Flood impacts on residential property prices in frequently flooded areas: Evidences from Kanda river basin, Tokyo

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Abstract

Governments publicize flood risk information in an effort to mitigate future damage and the loss of life and property of residents; however, residents' awareness of flood risk is unclear. Several studies have analyzed real estate property prices to quantify residents' flood risk awareness by assuming that price discounts represent the level of awareness, and confirmed a sudden decline in real estate property prices after floods. If floods rarely occur, their occurrence might heighten awareness of risk; however, the reaction would be different where flooding is frequent. This study examines the risk awareness in flood-prone areas by analyzing the relationship between flood events and transaction price changes. We found that flood events induced no price change in frequently flooded areas, and properties in hazard areas are devaluated. These finding indicates that risk awareness of residents in frequently flooded areas are appropriate and stable based on their experiences.

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1. Introduction

Frequency of heavy rainfalls and damage caused by flood events is increasing with global warming. To mitigate future damage and protect residents' lives and assets, governments are proactively sharing flood risk information, such as hazard maps and flood histories, in addition to construction of facilities like dams and levees to prevent flood. Governments are publishing flood risk information in hope to support residents' decision making; short-term decisions on evacuation timings, places, and routes, and long-term decisions on housing locations. However, shared flood risk information seems minimum impact on people – residents often neglect to evacuate even when floods are about to occur, and many are living near shorelines and rivers where flood risk is high. Thus, awareness level of residents on flood risk information is unclear.

Several studies analyzed real estate property values to quantify flood risk awareness of homebuyers and local residents. These studies assumed that flood risk affects real estate property values only if homebuyers and local residents perceive that such risks are related to property, and analyzed degree of devaluation. Many studies focused on the timing of flood occurrences, analyzed property value devaluation in flooded areas after a flood, and confirmed a sudden drop relates to the timing immediately after the flood (e.g., Bin and Landry, 2013; Atreya and Ferreira, 2015; Nyce, 2015; Votsis and Perrels, 2016). Moreover, Atreya et al. (2013) pointed out that the gradual resurfacing of real estate property prices occurs after floods.

If floods rarely occur, it is natural to consider that residents seldom regard flood risk. Previous studies analyzed real estate property values in areas in which flood occurrences are not frequent. However, is it the same in areas of frequent flooding? This study examines the flood risk awareness of residents in flood-prone areas by analyzing the relationship between flood events and changes in transaction prices of real estate properties.

2. Previous studies on the relation between flood risk and real estate property prices

2.1 Hedonic approach

It is impossible to observe directly the values of environmental amenities such as flood risk, because they are non-marketed goods and do not have market values. Then, the hedonic pricing method, which measures the economic values of non-market goods on the basis of the capitalization hypothesis, is often used to quantify their values (Rosen, 1974). The capitalization hypothesis in the real estate market assumes that the benefit of environmental improvements is reflected in real estate property values if residents are homogeneous in an open economy (e.g., Hidano, 2002).

The hedonic pricing method assumes that total values are settled by the composition of multiple attributes. The value of good i, V_i, can be represented as a linear combination of attributes $z_{i1}, \ldots, z_{ik}$,

$$V_i = \beta_0 + \beta_1 z_{i1} + \cdots + \beta_k z_{ik} + \varepsilon_i \tag{2.1}$$

where β_j is the parameter for attribute j and ε_i is a disturbance term.

Real estate property values reflect evaluations by real estate market participants and local residents of property attributes, such as size, zoning, and accessibility, among others. Flood risk is an attribute that might affect real estate property values if market participants include it in their evaluations. To date, previous studies analyzed the relationship between flood risks and real estate property values using hedonic pricing models. Flood history, estimated flood depth, distance to rivers and coastlines, and elevation have been used as indices to represent the flood risk of properties.

2.2 Previous studies on relationship between flood risk indices and real estate property values

This section introduces several types of previous studies that have analyzed relationships between flood risk indices and real estate property values.

Harrison et al. (2001) analyzed price differentials inside and outside 100-year floodplains utilizing residential sales data over 18 years. They concluded that prices of properties located in floodplains were devaluated although less than the present values of future flood insurance premiums. They also focused on the enforcement of the National Flood Insurance Reform Act of 1994 and analyzed price differentials before and after the act was enforced, but did not focus on the impact caused by the occurrence of floods.

