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Residential Land Price Fluctuations Caused by Behavioral Changes on Work-from-home Based on COVID-19*

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Abstract

This study analyzes how the behavioral changes associated with novel coronavirus disease (COVID-19) have affected residential land prices. Under previous pandemics (e.g., Spanish flu and SARS), avoidance of real estate transactions accompanied by going-out behavior and contraction of the real economy have caused a decrease in residential land prices. On the other hand, under the COVID-19 pandemic, it has been reported that residential land prices were stable or increasing due to behavioral changes such as the promotion of work-from-home (WFH). In order to confirm this phenomenon, this study first constructs a yearly panel dataset of Japan with the average published land price at the prefectural level as the dependent variable and treatment variables based on policy interventions for COVID-19, or WFH implementation. Second, this study uses the dataset to examine the relationship between land prices and changes in these conditions before and after the pandemic using the difference-in-differences method. The results of the above empirical analysis suggest that residential land prices were higher in prefectures where policy interventions related to COVID-19 were more robust than in other prefectures and where WFH was promoted more. This result supports the upward trend in residential land prices during the COVID-19 pandemic in the prefectures where policy interventions on COVID-19, including requests for WFH, are more implemented and where WFH is more prevalent.

Keywords: COVID-19, Land price, Work-from-home, Telework

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1 Introduction

Novel Coronavirus Disease in 2019 (SARS-CoV-2, COVID-19) is a global and ongoing pandemic that has now confirmed 209,876,613 infected cases and 4,400,284 deaths (WHO, 2021a) since the People's Republic of China reported the outbreak of a cluster of infected cases in Wuhan to WHO on December 31, 2019, (WHO, 2021b). In order to mitigate as much as possible the enormous damage to the nation caused by this infectious disease, governments have undertaken various policy interventions, taking into account the trade-off between economy and life. These policy interventions can be broadly divided into two categories: first, non-pharmaceutical policy interventions (NPI) aimed at restricting people's behavior, such as urban lockdowns and travel restrictions; and second, pharmaceutical policy interventions (PPI) aimed at controlling the spread of infection, such as vaccines and medicines.

PPIs have been active since the second half of 2020 due to the rapid development of vaccines (Graham, 2020; Kashte et al., 2021; Li et al., 2021), but from the beginning of the epidemic in 2019 until 2020, no effective medicines were developed, forcing governments and public health authorities to rely on NPIs (Hartley and Perencevich, 2020). NPIs aimed at restricting people's behavior have been successful in terms of reducing the number of infections and deaths (Askitas et al., 2021; Flaxman et al., 2020; Katafuchi et al., 2020), as droplet transmission through human contact is the primary route of transmission of COVID-19 (Yong and Chen, 2020; Kohanski et al., 2020; Matava et al., 2020). Such NPIs that restrict the behavior of people include lockdowns (e.g., the New Zealand lockdown in March 2020 to close public facilities and purchase necessities (BBC, 2020a)), restrictions on private gatherings (e.g., restrictions on indoor and outdoor gatherings by large groups in the UK in September 2020 with penalties (BBC, 2020b)), school closures (e.g., the closure of public schools in New York State, USA, in March 2020 (BBC, 2020c)), and restrictions on international travel (e.g., restrictions on travel for travel purposes worldwide as of 2021), and restrictions on commuting through work-from-home (WFH) alternatives (for example, in April 2020, the Japanese government requested a 40% reduction in the number of employees coming to work through the use of WFH (Office for Novel Coronavirus Disease Control, Cabinet Secretariat, Government of Japan, 2020)).

While many studies have shown that these NPIs have indeed contributed to the control of infection (Neidhöfer and Neidhöfer, 2020; Lau et al., 2020; Alfano and Ercolano, 2020; Yoo and Managi, 2020; Atalan, 2020), there have been socio-economic side effects such as deterioration of people's mental health (Armbruster and Klotzbücher, 2020; Elmer et al., 2020; Pieh et al., 2020; Xu and Banks, 2020) and contraction of the real economy (Asahi et al., 2021; Nicola et al., 2020; Buera et al., 2021; Sarkodie and Owusu, 2021; Maliszewska et al., 2020). The contraction of the real economy has been discussed in many papers such as described above, with estimates of a median GDP decline of -2.8% in 2020 for a sample of 30 countries (Fernandes, 2020) and a global GDP decline of about -4.0% in 2020 (Boissay et al., 2020).

On the other hand, based on experience, the real estate market under a pandemic is expected to experience a decrease in land prices due to a contraction in the real economy and a decrease in real estate transaction opportunities associated with reduced contact opportunities (Francke and Korevaar, 2021). For example, in the Spanish flu of 1918, housing prices fell by 50% in the US due to a drop in housing demand triggered by the contraction of the real economy (Shiller, 2015; Sorensen, 2008). Furthermore, the 2003 SARS epidemic showed that in Hong Kong, one of the centers of the epidemic, the volume of land transactions dropped significantly (-72%) as customers avoided human contact, resulting in a temporary 1.6% drop in housing prices and a 2.8% drop in housing prices in infected areas (Wong, 2008). However, contrary to this intuitive phenomenon of declining house prices during a pandemic, some states in the US experienced an increase in house prices immediately after the COVID-19 epidemic (Wang, 2021), and there are observations that house prices are rising in almost all countries (Cheung et al., 2021). Moreover, in Japan, it has been reported that residential land prices will be stable in 2020, the early stage of the COVID-19 epidemic (Global Link Management, 2020).

