論　説

How the change of information on liquefaction risk affects land prices?

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【Abstract】 In this study, we analyze the effect of information change on liquefaction hazard levels by using the update of liquefaction hazard map in Tokyo. For the estimation, we employ matching difference in differences (DD) design to identify the causal effect of the information change without specifying functional form strictly. Estimated effects are negative in many wards in Tokyo. This suggests that both liquefaction risk and information change can affect land price.

【Keywords】 risk, land price, difference in differences

目　次

1 Introduction

Information change of land attributes can affect land and building prices. In fact, some studies report significant impact. For example, Pope (2008) observed significant impact of disclosed information on property prices. Massive earthquake can cause liquefaction. In fact, liquefaction occurred in a wide area on March 3 2011. The damage caused by liquefaction is smaller than that of tsunami or nuclear accident. However, liquefaction increases the risk of landowning and residence, and this can depress the value of landed property severely. For example, liquefaction has a trait that it can be occurred even by earthquakes that are not huge enough to cause tsunamis. Soil improvement work which take tremendous amount of money is often required if it would occur. Since soil improvement work take tremendous amount of money, precise economic evaluation of the work is required. Even if expected earthquakes are the same, liquefaction risk is not the same. However, few researches on the economic impact of information change on liquefaction risk have conducted.

Since liquefaction is a land attribute, the price of the land is considered to be affected by liquefaction risks. However, earthquake insurances does not cover all damage caused by liquefaction. Hence, information on these risks can affect land prices, and land price hedonic method is considered appropriate to evaluate the effect of information change. For the hedonic evaluation of risks, a number of papers have shown the significant relationship between risks and land prices. For example, Holway and Burby (1990) find positive effect of reducing flood risk on land prices, Folland Hough (1991) observe negative effect of nuclear power plants. In Japan, Nakagawa et al (2009) found significant relationship between land prices and earthquake risk, Naoi et al (2010) find significant negative effects of earthquake occurance probability, Naoi et al (2009) find that households' estimate of earthquake occurance probability are changed by major earthquake events. In these analysis, since risks are highly related to land attributes such as altitude, ground parameter, and distance from the sea, hedonic price regression have been widely employed to evaluate the effect of risks on land prices. In most cases, negative effects have reported. Large part of these discussions can be also applied to the relationship between liquefaction-related risks and land prices. It is also reported that information change on risks can affect land prices (e.g. Nakanishi (2014))

However, to evaluate the effect of information change of liquefaction-related risks on land prices precisely, simple price regression may not appropriate in many cases. There are two major reasons for this. First, liquefaction is highly related to earthquake occurrence. Hence, we would confuse the effect of earthquake risk with liquefaction risk if we do not control earthquake variables correctly. This control is difficult if observation is not collected from narrow area because earthquakes that are expected to hit the area are different if observations are taken from wide area. Hence, observations from narrow area are required. Second, potential risk of the lot affects land use which also affects transaction prices. This endogeneity causes biased estimation of price function. In particular, in metropolitan areas where city structure is complicated and dense, it is not easy to control covariates that can be related to both land use and other variables that are correlated to risk variables. Moreover, omitted variables seriously affect the estimation accuracy of land price function by the complexity of the cities. These issues cause imprecise estimation of risk effect on land prices.

To identify the causal effect of information change, in this study, we employ direct difference in differences (DD) and matching method to identify the effect of liquefaction-related risks on land prices. Numbers of studies employ DD regression since estimation of land price function enables to estimate marginal willingness to pay as Rosen (1987) suggests. However, DD regression can also result in biased estimation because city structure is complicated in Tokyo, and it causes omitted variable biases as we discussed. Hence, we employ direct estimation of causal effects. For DD estimation, we set up the change of liquefaction risk as a treatment. There are two reasons for the employment of a DD design. First, the area where the risk information was changed was decided exogeneously. Second, the balanced panel data of official land price is provided by the Japanese government. In DD design, balanced panel data and the direct differencing operations help us to avoid imprecise estimation caused by complicated structure of Tokyo and by misspecification of land price function. However, since the data includes different cities in Tokyo, the difference of city law can cause the violation of the condition for identification, and the decision that Tokyo to be the host of the Olympic games in 2020, can also cause the violation. Therefore, we also employ matching with respect to wards. Comprehensive review of apprication of quasi experimental methods, that includes both DD and matching, on land price analysis is presented in Parmeter and Pope (2013)