Similarly, Bin and Kruse (2006) and Bin et al. (2008) analyzed residential sales data over a five-year period for 100-year and 500-year floodplains, and concluded that sales prices capitalized on flood risk. Their study area was exposed to several hurricanes; however, the impact was minor during the sales data target period. These studies also did not intend to extract price changes caused by floods; rather, they engaged in static analyses for which timing was not a significant factor.

Bin and Polasky (2004) analyzed real estate sales prices over 11 years when floods occurred during the period, and found that the sales price discount for properties in a floodplain was significantly larger after hurricanes. This study was one of the initial studies that focused on the change in real estate property values attributable to flood events.

Other types of studies that analyzed the relationship between flood risk and real estate property values have later appeared. They assumed that "residents' awareness of flood risk affects real estate property values." Because a flood is a rare event, its risk is difficult to perceive in daily life; therefore, it is highly probable that flood risk—different from other environmental amenities, such as accessibility and proximity to natural environments—does not affect real estate property values. These studies considered that objective and scientific flood risk indexes do not necessarily affect real estate property values. Nyce et al. (2015) analyzed home sales over six years and found that experience with hurricanes caused prices to decline. Bin and Landry (2013) analyzed residential home sales data over 17 years; during this period, two major hurricanes occurred. They detected that no market risk premium existed for houses in flood zones before the first hurricane but also that prices declined after both hurricanes. They also found that price discounts did not last long and disappeared in five or six years. Atreya et al. (2013) also found similar patterns: the discount disappeared between four and nine years.

These previous studies utilized 100-year and 500-year floodplain data assessed by the Federal Emergency Management Agency (FEMA) and analyzed flood risk information and price discounts of real estate properties. Atreya and Ferreira (2015) used the flood inundation map for their analysis and found that property discounts are substantially larger in inundated areas. They concluded that this result "supports the hypothesis that homeowners respond better to what they have visualized."

Previous studies indicated that the occurrence of a flood event causes a price discount in real estate properties in inundated areas because residents who experienced flood hazards have an enhanced awareness of flood risk. This statement may suffice for areas in which flooding is infrequent. However, is this statement true in flood-prone areas? Inoue et al. (2016) analyzed appraised and transaction prices of real estate properties in residential areas of Tokyo that experienced frequent flooding. They found that no significant changes in prices occurred but that the appraised price data used in the study were not sensitive to market trends. This study focuses on transaction price data and examines whether changes in real estate prices result from flood occurrences.

3. Estimation of changes in parameters and their timings

This study utilizes the difference in differences (DID) approach to depict differences in prices between transactions in flood hazard areas and in nonhazardous areas, and before and after some unknown time points, and a turning point detection method to estimate that time points. The following sections introduces the DID and the turning time point detection method.

3.1 Difference in differences (DID)

DID is a common approach to represent the price change caused by floods, and is used in many previous studies (e.g., Atreya et al., 2013; Bin and Landry, 2013; Nyce et al., 2015; Atreya and Ferreira, 2015). DID simulates an experimental research design by splitting observations into a treatment group and a control group and estimating the differences in reactions to a treatment. Let i denote an observation, $x_{i\ Group(treat)}$ denote a dummy variable that takes the value of one if observation i is in the treatment group and zero if not, and $x_{i\ after}$ denote a dummy variable that takes the value of one if observation i is after the treatment and zero if not. Equation (3.1) represents the model used in the analysis:

$$\begin{aligned} y_i &= \beta_0 + x_{i\ Group(treat)}\beta_{Group(treat)} + x_{i\ after}\beta_{after} \\ &+ x_{i\ Group(treat)}x_{i\ after}\beta_{Group(treat)\_after} + \varepsilon_i . \end{aligned} \tag{3.1}$$

The parameter $\beta_{Group(treat)\_after}$ represents the difference in reactions to a treatment between the treatment and the control group.

3.2 Turning time point detection

Because there are several timings when floods occurred and might have affected real estate property values in frequently flooded areas, we cannot set the treatment timings in advance. Thus, we must estimate the timings when parameter changes occur. We introduce a general form of a linear regression model with a time point at which parameters of the linear regression changes.