NHK (2020); Sankei Shimbun (2021); Mainichi Shimbun (2021) have suggested that this phenomenon in Japan is due to the spread of WFH, a behavioral change associated with the NPIs of limiting commuting, which has increased demand for real estate in the suburbs[1]. Even though there are studies that have analyzed WFH after COVID-19 has been expanded, most of these studies take a labor economics perspective, such as determining the extent to which WFH has actu-

[1]There is a study that suggests that the government's declaration of a state of emergency does not seem to have affected the long-term consumption behavior of real estate transactions (Delgado Narro and Katafuchi, 2020). However, the paper focuses on the number of new construction starts and the area of new construction starts as indicators of the real estate market, which is a different approach from this study, which focuses on land prices.

ally expanded (Bick et al., 2020), determining for which occupations WFH has expanded more (Kawaguchi and Motegi, 2021; Dey et al., 2020; Redmond et al., 2020), developing indicators of WFH availability (Yasenov, 2020; Alipour et al., 2020), classifying occupations based on such indicators of WFH (Mongey and Weinberg, 2020), and determining how WFH has affected actual labor productivity (Purwanto et al., 2020). Thus, no study analyzes the real estate market impact of COVID-19 considering the behavioral change through NPIs such as promoting WFH in the whole world.

This paper constructs a prefectural-level panel data set for Japan. It uses the data set to conduct an empirical analysis using the difference-in-differences (DID) method to determine whether such behavioral changes positively impact residential land prices. The results of the empirical analysis support the robustness of suburban land prices under the COVID-19 pandemic in prefectures with more intensive COVID-19 policy intervention and more WFH prevalence.

This paper is organized as follows: Section 2 details the econometric methods and data used in the empirical analysis; Section 3 presents the results of the empirical analysis, and Section 4 is the conclusion.

2 Design and Data

In order to analyze how the behavioral change of WFH diffusion based on COVID-19 has affected residential land prices, this paper uses the DID method. In the econometric model, the dependent variable of interest in this paper is residential land price. On the other hand, this paper's treatment variable of interest is related to WFH decision-making and its actual diffusion.

The data of residential land price is logarithmically converted from the data of the average residential land price per square meter in Japanese Yen by prefecture in the Prefectural Land Price Survey (Ministry of Land, Infrastructure, Transport and Tourism, Japan, 2020). The Prefectural Land Price Survey publishes the average price of standard sites in each prefecture as of July 1 every year, intending to provide an index for general land transaction prices [2]. Standard sites are considered standard in terms of factors affecting the use and value of land in neighboring areas. This standard site has a sample size of 14,791 for 47 prefectures in Japan in the 2019 Prefectural Land

[2] `https://www.mlit.go.jp/totikensangyo/totikensangyo_fr4_000132.html`, in Japanese, accessed on August 14, 2020

Price Survey[3]. The land price information provided by this land price survey is not a transaction price, but because it is normalized and adjusted for site-specific factors such as the characteristics of nearby sites, this can be considered a representative transaction price in the neighborhood sites of a standard site (Sato and Shiba, 2021). Therefore, the average land price by prefecture, which is calculated by aggregating the land prices of these representative standard sites, represents the average land price in that prefecture.

The treatment variables of interest in this paper are the policy interventions that lead to the behavioral change of WFH diffusion and the actual spread of WFH. First, this study focuses on prefectural-level emergency declarations enacted by the Japanese government as a policy intervention that may cause a behavioral change in the form of WFH diffusion[4]. Although emergency declarations are categorized as unenforceable policy interventions because they do not have penalties, they are considered to have a particular influence on people's decision-making toward WFH because these interventions request a 70% reduction in the number of workers (Ministry of Health, Labour, and Welfare, Japan, 2021). In this paper, based on the data in (Katafuchi, 2020), we create data on the number of days of emergency declarations announced by July 1, 2020, by each prefecture. If the number of days per prefecture exceeds the median of all prefectures, the prefecture is considered the one where emergency declarations were intensively announced. A dummy variable that takes 1 for those prefectures is used as one treatment variable for WFH decision-making.