The estimation result by matching DD reveals both positive and negative effects of new risk announcements. Specifically, negative effects to land prices are observed in wards where the area for both control and treatment group are sufficiently large. The observed result that new hazard map on liquefaction risk cause change in land prices implies, both information change on risks and liquefaction risk can affect households' and firms' decision.

The rest of the paper is structured as follows. Section 2 presents the background of our study, Section 3 presents the specification of the treatment effect and the estimation procedure, Section 4 describes the data, Section 5 presents the estimation results and a discussion of the treatment effect, and Section 6 summarizes the paper and presents the conclusions.

2 Background of the study

Japan is an earthquake-prone country because it lies at the nexus of four tectonic plates. Since these earthquakes can cause liquefaction, Tokyo published hazard map of liquefaction in Tokyo on the internet from 2006. Hazard map indicates the hazard levels (3 levels) of each points in Tokyo. These three levels of hazard are determined by calculating the coefficients that are shown to be related to the liquefaction of the ground. These coefficients are calculated using the data on the characteristics of ground such as distribution of groundwater, reclamation work records, landform classification that are estimated by boring log, geological map and topographic map. Liquefaction records are also used to evaluate hazard level.

The hazard map was updated in March 2013. This update is based on the development of the geological database, and change of the information caused by the change of liquefaction records related to East Japan Great Earthquake occured in March 11 2011. In the updated map, change of hazard levels are observed in some area of Tokyo. However, true risk did not change by the update of hazard map. Hence, by comparing land price change between the land in the area where hazard level increased and the land in the area where hazard level did not change, we can estimate the causal effect of information change. To identify the effect

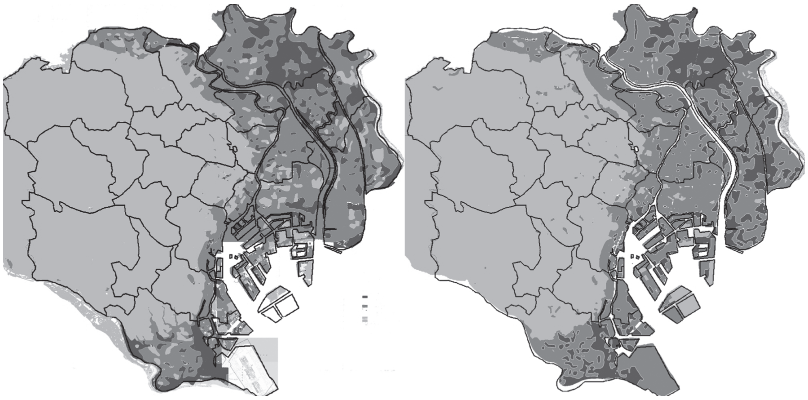

Figure 1: Hazard maps updated in 2006 and 2013. The left figure is the hazard map uploaded in 2006 on the internet. The right figure is the updated hazard map published in 2013 March on the internet. Thick gray indicates higher risk of liquefaction.

of liquefaction risk on land price, we set up the treatment as the change of information on hazard levels.

Tokyo has complex structure, and this cause misspecification of land price function. Hence direct DD estimation, which does not require parametric or semi-parametric specification on price functions, discussed in Section 3, would be appropriate. However, it is required to control regional effects by the nature of available data set. For direct estimation of DD, panel data is required. Hence we employ official land price data of Japan. The evaluation point of official land price is January 1 of 2013 and 2014. In September 7 th 2013, Tokyo was selected as the city for Olympic games of 2020. Bay areas have been planned to be the main venue of the event. That includes new stadiums and new Olympic village. This causes increasing demand for land in bay area and other Olympic related areas in Tokyo. Hence potential price change of land price may be different between Olympic related areas and other areas, and this can cause misunderstanding of causal effect of information change on liquefaction risks. To avoid this misunderstanding, we employ the statistical method that can control potential difference of wards and other geographical property of Tokyo in our analysis. That is, matching on attributes of lands which is discussed in Section 3.