Let i denote an observation, θ denote a discrete time point between one and T when a change in parameters occur, and y_i, $\mathbf{x_i}$, ε_i, and t_i denote a dependent variable, a vector of explanatory variables, a disturbance, and time of observation i, respectively. Let $I(\theta < t_i)$ denote an indicator function that outputs one when $\theta < t_i$ and zero when $\theta \geq t_i$, and $\boldsymbol{\beta}_{\mathbf{before}}$ and $\boldsymbol{\beta}_{\mathbf{change}}$ denote parameter vectors before θ and change amounts of parameter vectors at θ, respectively. Then, equation (3.2) is a model for a turning timing estimation:

$$y_i = \mathbf{x}_\mathbf{i}'\boldsymbol{\beta}_{\mathbf{before}} + I(\theta < t_i)\mathbf{x}_\mathbf{i}'\boldsymbol{\beta}_{\mathbf{change}} + \varepsilon_i . \tag{3.2}$$

The vector of the sum of $\boldsymbol{\beta}_{\mathbf{before}}$ and $\boldsymbol{\beta}_{\mathbf{change}}$ is a parameter vector after θ.

An estimation method for a time point with parameter changes is the Chow test (Chow, 1960). This test repeats OLS estimations by changing a discrete time point θ, finds a value when model fitness is at a maximum, and outputs the estimated parameters of $\boldsymbol{\beta}_{\mathbf{before}}$ and $\boldsymbol{\beta}_{\mathbf{change}}$. Because the estimated parameters follow a conditional distribution under the setting of θ, they are biased. In addition, the distribution of θ is unknown.

Spirling (2007) proposed an estimation turning timing method of the equation (3.1) model using the Markov Chain Monte Carlo method (MCMC). This method simultaneously estimates parameters and a time point of parameter changes; the estimated parameters are unbiased and the distribution of an estimated turning timing can also be estimated.

In this study, we analyze real estate property value data using a composite DID model and a turning point detection method.

4. Case study

4.1 Target area and period

This study focuses on the Kanda River, which runs through urban areas of Tokyo. The target area is residential districts in an upper part of the Kanda River basin that consists of basins of Kanda River branches—the Ekoda, Myosyoji, Zempukuji, and Kanda Rivers—and includes parts of Shinjuku, Shibuya, Nakano, Nerima, and Suginami wards, and Musashino and Mitaka cities (Figure 1). We select residential and light-industrial zones using the City Planning Act of Japan because common land use in these zones is residential.

The target period is from 2000 to 2015. During this period, several events occurred that might have affected awareness of flood risk in the target area.

The Kanda River was once a river that overflowed almost every year. Nine floods with an inundation area exceeding one hectare occurred during the target period, and the worst flood occurred on September 4, 2005 (Table 1). Flood control facilities were constructed from the late 1980s, and flood damage were reduced after the Kanda River underground diversion channel started operating in 2005. Thus, the change in flood control safety might have affected awareness of flood risk.

In addition to historic recurrent flooding, two other events occurred that might have affected residents' awareness of flood risk. One is the publication of hazard maps in August 2001, and the second is the occurrence of the Great East Japan Earthquake (GEJE) in March 2011. This earthquake may have reinforced residents' awareness of disaster risk, although no critical damage was found in the target area.