Second, as a treatment variable representing the behavioral change of WFH prevalence, this paper considers two types of data: data based on questionnaire surveys and data on actual mobility to the workplace. The first data on the spread of WFH is given by several questionnaire surveys on the actual spread of WFH. These data are based on the data reported by Persol Research and Consulting Co., Ltd. (2020a) on the implementation of WFH in Japan in mid-March 2020, based on an internet questionnaire survey reported on April 24, 2020, and the data reported by Persol Research and Consulting Co., Ltd. (2020b) on the implementation of WFH in Japan in May 2020, based on the same methodology, reported on June 19, 2020. The sample size for the data for March 2020 is 21,448, which is the total number of male and female full-time employees aged 20-59 in Japan, and the number of employees at their place of work is ten or more. In contrast, the sample size for the

[3] `https://www.land.mlit.go.jp/landPrice/AriaServlet?MOD=0&TYP=0#`, in Japanese, accessed on August 14

[4] This paper does not focus on emergency declarations issued by local municipality governments.

data for May 2020 is 21,000, which is the total number of male and female respondents aged 20-59 who are employed in Japan and have ten or more employees at their place of work. Although there is a difference in the data in terms of the target of the sample, with the data for March 2020 being full-time employees and the data for May 2020 including both full-time and part-time employees, it is noted that the data for May 2020 mainly uses data of full-time employees for comparison with the previous data[5]. This paper uses these data on the implementation of WFH as a percentage of the total number of workers who work from home, aggregated by prefecture in Japan. Furthermore, we define the difference between the prefecture's WFH implementation status in March 2020 and May 2020 as the amount of newly introduced WFH by the prefecture. Prefectures whose incremental WFH implementation status exceeds the median of all prefectures will be deemed to have introduced more WFH. For those prefectures, a dummy variable that takes the value of 1 is used as a treatment variable for the actual diffusion of WFH based on questionnaire surveys.

The second type of data related to the spread of WFH is data on actual mobility. This data is reported by Google (2021) on mobility to the workplace by prefecture and day, based on the location of mobile devices logged into Google Accounts. The values of the mobility status to the workplace in this data are shown as the amount of increase of visits to the workplaces relative to the reference value[6]. In this study, we calculate the prefectural-level average of workplace mobility from February 15, 2020, when data are available, to June 30, 2020, the day before the target date of the land price survey. We consider prefectures where WFH is more widespread to be those where the mean of the prefectural-level mobility to work is below the median of all prefectures. For those prefectures, we use a dummy variable that takes the value of 1 as a treatment variable for the actual diffusion of WFH based on the mobility status. Since mobility is defined as the increase in the number of visits to workplaces relative to the reference value before the pandemic, it is not a pure quantity of mobility to workplaces, but rather an increase in mobility to workplaces after the pandemic. Therefore, this treatment variable can be interpreted as a decrease in the amount of workplace visits after the pandemic, i.e., WFH spread more than in other prefectures after the pandemic, rather than a decrease in the amount of workplace visits, i.e., WFH spread more than

[5]In the summary of the third survey (Persol Research and Consulting Co., Ltd., 2020b), there is a statement that "For the purpose of comparison with the first and second surveys, the analysis mainly uses figures for full-time employees".

[6]The reference value is defined by the median number of visits to the workplace by day of the week from January 3, 2020, to February 6, 2020, which is before the COVID-19 pandemic. (`https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927`), accessed on August 14, 2021)

in other prefectures before the pandemic.

As explained above, this paper considers the treatment variables related to emergency declarations that affect WFH decisions, the treatment variables related to the actual diffusion of WFH based on questionnaire surveys, and the treatment variables related to the actual diffusion of WFH based on mobility data. In the econometric analysis, we estimate three models for each of these three treatment variables to clarify how behavioral changes related to WFH have affected residential land prices.

3 Econometric Method

In order to analyze how behavioral changes based on the spread of COVID-19 have affected residential land prices, this paper uses the following econometric model based on the DID method:

$$y_{it} = D_i \times A_t + \lambda_t + \alpha_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is a dependent variable for prefecture i and time t, D_i is treatment variable for prefecture i, A_t is after-treatment dummy variable which takes 1 if $t = 2020$ and 0 otherwise, λ_t is time fixed effect for $t = 2019, 2020$, α_i is prefectural fixed effect, and ε_{it} is stochastic disturbance term for prefecture i and time t. In this model, $i = 1, \cdots, 47$ because Japan is composed of 47 prefectures, and $t = 2018, 2019, 2020$ because it covers the three-year period from 2018 to 2020. Thus, $N = 47 \times 3 = 141$.

Based on this model setup and the data described in Section 2, each variable can be interpreted as follows: y_{it} is the residential land price for prefecture i and time t, D_i is either a treatment variable related to the declaration of emergency that affects the decision to WFH, a treatment variable related to the actual diffusion of WFH based on questionnaires, or a treatment variable related to the actual diffusion of WFH based on mobility data.

4 Result

In this section, first, we review the descriptive statistics of the data used in the empirical analysis; second, we review the statistics related to the parallel trend assumption in the DID method; and third, we review and interpret the results of the actual DID analysis.

Table 1 shows the descriptive statistics for the overall sample (47 prefectures, 3 years, $N = 141$). Firstly, the logarithmically transformed residential land price per square meter (`log_residential_land`), the dependent variable of interest in this study, is distributed between 9.488 and 12.843 across the prefectures, which, when back-transformed by the exponential function, ranges from about 13,000 to 380,000. In contrast, the mean value is 10.554 (about 39,000 yen when back-transformed), suggesting a skewed distribution, so this study uses the log-transformed value of residential land price per square meter as the dependent variable, as described above. Secondly, we check the descriptive statistics on the treatment variables (`emergency`, `wfh_survey`, `wfh_mobility`) for the declaration of emergency, WFH diffusion based on survey, and WFH diffusion based on mobility. The mean value of 0.191 for `emergency` suggests that there are many emergency declarations of the same length below the median, as this variable is constructed by a dummy variable based on the median length of emergency declarations. On the other hand, we can confirm that the distribution of `wfh_survey` and `wfh_mobility`, which are variables related to the diffusion of WFH, is very similar.