Naoi et al. (2009) reports that information of massive earthquake can change land prices in Japan, hence if we omit variable that is related to earthquake risks, estimation results might be biased. However, Tokyo is small enough to have similar probability of massive earthquakes,and long term hazard of massive earthquake changed little from 2008 to 2013 as reported in "www.j-shis.bosai.go.jp/" by Japan Seismic Hazard Information Station (JSHIS). Hence, these earthquake risks are canceld out by differencing operation of direct DD estimator.

Table 1: Time series description of official land prices and update of the hazard map

March, 2006	Hazard map for liquefaction was uploaded on the Internet
11 March 2011	East Japan Great Earthquake hit Japan
1 January 2013	Evaluation point for the official 2013 land prices
28 March 2013	Hazard map for liquefaction was updated
7 September 2013	Tokyo is selected as the host of Olympic games
1 January 2014	Evaluation point for the official 2014 land prices

3 A matching difference in differences design

Difference in differences (DD) design has been widely employed in program evaluation literature. Hedonic price regression can result in biased estimates because of endogeneity of land use and liquefaction risk. And it is difficult to achieve unbiased estimation of price function because of complex structure of Tokyo. Hence, in this paper, we estimate the causal effect directly by employing direct DD and matching method which is also employed in Nakanishi (2014).

Let $P_{it}(r)$ be potential price of land i (=1,..,N) at time t $(= a, b; a = 2014, b = 2013)$ in region r $(= 0, 1)$, $X_{k,it}(k = 1, ..., K-1)$ be the dummy variable for wards of Tokyo, X_{it} be $(X_{1,it}, ..., X_{K-1,it})\prime$, Z_{it} be vector of other attributes of lands such as land use, r_i be the dummy variable that indicates treatment group where hazard level had changed from level 1 to level 2 or 3, τ_t be the dummy variable that is equal to 1 if time is equal to $a(= 2014)$. In this study, we removed the observations whose attributes of the land had varied in time period [2013, 2014] for simplicity of analysis. Hence, index t is removed from X_{it} and Z_{it}. The hazard map is updated in all area of western Tokyo. And, a lot does not move. Hence the changes of hazard levels are considered exogeneous. In this setting, observed response P_{it} is

$$P_{it} = (1 - r_i\tau_t)P_{it}(0) + r_i\tau_t P_{it}(1) \quad (1)$$

Since r_i is determined exogeneously, $E(P_a(1) - P_a(0)|r = 1)$ is the causal effect of information change evaluated at region 1 after the update of the hazard map. The term $E(P_a(1) - P_a(0)|r = 1)$ can be estimated from observable data if potential price changes are pararell on average between treatment and control group. Strictly speaking, if the observations are take from the distribution that satisfies equation (2), we can derive equation (3) as discussed in Lee (2005).

$$E(P_a(0) - P_b(0)|r = 1) = E(P_a(0) - P_b(0)|r = 0) \quad (2)$$

$$E(P_a - P_b|r = 1) - E(P_a - P_b|r = 0) = E(P_a(1) - P_a(0)|r = 1) \quad (3)$$

$E(P_a - P_b|r = 1)$ and $E(P_a - P_b|r = 0)$ are estimated from observable data. Hence causal effect is identified by DD estimation. Since equation (3) is valid under equation (2), plausibility that DD estimation can be regarded as causal effect depends on plausibility of condition 1. However, as suggested in Section 2, in September 7 th 2013, Tokyo was selected as the city for Olympic games of 2020 which can make market of Bay area different form that of inland area. That is between evaluation point of official land prices of 2013 and 2014. This can make potential change of land price in bay area different from that of inland area. And, large number of the lands whose attributes of liquefaction risk changed worse are distributed in bay area while the lands whose attributes of liquefaction risk did not change are not. Hence, equation (2) is not considered to be satisfied. Moreover, Tokyo includes different administrative districts that have difference in the law, the administration, and market condition. This result in biased estimate of the treatment effect. To avoid such implausibility we impose the same time effect assumption conditional on administrative districts, and land use.