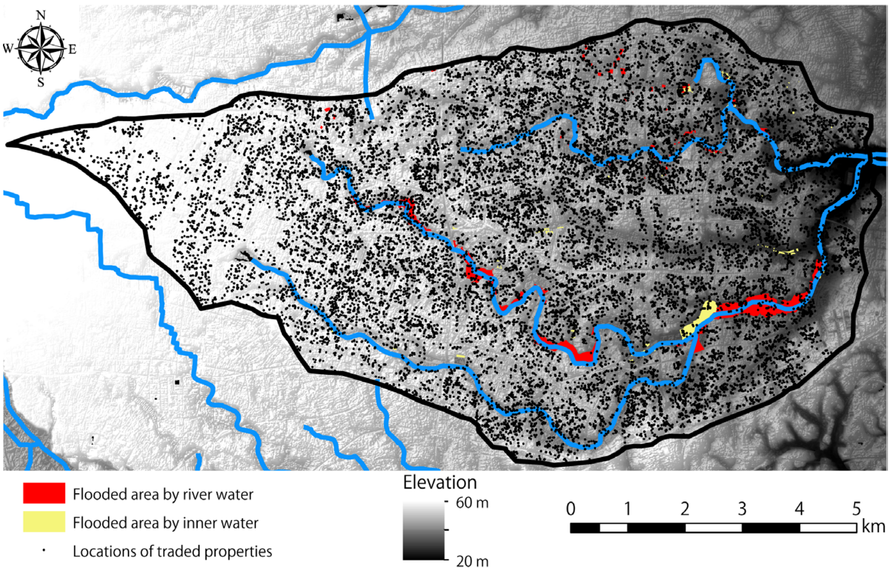

Figure 1. Locations of flooded areas and traded properties in the target area

Table 1. Flood events with an inundation area exceeding one hectare

Year	Date	Inundated area (hectare)
2001	Jul 18	12.8
2003	Oct 13	3.5
2004	Oct 9	10.5
	Oct 20	3.0
2005	Aug 15	3.5
	Sep 4	125.9
2008	Aug 5	3.9
2009	Oct 7	2.6
2011	Aug 26	2.9
2013	Aug 21	1.5
2014	Jun 29	2.4
	Jul 20	1.9
	Jul 24	3.6

4.2 Prices and attributes of traded properties

This study utilizes transaction records from the real estate transaction price data of residential land lots without buildings.[1] The Land Appraisal Committee under the Ministry of Land, Infrastructure, Transport and Tourism

[1] http://www.land.mlit.go.jp/webland_english/servlet/MainServlet

(MLIT) of Japan collects records using a survey of real estate property buyers. Each transaction record has many attributes, including but not limited to location, transaction period, transaction price, land lot area, width and types of frontage road, the name of the nearest station, and land use designation by city planning act. Detailed attribute information is hidden from the public for privacy reasons; however, this study utilized a dataset with detailed information provided by MLIT.

We selected transaction records to use in the analysis as follows.

First, we selected transactions of properties with a size of less than 200 square meters to analyze property values for private use excluding business use and to analyze local residents' actions related to flood risk. According to the 2013 Housing and Land Survey by the Statistic Bureau, the average size of a land lot in the Tokyo metropolitan area for detached houses was 117.98 square meters, and 81.1% of total houses are less than 200 square meters in size.

Second, we excluded transaction records with missing values or unexpected attribute values. Transactions of properties that faced a road that was more than 20 meters wide were excluded because such properties are usually not used as private detached houses.

Table 2 provides a summary of the transaction data. Because these data include particular transactions with extremely low and high prices, we excluded the top and bottom 5% of transaction prices. As result, this study utilized 18,775 transactions.

We used the following traded property attributes for the analysis: transaction date, location, size, name of the nearest train station, route length to the nearest station, floor area ratio regulation, front road width, existence of a side road, and unfairness of shape.

An attribute of accessibility by train service is set as "railway travel time from the nearest station to the major stations in Tokyo," which is the weighted average travel time to the five major stations of Shinjuku, Shibuya, Ikebukuro, Tokyo, and Shinagawa. Travel time data are from Yahoo!

Table 2. Summary of transaction prices

	All data	Data used for analysis
Number of transactions	20,860	18,775
Average (JPY/m^2)	468,167	468,207
Median (JPY/m^2)	467,434	467,431
Minimum (JPY/m^2)	44	173,649
Maximum (JPY/m^2)	6,145,316	698,080
Standard deviation (JPY/m^2)	164,551	103,447

Table 3. Estimate results of the equation (4.1) model

Explanatory variables	Average	Minimum	Maximum	Standard deviation
Size of properties (m^2)	100.721	26.07	200	35.816
Floor area ratio (%)	130.231	50	480	40.652
Width of front road (m)	4.518	0.9	20	1.550
Side road (dummy)	0.192	0	1	0.394
Unfairness of shape (dummy)	0.182	0	1	0.386
Route length to station (m)	785.363	20	8000	367.944
Travel time by train (min)	27.778	10.574	48.331	6.832
Nikkei average (JPY)	12,610.19	8,774.75	19,013.51	3,030.55

transit.[2] We searched for travel times that include transfer time and average wait time when leaving each station at noon. The weights depend on the number of users of the five major stations in 2013 based on the National Land Numerical Information of MLIT.

We used the Nikkei 225 stock exchange average as attribute data of the economic conditions for transaction date. To remove short-term variations, the one-year average before the transaction date is used.

Table 3 provides a summary of the explanatory variables.