Table 2 shows the descriptive statistics of `log_residential_land` by year [7]. The table shows that, between 2018 and 2020, the average residential land price has been on an upward trend (10.546, 10.556, and 10.560 for 2018, 2019, and 2020 respectively), while the standard deviation has also been on an upward trend (0.674, 0.683 and 0.686 for 2018, 2019 and 2020 0.674, 0.683 and 0.686 respectively), indicating that the residential land price gap at the prefecture-level may be widening.

Secondly, the statistics for the parallel trend assumption in the DID method are presented. Figures 1, 2, and 3 show the annual averages from 2017 to 2020, calculated for the treatment and control groups, respectively, for the three treatment variables (`emergency`, `wfh_survey`, `wfh_mobility`). In all Figures, we can see an upward trend in the mean log-transformed residential land value for the treatment group in the pre-treatment period, but it is difficult to confirm the trend for the control group because the difference in trend for the control group is smaller than that for the treatment group. The study therefore presents in Tables 3, 4, and 5 the average residential land price figures by treatment and control group by the sample years shown in the Figures 1, 2, and

[7] Descriptive statistics for the treatment variables by year are not shown as it does not vary by time point.

Table 1: Descriptive statistics for the overall sample

variable	mean	sd	min	max	N
`log_residential_land`	10.554	0.676	9.488	12.843	141
`emergency`	0.191	0.395	0.000	1.000	141
`wfh_survey`	0.489	0.502	0.000	1.000	141
`wfh_mobility`	0.489	0.502	0.000	1.000	141

Notes: sd is the standard deviation, min is the minimum value, and max is the maximum value. `emergency` is a dummy variable that takes the value of 1 for each prefecture in which the cumulative number of days of declared emergencies until 30 June 2020 exceeds the median. `wfh_survey` is a dummy variable that takes the value of 1 for each prefecture where the difference in the WFH implementation status based on the internet survey from May 2020 to March 2020 exceeds the median value. `wfh_mobility` is a dummy variable that takes the value of 1 for each prefecture in which the mean of the mobility to work by 30 June 2020 exceeds the median.

Table 2: Descriptive statistics by year for `log_residential_land`

year	mean	sd	min	max	N
2018	10.546	0.674	9.503	12.779	47
2019	10.556	0.683	9.496	12.833	47
2020	10.560	0.686	9.488	12.843	47

Notes: sd is the standard deviation, min is the minimum value, and max is the maximum value.

3. As can be seen above, these tables show numerically the upward trend in the pre-treatment period for the treatment groups (`emergency`, `more_wfh_survey`, `more_wfh_mobility`) for all treatment variables. On the other hand, in the control group (`shorter_emergency`, `less_wfh_survey`, `less_wfh_mobility`), the treatment variable on emergency declarations shows an upward trend in the pre-treatment period, while the other treatment variables on WFH show a tend to be higher in 2017 than in 2018. However, if we look at the pre-treatment period, which is limited to the sample period 2018 onwards (2018-2019), we can confirm that the trend concerning the control group on the variables related to WFH is also on the upward trend, as in the treatment group. Therefore, the causal inference interpretation of the treatment variable using the DID method in these data can ensure a certain level of accuracy in the model for estimating the treatment effect on the declaration of a state of emergency. However, caution is needed in the model for estimating the treatment effect on the diffusion of WFH.

Tables 6, 7, and 8 present the results of the analysis using the DID method based on Equation 1. Table 6 shows the estimated results of the treatment effect based on the declaration of emergency, Table 7 shows the estimated results of the treatment effect of WFH diffusion based on the survey, and Table 8 shows the estimated results of the treatment effect of WFH diffusion based