$$E(P_a(0) - P_b(0)|r = 1, x, z) = E(P_a(0) - P_b(0)|r = 0, x, z) \quad (4)$$

This condition requires that if lots in both treatment and control group are in the same administrative districts and in the same land use regulation, potential change of land prices in time period $[2013, 2014]$ are parallel on average. The analysis under equation (4) is more controlled than the analysis under equation (2).

Under equation (4), we can derive following equation.

$$\begin{aligned} &E(P_a - P_b|r = 1, x) - E(P_a - P_b|r = 0, x, z) \\ &= E(P_a(1) - P_a(0)|r = 1, x, z) \quad (5) \end{aligned}$$

Since number of our conditioning variable is large, estimation result of (5) is not easy to interpret. The idea of semiparametric matching DD estimation proposed by Abadie (2005) is effective. That is parametric approximation of the local average treatment effect. Average treatment effect and local average treatment effect on treated can be derived from simple integrate out procedure using equation (5). Under equation (4), we can estimate $E(P_c(1) - P_c(0)|r = 1)$ because following relationship is satisfied from similar discussion of Heckman et al (1997; 1998).

$$\begin{aligned} &E(P_a(1) - P_a(0)|r = 1, x) \\ &= E[P_a - P_b - E(P_a - P_b|r = 0, x, z)|r = 1, x] \end{aligned} \quad (6)$$

For estimation, sample analogue of last expression can be calcurated with slight modification of the procedure employed in Nakanishi (2014). First step is the partially linear estimation of $E(P_{ja} - P_{jb}|r = 0, x, z)$ with the observation from control group for the value x where subscript j denotes the observation from control group. Second step is the estimation of the local average of $P_{ia} - P_{ib} - \hat{E}(P_a - P_b|r = 0, X_i, Z_i)$ where subscript i denotes the observation from treatment group. In the second step, we employ linear regression for the estimation. By this set up, we can estimate causal effect of information change without fully specifying functional form of land price function.

4 Data description

4.1 Official land price and hazard level of liquefaction

For the DD design risk evaluation, we employ official Japanese land price data to conduct direct DD estimation. The official land prices in Japan are reported annually in March according to law. This price is calculated as the unit price of the land as of January 1 in a competitive market. These prices are calcurated with the data on actual rent and transaction price of neighboring lands. Thus, these data are composed of balanced panel data of selected lots with no movement either in or out of the regions. This allows us to estimate the treatment effect directly. The evaluation is conducted by at least two real estate appraisers and is based on the actual trades of neighboring land. These official land price data is employed by Nakagawa et al. (2009) and Tsutsumi and Seya (2009), and Nakanishi (2014). Official land price data include land prices for each year, land use, address, presence or absence of electric, gas, water facilities, and the regulations of the City Planning Act such as floor area ratio. This is available at the web site of the National Land Numerical Information Download Service http://nlftp.mlit.go.jp/ksj/. As of 2013, the data of 2162 lots are available for Tokyo. Authors (e.g., Ma and Swinton 2012) question the accuracy of the assessed land value; however, the assessed price eliminates the potential problems that could bias the market as a result of special transaction, and biased sample caused by small number of transaction in dangerous area (Official land price loses efficiency by small number of transaction, but estimated treatment effect is not biased by this. Estimation result by other possible panel data such as repeated sales can be biased by small number of transaction). Moreover, we employ a differencing operation in this study. Therefore, these noises are differenced out in the estimation of treatment effect, whereas biases may arise in the ordinal hedonic regression.