4.3 Estimation of transaction price change for the largest flood

This section analyzed the effect of the largest flood, which occurred in September 2005, on transaction prices. Equation (4.1) is a transaction price model, where y is a dependent variable, xs are explanatory variables, βs are parameters, and ε is a disturbance term. The explained variables are transaction prices per one square meter of property and the dummy variables of flooded area and transaction date after a flood. Their cross-term expresses the effect of a flood on transaction prices. The dummy variable of flooded area is based on the flood inundation maps of MLIT, or *suigai kuiki zu* in Japanese. The numbers of transactions after a flood in the targeted region, in floodplains over the targeted period, and in floodplains after the flood are 13,513, 248, and 186, respectively.

$$\begin{aligned} y_i &= \mathbf{x}_i'\boldsymbol{\beta} \\ &+ x_{i\ flooded}\ \beta_{flood} + x_{i\ after}\ \beta_{after} + x_{i\ flooded}\ x_{i\ after\_flood}\ \beta_{flooded\_after} + \varepsilon_i . \end{aligned} \tag{4.1}$$

[2] http://transit.yahoo.co.jp/

Table 4. Estimated results of the equation (4.1) model

Explanatory variables	Parameters	t value	p-value
Constant	5.95E+05	102.73	<0.001
Size of properties (m^2)	–5.81E+02	–30.02	<0.001
Floor area ratio (%)	–1.44E+02	–7.84	<0.001
Width of front road (m)	7.66E+03	16.69	<0.001
Side road (dummy)	1.69E+04	9.59	<0.001
Unfairness of shape (dummy)	–5.09E+04	–29.51	<0.001
Route length to station (m)	–4.42E+01	–22.89	<0.001
Travel time by train (min)	–4.54E+03	–44.53	<0.001
Nikkei average (JPY)	5.79E+00	26.07	<0.001
Flooded area (dummy)	6.28E+02	0.05	0.957
After flood (dummy)	1.45E+04	9.68	<0.001
[Flooded area] × [After flood]	–1.11E+04	–0.82	0.411

Table 4 provides the explanatory variables and estimated results. The coefficient of determination is 0.217.

The estimation result shows that the flooded area was not devaluated before and even after the flood event. The dummy variable parameter "after flood" is positive and indicates that transaction prices in the target area increased after the flood, which was caused by the upward trend in the real estate market.

As is shown, the occurrence of a flood may not affect real estate transaction prices in the target area, a finding that differs from that derived from previous studies. In the next section, we apply the turning timing detection method to determine whether differences exist in price changes related to flood risk.

4.4 Detection of transaction price change from flood risk

We applied a turning time point detection method to the transaction price data and attempted to identify the timing for drastic changes in real estate property prices caused by flood hazards. Because the analysis method needs discrete time data, we discretize the data into three-month periods, and the total number of time points is 64.

Equation (4.2) is a hierarchical Bayesian model used for the analysis, and Gibbs sampling is used to estimate the parameters. The uninformative priors are set on all parameters, βs, θ, and τ.

$$y_i = \mathbf{x}_i'\boldsymbol{\beta} \tag{4.2}$$
$$+x_{i\_hazard}\ \beta_{hazard} + I(\theta < t_i)\ \beta_{after} + x_{i\ hazard}\ I(\theta < t_i)\ \beta_{hazard\_after} + \varepsilon_i.$$

$$y_i \mid \boldsymbol{\beta}, \beta_{hazard}$$
$$\sim N\left(\mathbf{x}_i'\boldsymbol{\beta} + x_{i\_hazard}\ \beta_{hazard},\ \tau\right) \quad \text{if } t_i \le \theta$$
$$y_i \mid \boldsymbol{\beta}, \beta_{hazard}, \beta_{after}, \beta_{hazard\_after}$$
$$\sim N\left(\mathbf{x}_i'\boldsymbol{\beta} + x_{i\_hazard}\ \beta_{hazard} + \beta_{after} + x_{i\_hazard}\beta_{hazard\_after},\ \tau\right) \ \text{ if } t_i > \theta$$
$$\beta_j \sim N(0,\ \tau)\ \forall j$$
$$\tau \sim \Gamma(0.001,\ 1000)$$
$$\theta \sim unif\left\{t_1,\ t_{64}\right\}$$

In this section, flood hazard areas are set using flood histories and terrain data. The flood inundation maps are a source of flood histories. The terrain data are from the five meter-grid elevation data of the Basic Map Information by the Geospatial Information Authority of Japan, and “river” and “basin and non-water catchment area” data are from the National Land Numerical Information by MLIT.