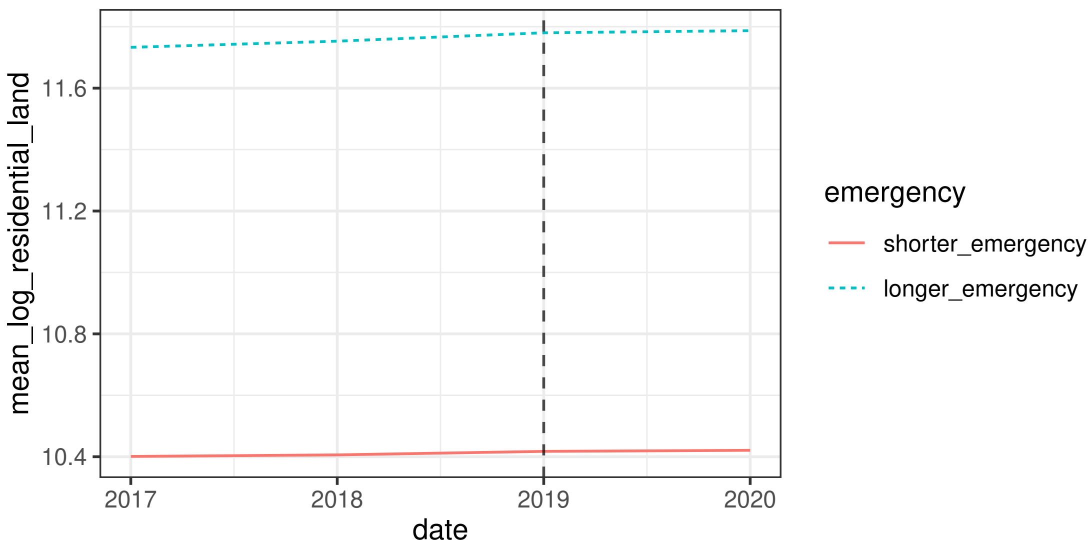

Figure 1: Trend lines in average log-transformed residential land prices by year based on the treatment variable for emergency declarations

Notes: For the treatment variable `emergency`, we show the mean values for the mean logarithmic residential land prices by treatment and control group and by year. The treatment group is denoted by the category name `longer_emergency` and has a sample size of 9. On the other hand, the control group is called `shorter_emergency`, and the sample size is 38. The solid line shows the trend of the annual mean values for the prefectures belonging to the control group, the dotted line shows the trend of the annual mean values for the prefectures belonging to the treatment group, and the dashed line shows the period of the treatment, 2019.

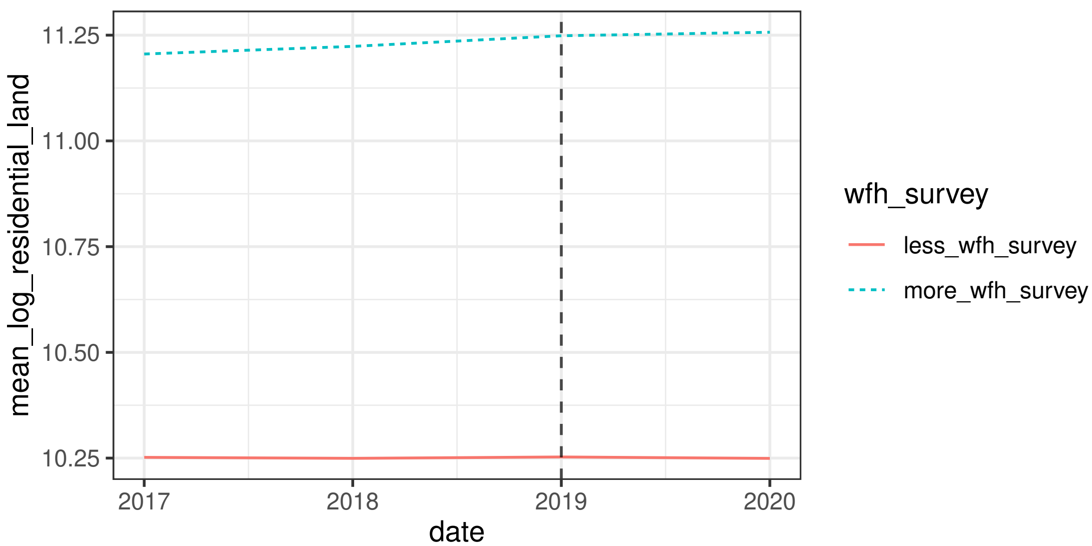

Figure 2: Trend lines in average log-transformed residential land prices by year based on treatment variables for WFH diffusion based on survey

Notes: For the treatment variable wfh_survey, we show the mean values for the log-transformed residential land price averages by treatment and control group and by year. The treatment group is denoted by the category name `more_wfh_survey` and has a sample size of 23. On the other hand, the control group is named `less_wfh_survey`, and the sample size is 24. The solid line shows the trend of the annual mean for the prefectures belonging to the control group, the dotted line shows the trend of the annual mean for the prefectures belonging to the treatment group, and the dashed line shows the time of the treatment, 2019.