To estimate the effect of the change of liquefaction risk information on land prices, we utilize the hazard map data of both before and after the update of the map, which is presented in Figure 1. There are 3 levels of liquefaction risks. Level 1, indicated by thin gray, indicates low risk area, level 2, indicated by gray, indicates middle risk area, and level 3, indicated by thick gray, indicates high risk area. In this study, we use the lots that were in level 1 area before the change of hazard map, and set up control group as the lands whose hazard level have not changed, and treatment group as the lands whose hazard level changed from level 1 to 2 or 3. Original hazard map is available on the internet at http://doboku.metro.tokyo.jp/start/03-jyouhou/ekijyouka/. Since Official land price data includes exact address of lands, hazard level of each lands can be recovered from the information of longitude and latitude.

4.2 Data used in the research

To estimate the effect of liquefaction risk, we conduct analysis with lands whose liquefaction

Figure 2: Wards that include both treatment and control group. Dummy variables for wards measure relative effect of the update compared with Toshima ward.

risk was level 1 before the update of the hazard map. We set up the treatment group as lands whose hazard level got worse by the update of hazard map. Hence, our treatment group is the land whose hazard level was one in original map and two or three in new map. Our control group is the land whose hazard level was 1 in original map, and 1 in the updated map. In this setup, lands in control and treatment group are distributed in 12 wards of Tokyo which is presented in Figure 2. Hense, we setup these 12 wards as analyzed area of our research. In these 12 wards, Toshima ward is defined to be control point for evaluating treatment effect. Definition of variables and summary statistics are presented in Table 2 and 3. Lands that does not belong to fire protection area is not distributed in treatment group. However, as price regression reveals, this attribute does not affect land price significantly in Tokyo. Hence, this is not considered to violate the condition for identification of the treatment effect. Site Amp (Site Amplification) represents foundation strength which is reported by Fujimoto and Midorikawa (2006). This variable is related to earthquake risk. Earthquake risk is high in the area where the value of Site Amp is high. However, this variable had not changed from 2013 to 2014. This ensures that earthquake risk is considered to remain same in this period. Hence DD result is considered to be the effect of information change on liquefaction risk. In table 3, it is observed that there are no observations in low building area in treatment group. For attributes that are expected to affect potential change of land price, overlap of attribute is required for identification. However, for low building land use, these phenomenon is not expected because there are no major events that can affect both low building land use and land prices.

The original official land price data includes is 2162 lots for Tokyo. We removed lots that do not belong to Tokyo 23 wards, and its attributes have changed between 2012 and 2013. For treatment group, observations of 81 lots are available. For control group, observations of 704 lots are available. Since we can use the observation of both 2013 and 2014, our sample size is 1562.

5 Results

In the following analysis, we estimate treatment effect of the announcement. For the comparison, we also estimate familiar linear DD model. Corresponding dependent variables of following baseline regressions are the logarithms of unit land prices.

As we discussed in section 3, equation (2) might be strong. In fact Table 3 shows that the distribution of covariates are not same while control and treatment group are similar as discussed in Section 2. This implies that it is required to control these variables to avoid confusing causal effect with price change caused by longer term process. Hence, we report the estimation result under assumption 2. Estimated treatment effects are presented in Table 4, result of baseline linear estimation is presented in Table 5, and geographical distribution of treatment effect estimaed by matching DD is presented in Figure 3.

With matching DD design, the effects of the change of the hazard level is allowed to be different with respect to land use and ward in which lands belong to. On land use, negative effects are observed in commercial and residential land use area, while positive effects are observed in commercial land use area. In Tokyo, commercial land use areas are distributed around main streets, and residential and industrial land use areas are distributed widely compared with that of commercial area. One of the possible reasons of these positive and negative observations is that while households that borrow rooms can react quickly to the information change, owners of stores and offices could not move for their business. Intercept of estimated local average treatment effect is negative. Since we setup Toshima ward as basing point, negative effect is observed in Toshima ward. Effects for other wards can be calcurated by adding the value of intercept to each estimated coefficients. These effects are presented in Figure 3. In most wards negative effects are observed. This is consistent with results reported in other studies on risks. For example, in Japan, Nakagawa et al (2007, 2009) report negative effect of earthquake risk. However, in Shinagawa, and Chuo ward, large positive effects are observed. A possible reason is that, in these areas, since lands in treatment group are distributed near main stations and studium for Olympic games, these effects are estimated as regional effect. It is possible to control these effect with large number of control variables, but sample size of our official land price data is not enough to conduct this control in exchange for detailed observation.