We show the estimation results when flood hazard areas are set as areas in which a river water flood occurred within a 100-meter distance and a one-meter elevation from the highest elevation of the flooded area. The total number of property transactions in the flood hazard areas is 1,396.

Because the analysis method cannot search multiple turning points, we repeated the search procedure until no timing is detected. Tables 5, 6, and 7 provide the estimation results. The estimated parameters using bold letters indicate that they are significant at the 5% confidence level.

The detected change timings are at the end of March 2002, June 2009, and June 2013. None of these dates is related to flood events shown in Table 1. These results show that no turning time points are detected that are triggered by floods.

However, the estimated parameters for the dependent variables of the cross term of the hazard area dummy and the after change dummy are not significant in every analysis. It indicates that the detected turning time points do not represent the timing when flood risk affected price formation process in the real estate market.

The parameters for the after change dummy are significant in every case, indicating that transaction prices changed before and after the detected timings and supposedly represent a real estate market trend. Figure 2 indicates the temporal distribution of real estate transaction prices and the transition

Table 5. Turning time point analysis between January 2000 and December 2015

	Mean	SD	2.5%	50.0%	97.5%
Turning time point (Year)	**2013.42**	0.14	2013	2013.5	2013.5
Constant	**5.97E+05**	5.74E+03	5.86E+05	5.97E+05	6.08E+05
Size of properties (m^2)	**–5.83E+02**	1.95E+01	–6.20E+02	–5.83E+02	–5.44E+02
Floor area ratio (%)	**–1.27E+02**	1.93E+01	–1.64E+02	–1.28E+02	–8.74E+01
Width of front road (m)	**7.60E+03**	4.40E+02	6.76E+03	7.59E+03	8.50E+03
Side road (dummy)	**1.55E+04**	1.77E+03	1.21E+04	1.55E+04	1.90E+04
Unfairness of shape (dummy)	**–4.93E+04**	1.77E+03	–5.27E+04	–4.93E+04	–4.58E+04
Route length to station (m)	**–4.37E+01**	1.96E+00	–4.75E+01	–4.36E+01	–3.98E+01
Travel time by train (min)	**–4.47E+03**	1.02E+02	–4.67E+03	–4.47E+03	–4.27E+03
Nikkei average (JPY)	**6.37E+00**	2.56E–01	5.86E+00	6.37E+00	6.87E+00
Hazard area (dummy)	**–1.31E+04**	2.93E+03	–1.88E+04	–1.31E+04	–7.35E+03
After change (dummy)	**–1.06E+04**	1.89E+03	–1.43E+04	–1.07E+04	–6.94E+03
[Hazard area (dummy)]× [After change (dummy)]	–5.52E+03	6.02E+03	–1.76E+04	–5.43E+03	6.15E+03

Table 6. Turning time point analysis between January 2000 and June 2013

	Mean	SD	2.5%	50.0%	97.5%
Turning time point (Year)	**2002.25**	0.01	2002.25	2002.25	2002.25
Constant	**5.32E+05**	7.54E+03	5.18E+05	5.32E+05	5.46E+05
Size of properties (m^2)	**–5.76E+02**	2.12E+01	–6.16E+02	–5.76E+02	–5.34E+02
Floor area ratio (%)	**–1.71E+02**	2.11E+01	–2.11E+02	–1.72E+02	–1.28E+02
Width of front road (m)	**7.66E+03**	4.82E+02	6.75E+03	7.65E+03	8.64E+03
Side road (dummy)	**1.67E+04**	1.83E+03	1.32E+04	1.67E+04	2.04E+04
Unfairness of shape (dummy)	**–5.95E+04**	2.03E+03	–6.34E+04	–5.95E+04	–5.55E+04
Route length to station (m)	**–4.38E+01**	2.15E+00	–4.81E+01	–4.38E+01	–3.97E+01
Travel time by train (min)	**–4.35E+03**	1.10E+02	–4.57E+03	–4.35E+03	–4.13E+03
Nikkei average (JPY)	**9.10E+00**	3.14.E–01	8.51E+00	9.10E+00	9.71E+00
Hazard area (dummy)	**–1.75E+04**	7.33E+03	–3.20E+04	–1.75E+04	–2.79E+03
After change (dummy)	**4.19E+04**	2.71E+03	3.64E+04	4.19E+04	4.70E+04
[Hazard area (dummy)]× [After change (dummy)]	4.92E+03	7.92E+03	–1.05E+04	4.95E+03	2.05E+04

of stock index. It reveals that the sharpness of reactions to economic fluctuations are different between real estate market and stock market, and the detected time points in this study correspond to the timings when trend of stock index changes suddenly. This result suggests the necessity of redesigning the temporal attributes that explain the economic fluctuation.