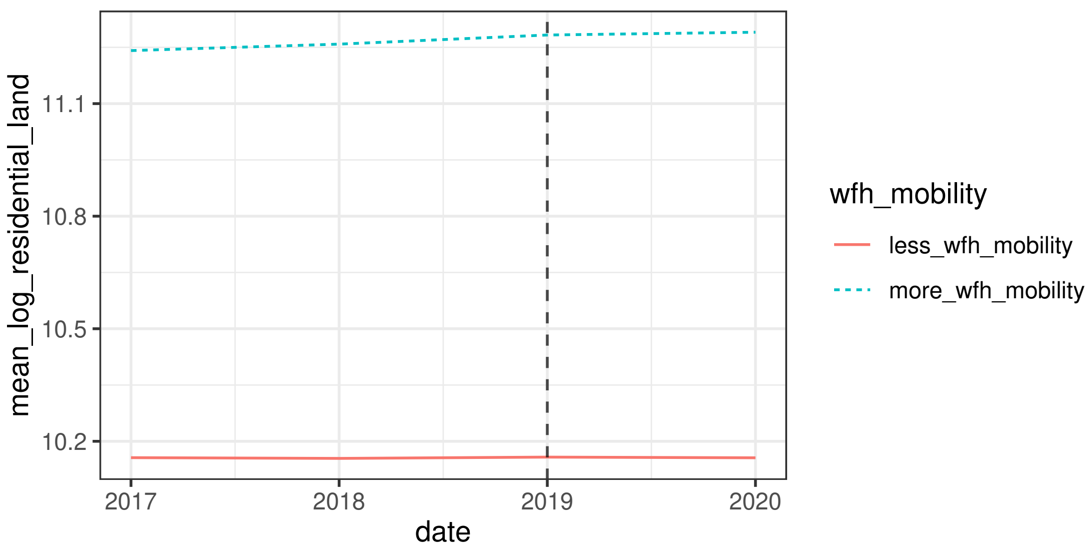

Figure 3: Trend lines in average log-transformed residential land prices by year based on treatment variables for WFH diffusion based on mobility

Notes: For the treatment variable `wfh_mobility`, we show the mean values for the log-transformed residential land price averages by treatment and control group and by year. The treatment group is denoted by the category name `more_wfh_mobility` and has a sample size of 23. On the other hand, the control group is named `less_wfh_mobility`, and the sample size is 24. The solid line shows the trend of the annual mean for the prefectures belonging to the control group, the dotted line shows the trend of the annual mean for the prefectures belonging to the treatment group, and the dashed line shows the time of the treatment, 2019.

Table 3: Trend in average log-transformed residential land prices by year based on the treatment variable for emergency declarations

year	emergency	mean_log_residential_land
2017	shorter_emergency	10.401
2018	shorter_emergency	10.406
2019	shorter_emergency	10.417
2020	shorter_emergency	10.421
2017	longer_emergency	11.733
2018	longer_emergency	11.753
2019	longer_emergency	11.780
2020	longer_emergency	11.787

Notes: For the treatment variable `emergency`, we show the mean values for the mean logarithmic residential land prices by treatment and control group and by year. The treatment group is denoted by the category name `longer_emergency` and has a sample size of 9. On the other hand, the control group is called `shorter_emergency` and the sample size is 38.

Table 4: Trend in average log-transformed residential land prices by year based on treatment variables for WFH diffusion based on mobility

year	wfh_survey	mean_log_residential_land
2017	less_wfh_survey	10.252
2018	less_wfh_survey	10.249
2019	less_wfh_survey	10.253
2020	less_wfh_survey	10.249
2017	more_wfh_survey	11.205
2018	more_wfh_survey	11.224
2019	more_wfh_survey	11.249
2020	more_wfh_survey	11.257

Notes: For the treatment variable `wfh_survey`, we show the mean values for the log-transformed residential land price averages by treatment and control group and by year. The treatment group is denoted by the category name `more_wfh_survey` and has a sample size of 23. On the other hand, the control group is named `less_wfh_survey` and the sample size is 24.

on mobility. For all estimated models, the standard errors presented in these tables are cluster robust. Furthermore, in the estimation of these models, we include a prefecture-specific fixed effect. Focusing on the coefficients of the interaction terms ($D_i \times A_t$) for each of the treatment variables (D_i) that are central to the DID interest, given by bottom rows in the Tables 6, 7, and 8, they are all positive, suggesting that they ensure a high degree of statistical significance ($p = 0.031$, $p = 0.007$, and $p = 0.012$). Thus, the study confirms that these interventions of intensive emergency declaration, survey-based WFH dissemination, and mobility-based WFH dissemination have a positive treatment effect with a certain statistical significance.

In order to check whether the results obtained by the Tables are robust or not, we perform sensitivity analyses focusing on the definition of the treatment variables. First, Tables 9 and 10

Table 5: Trend in average log-transformed residential land prices by year based on treatment variables for WFH diffusion based on survey

year	wfh_mobility	mean_log_residential_land
2017	less_wfh_mobility	10.156
2018	less_wfh_mobility	10.154
2019	less_wfh_mobility	10.158
2020	less_wfh_mobility	10.156
2017	more_wfh_mobility	11.241
2018	more_wfh_mobility	11.259
2019	more_wfh_mobility	11.283
2020	more_wfh_mobility	11.290

Notes: For the treatment variable wfh_mobility, we show the mean values for the log-transformed residential land price averages by treatment and control group and by year. The treatment group is denoted by the category name more_wfh_mobility and has a sample size of 23. On the other hand, the control group is named less_wfh_mobility and the sample size is 24.