Table 2: Definition of variables

Variables	Definition	Variables	Definition
Station	Commom logarithm of the distance from the nearest station	Wd.Edogawa	Dummy variable for Edogawa ward
Area	Commom logarithm of land area	Wd.Shinagawa	Dummy variable for Shinagawa ward
LU.ind	Dummy variable for industrial land use	Wd.Chuo	Dummy variable for Chuo ward
LU.com	Dummy variable for commercial land use	Wd.Katsushika	Dummy variable for Katsushika ward
LU.res	Dummy variable for residential land use	Wd.Bunkyo	Dummy variable for Bunkyo ward
Odd shape	Dummy variable for irregularly shaped land	Wd.Taito	Dummy variable for Taito ward
LU low	Dummy variable for low building area	Wd.Shinjuku	Dummy variable for Shinjuku ward
LU mid high	Dummy variable for midium or high building area	Wd.Sumida	Dummy variable for Sumida ward
Road width	Width of frontal road	Wd.Arakawa	Dummy variable for Arakawa ward
Fire pro	Dummy variable for fire protection area	Wd.Chiyoda	Dummy variable for Chiyoda ward
Site amp	Site amplification of the ground where the lot belongs to.	Wd.Kita	Dummy variable for Kita ward
Wd.Minato	Dummy variable for Minati ward	Wd.Itabashi	Dummy variable for Itabashi ward
Wd.Oota	Dummy variable for Oota ward	lopP14	Common logarithm of unit land price in 2014
Wd.Kouto	Dummy variable for Kouto ward	lopP13	Common logarithm of unit land price in 2013

Table 3: Summary statistics for land use and other land attributes

	Treatment					Control				
	min	median	mean	max	sd	min	median	mean	max	sd
lopP14	5.397	5.988	6.112	7.457	0.549	5.354	5.786	5.884	7.332	0.341
lopP13	5.394	5.98	6.1	7.431	0.542	5.348	5.779	5.874	7.294	0.336
logP14-logP13	0.001	0.009	0.012	0.038	0.008	0	0.008	0.01	0.041	0.006
Station	0	2.478	2.107	3.255	1.006	0	2.634	2.465	3.462	0.686
Area	1.672	2.29	2.466	4.707	0.566	1.748	2.241	2.311	4.159	0.324
LU.ind	0	0	0.111	1	0.316	0	0	0.015	1	0.124
LU.com	0	1	0.765	1	0.426	0	0	0.448	1	0.497
LU.res	0	0	0.086	1	0.282	0	0	0.112	1	0.315
LU. low	0	0	0	0.265	1	0	0	0	0	0
LU. mid high	0	0	0.037	1	0.190	0	0	0.157	1	0.364
Odd shape	0	0	0.074	1	0.263	0	0	0.036	1	0.188
Road width	0	2.045	2.063	2.699	0.520	0	1.785	1.893	2.699	0.372
Fire pro	1	1	1	1	0	0	1	0.992	1	0.084
Site amp	1.425	1.561	1.776	2.425	0.354	1.238	1.484	1.538	2.425	0.153
Number of observatiions	162					1408				

