                     |
| Kanagawa   | 2020-04-07      | 2020-05-25    | 48                  | 24                     |
| Niigata    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Toyama     | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Ishikawa   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Fukui      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Yamanashi  | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Nagano     | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Gifu       | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Shizuoka   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Aichi      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Mie        | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Shiga      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Kyoto      | 2020-04-16      | 2020-05-21    | 35                  | 15                     |
| Osaka      | 2020-04-07      | 2020-05-21    | 44                  | 24                     |
| Hyogo      | 2020-04-07      | 2020-05-21    | 44                  | 24                     |
| Nara       | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Wakayama   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Tottori    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Shimane    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Okayama    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Hiroshima  | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Yamaguchi  | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Tokushima  | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Kagawa     | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Ehime      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Kochi      | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Fukuoka    | 2020-04-07      | 2020-05-14    | 37                  | 24                     |
| Saga       | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Nagasaki   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Kumamoto   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Oita       | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Miyazaki   | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Kagoshima  | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| Okinawa    | 2020-04-16      | 2020-05-14    | 28                  | 15                     |
| - CAIIIawa | 2020-04-10      | 2020-00-14    | 20                  |                        |

Table 2: Descriptive statistics: mean

| month | new_building_num | new_building_area | new_building_cost | birth_per_population | marriage_per_population |
|-------|------------------|-------------------|-------------------|----------------------|-------------------------|
| 2     | 0.7884           | 0.7591            | 0.8165            | 0.0005               | 0.0005                  |
| 3     | 0.9795           | 1.0188            | 1.0805            | 0.0006               | 0.0003                  |
| 4     | 0.8789           | 0.9231            | 0.9640            | 0.0006               | 0.0003                  |
| month | job_per_seekers  | cpi_all_item      | positive_perm     | mobility             |                         |
| 2     | 1.5068           | 101.8468          | 1.1987            | 0.8053               |                         |
| 3     | 1.4453           | 101.8319          | 9.7127            | -0.0187              |                         |
| 4     | 1.3711           | 101.7532          | 63.1869           | -9.3936              |                         |

Table 3: Descriptive statistics: standard deviation

| month | new_building_num | new_building_area | new_building_cost | birth_per_population | marriage_per_population |
|-------|------------------|-------------------|-------------------|----------------------|-------------------------|
| 2     | 0.2001           | 0.2730            | 0.3427            | 0.0001               | 0.0001                  |
| 3     | 0.1275           | 0.2586            | 0.3017            | 0.0001               | 0.0000                  |
| 4     | 0.1380           | 0.2548            | 0.3034            | 0.0001               | 0.0000                  |
| month | job_per_seekers  | cpi_all_item      | positive_perm     | mobility             |                         |
| 2     | 0.1886           | 0.7632            | 2.8752            | 1.6434               |                         |
| 3     | 0.1779           | 0.8003            | 9.4984            | 2.9477               |                         |
| 4     | 0.1816           | 0.7734            | 57.9610           | 4.7273               |                         |

Table 4: Estimation result of month-effect on housing market

|              |                  | Dependent variable: |                   |
|--------------|------------------|---------------------|-------------------|
|              | new_building_num | new_building_area   | new_building_cost |
| March        | 0.433***         | 0.683***            | $0.584^{*}$       |
|              | (0.160)          | (0.214)             | (0.299)           |
| April        | 0.191            | 0.389               | 0.188             |
|              | (0.154)          | (0.246)             | (0.291)           |
| Observations | 141              | 141                 | 141               |
| $R^2$        | 0.391            | 0.264               | 0.216             |
| Covariates   | Yes              | Yes                 | Yes               |

Notes: Numbers in parentheses represent clustered-robust standard error. Above \*,\*\*,\*\*\* indicate statistical significance at 10%, 5%, 1%, respectively.