Table 6: The estimation result of the treatment effect of emergency declarations on residential land prices using the DID method

variable	estimate	se	t-statistic	p-value	N
year_2019	0.010	0.003	3.210	0.002	
year_2020	0.010	0.005	1.849	0.068	141
year_2020:emergency	0.018	0.008	2.186	0.031	

Notes: emergency is a dummy variable that takes the value of 1 for those prefectures where the cumulative number of days of declared emergency until 30 June 2020 exceeds the median value among all prefectures; year_2020 is a dummy variable that takes the value of 1 for $t = 2020$; year_2020:emergency denotes the interaction term for emergency and year_2020; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

are the results of changing the cutoff value used to define the treatment variable from median to 0.75th quantile (wfh_survey) and 0.25th quantile (wfh_mobility), respectively. The reason why we did not conduct the same sensitivity analysis for emergency is that even if the cutoff value is changed from median to 0.75th, there is no change in the sample size of the treatment group (9 prefectures, shown in Table 3) and the contents of the constituent prefectures. As a result of this change in the cutoff value, the sample size of the treatment group in the results for Tables 9 and 10 has been reduced from 23 prefectures in the results for Tables 7 and 8 to 12 prefectures. Similarly, Tables 11, 12, and 13 indicate results with change the cutoff value used to define the treatment variable from median to 0.90th quantile (emergency), 0.90th quantile (wfh_survey) and 0.10th quantile (wfh_mobility). By changing the cutoff value, the sample size of the treatment group of emergency is reduced from 9 prefectures to 4 prefectures, and the sample size of the treatment groups for WFH prevalence is reduced from 23 prefectures to 5 prefectures. These results show that the sign of the

Table 7: The estimation result of the treatment effect of WFH diffusion on residential land prices based on a survey using the DID method

variable	estimate	se	t-statistic	p-value	N
`year_2019`	0.010	0.003	3.210	0.002	
`year_2020`	0.004	0.003	1.325	0.188	141
`year_2020:wfh_survey`	0.019	0.007	2.763	0.007	

Notes: The `wfh_survey` is a dummy variable that takes the value of 1 for each prefecture where the difference between the May 2020 and March 2020 WFH implementation status based on the internet survey exceeds the median value among all prefectures; `year_2020` is a dummy variable that takes the value of 1 for $t = 2020$; `year_2020:wfh_survey` denotes the interaction term for emergency and `year_2020`; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

Table 8: The estimation of the treatment effect of WFH diffusion on residential land prices based on mobility using the DID method

variable	estimate	se	t-statistic	p-value	N
`year_2019`	0.010	0.003	3.210	0.002	
`year_2020`	0.005	0.003	1.587	0.116	141
`year_2020:wfh_mobility`	0.018	0.007	2.558	0.012	

Notes: `wfh_mobility` is a dummy variable that takes the value of 1 for each prefecture in which the mean of the mobility to work by 30 June 2020 less than the median among all prefectures; `year_2020` is a dummy variable that takes the value of 1 for $t = 2020$; `year_2020:wfh_mobility` denotes the interaction term for emergency and `year_2020`; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

treatment effects given in the bottom rows is positive, as in the baseline results where the cutoff value is median. Thus, we can confirm that the interventions of focused emergency declaration, survey-based WFH diffusion and mobility-based WFH diffusion have positive treatment effects. However, we can confirm that their statistical significance is much weaker than that of Tables 6, 7, and 8. This result does not imply that the results are not robust to the change in cutoff value, given the possible deterioration in estimation accuracy due to the decrease in the sample size of the treatment group. In other words, it is necessary to take into account the possibility that the small sample size due to the use of macro data worsens the robustness of the results. It is suggested that the use of micro data in conjunction with a broader definition of treatment groups may resolve these issues.

The analyses in this section aim to identify the treatment effects of WFH diffusion on residential land prices. The analysis of descriptive statistics confirms the findings of various media reports that residential land prices have indeed increased after the COVID-19 pandemic. The analysis using DID shows that the spread of WFH may have a positive treatment effect on residential land prices. On the other hand, there are several limitations of this study, which are described below.

Table 9: The estimation result of the treatment effect of WFH diffusion on residential land prices based on a survey using the DID method: sensitivity analysis using a different cutoff value for treatment variable (0.75th quantile)

variable	estimate	se	t-statistic	p-value	N
`year_2019`	0.010	0.003	3.210	0.002	
`year_2020`	0.011	0.005	2.335	0.022	141
`year_2020:wfh_survey`	0.011	0.010	1.088	0.279	

Notes: The `wfh_survey` is a dummy variable that takes the value of 1 for each prefecture where the difference between the May 2020 and March 2020 WFH implementation status based on the internet survey exceeds the 0.75th quantile among all prefectures; `year_2020` is a dummy variable that takes the value of 1 for $t = 2020$; `year_2020:wfh_survey` denotes the interaction term for emergency and `year_2020`; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

Table 10: The estimation of the treatment effect of WFH diffusion on residential land prices based on mobility using the DID method: sensitivity analysis using a different cutoff value for treatment variable (0.25th quantile)

variable	estimate	se	t-statistic	p-value	N
`year_2019`	0.010	0.003	3.210	0.002	
`year_2020`	0.011	0.006	1.858	0.066	141
`year_2020:wfh_mobility`	0.010	0.007	1.433	0.155	

Notes: `wfh_mobility` is a dummy variable that takes the value of 1 for each prefecture in which the mean of the mobility to work by 30 June 2020 less than the 0.75th quantile among all prefectures; `year_2020` is a dummy variable that takes the value of 1 for $t = 2020$; `year_2020:wfh_mobility` denotes the interaction term for emergency and `year_2020`; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