Table 3(continued): Summary statistics for dummy variables for wards of Tokyo

	Treatment					Control				
	min	median	mean	max	sd	min	median	mean	max	sd
Wd.Minato	0	0	0.061	1	0.242	0	0	0.048	1	0.214
Wd.Oota	0	0	0.049	1	0.218	0	0	0.028	1	0.166
Wd.Shinagawa	0	0	0.012	1	0.111	0	0	0.048	1	0.214
Wd.Chuo	0	0	0.172	1	0.38	0	0	0.005	1	0.075
Wd.Bunkyo	0	0	0.012	1	0.111	0	0	0.061	1	0.239
Wd.Taito	0	0	0.123	1	0.331	0	0	0.018	1	0.134
Wd.Shinjuku	0	0	0.012	1	0.111	0	0	0.088	1	0.283
Wd.Arakawa	0	0	0.037	1	0.19	0	0	0.002	1	0.053
Wd.Chiyoda	0	0	0.16	1	0.369	0	0	0.029	1	0.17
Wd.Kita	0	0	0.148	1	0.357	0	0	0.024	1	0.153
Wd.Itabashi	0	0	0.037	1	0.19	0	0	0.061	1	0.239

Table 4: Estimated treatment effects

	Matching	DD			Linear	DD		
	Coef	std.dev	t value	p value	Coef	std.dev	t value	p value
LU.ind	-7.567E-04	2.218E-03	-0.341	0.366	-0.041	0.180	-0.228	0.819
LU.com	7.643E-04	2.004E-03	0.381	0.648	-0.125	0.165	-0.759	0.447
LUres	-1.779E-03	2.383E-03	-0.746	0.227	-0.037	0.169	-0.219	0.826
Wd.Minato	-7.300E-03	3.337E-03	-2.187	0.014	0.160	0.132	1.209	0.226
Wd.Oota	1.267E-03	3.006E-03	0.421	0.663	0.130	0.137	0.953	0.340
Wd.Shinagawa	1.135E-02	5.779E-03	1.963	0.975	-0.761	0.220	-3.445	0.000
Wd.Chuo	1.408E-02	2.657E-03	5.3	0.999	0.022	0.117	0.190	0.848
Wd.Bunkyo	-5.312E-04	1.397E-03	-0.38	0.351	0.021	0.250	0.087	0.930
Wd.Taito	-1.490E-04	1.536E-03	-0.096	0.461	0.044	0.120	0.370	0.711
Wd.Shinjuku	-2.071E-04	8.781E-04	-0.235	0.406	0.051	0.211	0.244	0.807
Wd.Arakawa	2.638E-03	2.805E-03	0.94	0.826	0.066	0.159	0.418	0.675
Wd.Chiyoda	5.332E-04	2.579E-03	0.206	0.581	0.122	0.115	1.065	0.286
Wd.Kita	4.544E-04	1.216E-03	0.373	0.645	0.126	0.109	1.154	0.248
Wd.Itabashi	-2.160E-03	1.585E-03	-1.362	0.086	-0.101	0.149	-0.679	0.497
Intercept	-1.846E-03	1.727E-03	-1.069	0.142	0.053	0.165	0.323	0.746

Table 5: Estimated coefficients of linear DD

	Linear	DD		
	Coef	std.dev	t value	p value
Intercept	5.284	0.100	52.42	0
Station	-0.106	0.008	-13.18	1.2E-37
Odd shape	-0.008	0.024	-0.353	0.724
Area	0.272	0.015	17.61	2.5E-63
Road width	0.050	0.014	3.426	0.001
Fire pro	-0.017	0.060	-0.287	0.773
LU. low	0.124	0.037	3.276	0.001
LU. mid high	0.094	0.038	2.489	0.012
LU. res	0.087	0.038	2.256	0.024
LU. com	0.283	0.037	7.505	1.03E-13
Site amp	-0.090	0.029	-3.061	0.002
τ	0.010	0.009	1.021	0.307
r	-0.044	0.027	-1.629	0.103
Adj R^2	0.6694			

In summary, negative effects are observed in the area where enough number of lands are observed in both treatment and control group. This is consistent to the article that studies the effect of risks and information changes with land price data. While there are many studies that report negative effect of earthquake risk, there are, in our knowledge, no studies that reveal the effect of information change on liquefaction risk. Especially, statistically significant negative effect is observed in Minato ward where is near the stadiums of Olympic games. However, these negative effects are not statistically significant in many wards.