Table 5: Estimation result of state-of-emergency effect on housing market

|                          | Dependent variable: |                   |                   |
|--------------------------|---------------------|-------------------|-------------------|
|                          | new_building_num    | new_building_area | new_building_cost |
| March                    | 0.439***            | 0.683***          | 0.596*            |
|                          | (0.161)             | (0.213)           | (0.300)           |
| April                    | 0.196               | 0.389             | 0.199             |
|                          | (0.154)             | (0.244)           | (0.293)           |
| $treatment \times April$ | 0.040               | 0.004             | 0.089             |
|                          | (0.054)             | (0.142)           | (0.153)           |
| Observations             | 141                 | 141               | 141               |
| $R^2$                    | 0.393               | 0.264             | 0.218             |
| Covariates               | Yes                 | Yes               | Yes               |

Notes: Numbers in parentheses represent clustered-robust standard error. Above \*,\*\*,\*\*\* indicate statistical significance at 10%, 5%, 1%, respectively.

Table 6: Estimation result of state-of-emergency effect on housing market: sensitivity analysis

|                          |                  | Dependent variable: |                   |
|--------------------------|------------------|---------------------|-------------------|
|                          | new_building_num | new_building_area   | new_building_cost |
| March                    | 0.191***         | 0.260***            | 0.264***          |
|                          | (0.038)          | (0.063)             | (0.070)           |
| April                    | 0.100***         | 0.186***            | 0.154**           |
|                          | (0.030)          | (0.053)             | (0.062)           |
| $treatment \times April$ | -0.061           | -0.147              | -0.043            |
|                          | (0.038)          | (0.097)             | (0.102)           |
| Observations             | 141              | 141                 | 141               |
| $R^2$                    | 0.296            | 0.195               | 0.156             |
| Covariates               | No               | No                  | No                |

*Notes*: Numbers in parentheses represent clustered-robust standard error. Above \*,\*\*,\*\*\* indicate statistical significance at 10%, 5%, 1%, respectively.

Table 7: Estimation result of state-of-emergency effect on housing market: continuous treatment

|                                  |                  | Dependent variable: |                   |
|----------------------------------|------------------|---------------------|-------------------|
|                                  | new_building_num | new_building_area   | new_building_cost |
| March                            | 0.439***         | 0.683***            | 0.596*            |
|                                  | (0.161)          | (0.213)             | (0.300)           |
| April                            | 0.133            | 0.383               | 0.060             |
|                                  | (0.184)          | (0.354)             | (0.388)           |
| $treatment\_length \times April$ | 0.004            | 0.0005              | 0.010             |
| Ŭ <b>.</b>                       | (0.006)          | (0.016)             | (0.017)           |
| Observations                     | 141              | 141                 | 141               |
| $R^2$                            | 0.393            | 0.264               | 0.218             |
| Covariates                       | Yes              | Yes                 | Yes               |

 $\overline{Notes}$ : Numbers in parentheses represent clustered-robust standard error. Above \*,\*\*,\*\*\* indicate statistical significance at 10%, 5%, 1%, respectively.

Table 8: Estimation result of state-of-emergency effect on housing market: continuous treatment, without covariates

|                                  | Dependent variable: |                   |                   |  |
|----------------------------------|---------------------|-------------------|-------------------|--|
|                                  | new_building_num    | new_building_area | new_building_cost |  |
| March                            | 0.191***            | 0.260***          | 0.264***          |  |
|                                  | (0.038)             | (0.063)           | (0.070)           |  |
| April                            | 0.194**             | 0.415**           | 0.220             |  |
|                                  | (0.077)             | (0.177)           | (0.195)           |  |
| $treatment\_length \times April$ | -0.007              | -0.016            | -0.005            |  |
|                                  | (0.004)             | (0.011)           | (0.011)           |  |
| Observations                     | 141                 | 141               | 141               |  |
| $\mathbb{R}^2$                   | 0.194               | 0.187             | 0.101             |  |
| Covariates                       | No                  | No                | No                |  |

*Notes*: Numbers in parentheses represent clustered-robust standard error. Above \*,\*\*,\*\*\* indicate statistical significance at 10%, 5%, 1%, respectively.