Firstly, since the emergency declaration includes various contents[8] other than the request for WFH (request for 70% reduction in the number of commuting workers), it is difficult to interpret the positive impact of the emergency declaration on residential land prices as the impact of the spread of WFH on residential land prices. In other words, the first limitation of this study is the difficulty in distinguishing between the part related to WFH and the part related to other requests in the request for an emergency declaration, which is one of the treatment variables of interest. A second limitation of the study is that the two treatment variables for WFH penetration (`wfh_survey` and `wfh_mobility`) satisfy the parallel trend assumption only in the two most recent years before treatment, so the possibility of bias in the estimated treatment effects for these variables cannot be ruled out. The third limitation of this study is that, since the dependent variable is the average of standard sites' prices by a prefecture for residential land in all locations, including urban and suburban areas, it is not possible to identify whether the positive treatment effect of WFH diffu-

[8] e.g., request to refrain from going out, request to refrain from events and gatherings, request to shorten the opening hours of restaurants and large-scale retail shops, and so forth (Katafuchi, 2020).

Table 11: The estimation result of the treatment effect of emergency declarations on residential land prices using the DID method: sensitivity analysis using a different cutoff value for treatment variable (0.90th quantile)

variable	estimate	se	t-statistic	p-value	N
`year_2019`	0.010	0.003	3.210	0.002	
`year_2020`	0.013	0.005	2.336	0.022	141
`year_2020:emergency`	0.011	0.008	1.412	0.161	

Notes: `emergency` is a dummy variable that takes the value of 1 for those prefectures where the cumulative number of days of declared emergency until 30 June 2020 exceeds the 0.90th quantile among all prefectures; `year_2020` is a dummy variable that takes the value of 1 for $t = 2020$; `year_2020:emergency` denotes the interaction term for `emergency` and `year_2020`; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

Table 12: The estimation result of the treatment effect of WFH diffusion on residential land prices based on a survey using the DID method: sensitivity analysis using a different cutoff value for treatment variable (0.90th quantile)

variable	estimate	se	t-statistic	p-value	N
`year_2019`	0.010	0.003	3.210	0.002	
`year_2020`	0.012	0.005	2.294	0.024	141
`year_2020:wfh_survey`	0.009	0.007	1.274	0.206	

Notes: The `wfh_survey` is a dummy variable that takes the value of 1 for each prefecture where the difference between the May 2020 and March 2020 WFH implementation status based on the internet survey exceeds the 0.90th quantile among all prefectures; `year_2020` is a dummy variable that takes the value of 1 for $t = 2020$; `year_2020:wfh_survey` denotes the interaction term for emergency and `year_2020`; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

sion on residential land prices is for urban or suburban residential land[9]. The fourth limitation is that the results might not robust to changes in the definition of treatment groups in WFH. On the other hand, this paper is the first to show that the spread of WFH after COVID-19 may positively affect residential land prices. It is hoped that the limitations of the study described above can be addressed in future research by using more accurate microdata on land prices and more detailed microdata on the spread of WFH.

[9] Katafuchi and Delgado Narro (2020) discusses the heterogeneous hedonic prices regarding the degree of land price that the amenity of standard sites has, using data at standard sites (published land price) before they are aggregated as prefectural land price surveys and the method of penalized quantile regression. By using these methods, or by categorizing urban and suburban areas based on latitude and longitude information of standard land and administrative division information, it is possible to identify the treatment effect of the spread of WFH on residential land prices in urban and suburban areas.

Table 13: The estimation of the treatment effect of WFH diffusion on residential land prices based on mobility using the DID method: sensitivity analysis using a different cutoff value for treatment variable (0.10th quantile)

variable	estimate	se	t-statistic	p-value	N
year_2019	0.010	0.003	3.210	0.002	
year_2020	0.013	0.005	2.304	0.023	141
year_2020:wfh_mobility	0.008	0.007	1.167	0.246	

Notes: wfh_mobility is a dummy variable that takes the value of 1 for each prefecture in which the mean of the mobility to work by 30 June 2020 less than the 0.10th quantile among all prefectures; year_2020 is a dummy variable that takes the value of 1 for $t = 2020$; year_2020:wfh_mobility denotes the interaction term for emergency and year_2020; se denotes the cluster robust standard error. The covariates in the estimated model include the prefectural fixed effect.

5 Conclusion

This study aims to analyze how the behavioral changes associated with the novel coronavirus disease (COVID-19) have affected residential land prices. While in previous pandemics such as SARS, the contraction of the real economy has led to a decline in residential land prices, in the COVID-19 pandemic, land price increases based on behavioral change have been reported. In order to confirm this phenomenon, the study first constructed an annual panel dataset by prefecture, consisting of the average residential land price by the prefecture as the dependent variable and the following three variables as treatment variables: data on policy interventions affecting the decision to introduce WFH, data on WFH practices based on internet questionnaires, and WFH practices based on mobility data. The dataset was then used to estimate the treatment effect of DID on the spread of WFH on residential land prices. The results of the above empirical analysis reveal that the spread of WFH might have a positive treatment effect on residential land prices. This conclusion suggests that there may exist a phenomenon opposite to previous post-pandemic land price declines, namely an increase in residential land prices due to the spread of WFH after the COVID-19 pandemic.

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