With linear DD design, estimated effect of hazard map change was different from that of matching DD design. Especially, estimated treatment effects are positive except for Shinagawa ward. This can be caused by the misspecification of price function. While the effects of observed attributes can be differenced out by linear DD specification, the effects of unobserved variable that is canceled out in direct estimation is not canceled out. Especially, Tokyo has dense and complex structure, these unobserved attributes can affect estimation results severely. While, estimated treatment effect is different from that of direct estimation, other parts of the price function are consistent with the results reported in many studies. For example, negative sign for the distance from the nearest station, odd shaped land, positive sign for land area, road width are observed. Especially, significant negative effect of Site Amp is observed. This is consistent with the results that report negative effects of earthquake risks on land prices.

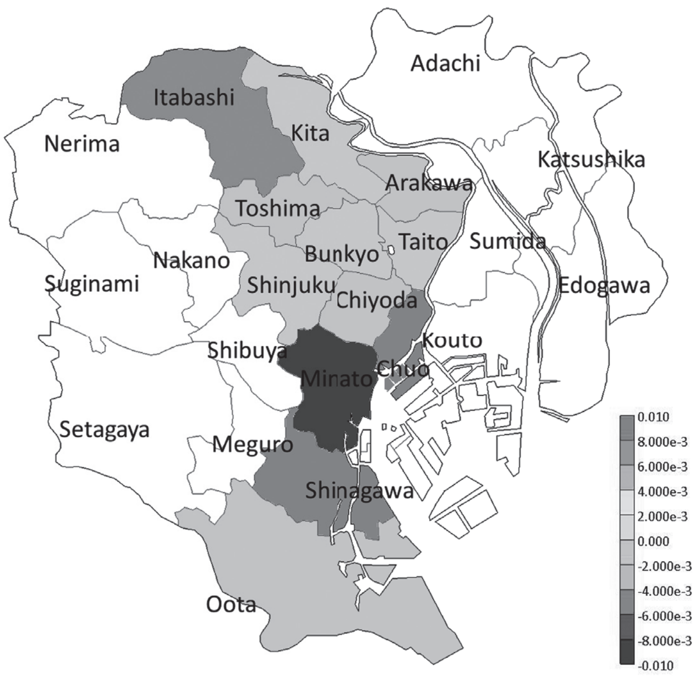

Figure 3: Estimated treatment effect of the information change on liquefaction risk.

6 Discussion and Conclusion

The purpose of this paper is to examine the effect of the change of liquefaction hazard level caused by the update of liquefaction hazard map of Tokyo 23 ward in March 2013. We used Japanese official land price panel data of 2013 and 2014, and the hazard maps of both before and after the update. In order to identify the treatment effect, we combined matching method and direct difference in differences design which is also used in Nakanishi (2014). Although popular linear DD regression and direct DD estimation can also estimate the causal effect of information change on liquefaction hazards, we employed matching procedure. This is because researched area, Tokyo, is determined to be the host of Olympic games that can cause to violate identification condition if these attributes are not controlled for. Under these set up, we found negative effect of information change in most of wards of Tokyo where both treatment and control groups are distributed.

However, some other factors exist which need to be considered.In this paper, we used the official land price data. While this enables us to estimate the causal effect directly, number of observations are restricted. And, since area for treatment group where hazard level got worse by the update of the hazard map is not wide, number of observations are not enough in some wards. In these areas positive effects are observed that are considered to be caused by omitted variables. These omitted variables are, in general, controlled if enough observations are confirmed, but number of observation of official land price is limited at the cost of detailed information on observed lands. Hence, the estimation of the causal effect with actural trade price data would be effective to support the result of this study. It is possible to increase the length of observation period. However, longer interval means higher risk of the violation of the same time effect condition which is the key to DD identification. Hence, in this study, we used the data of 2013 and 2014.

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