Table 7. Turning time point analysis between April 2002 and June 2013

	Mean	SD	2.5%	50.0%	97.5%
Turning time point (Year)	**2009.48**	0.22	2009.25	2009.5	2009.75
Constant	**5.48E+05**	7.75E+03	5.33E+05	5.47E+05	5.62E+05
Size of properties (m^2)	**–5.80E+02**	2.36E+01	–6.25E+02	–5.80E+02	–5.34E+02
Floor area ratio (%)	**–1.52E+02**	2.34E+01	–1.96E+02	–1.53E+02	–1.04E+02
Width of front road (m)	**7.31E+03**	5.33E+02	6.29E+03	7.29E+03	8.41E+03
Side road (dummy)	**1.78E+04**	2.01E+03	1.39E+04	1.78E+04	2.18E+04
Unfairness of shape (dummy)	**–5.94E+04**	2.22E+03	–6.38E+04	–5.94E+04	–5.50E+04
Route length to station (m)	**–4.32E+01**	2.38E+00	–4.79E+01	–4.32E+01	–3.85E+01
Travel time by train (min)	**–4.38E+03**	1.22E+02	–4.62E+03	–4.38E+03	–4.13E+03
Nikkei average (JPY)	**1.09E+01**	4.35E–01	1.01E+01	1.09E+01	1.18E+01
Hazard area (dummy)	**–1.20E+04**	3.96E+03	–1.97E+04	–1.21E+04	–4.16E+03
After change (dummy)	**1.22E+04**	2.18E+03	7.92E+03	1.22E+04	1.65E+04
[Hazard area (dummy)]× [After change (dummy)]	–1.86E+03	6.27E+03	–1.41E+04	–1.87E+03	1.04E+04

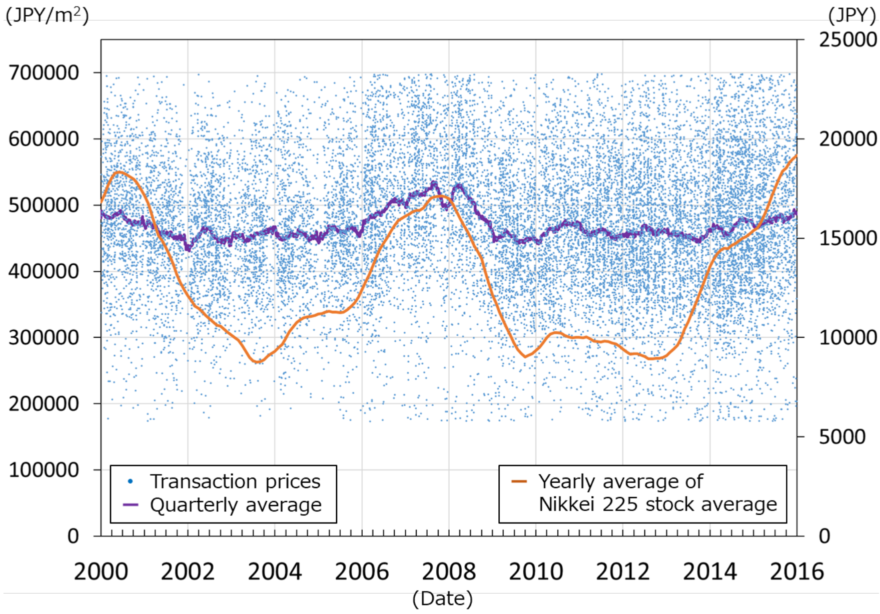

Figure 2. Distribution of real estate transaction prices and transition of stock index

Although extracting the timing when flood events affected real estate transaction prices did not succeed, the estimated parameters of the hazard areas dummy are significantly negative in all analyses. This result indicates that flood risk is not neglected in the target area. Frequent floods might have maintained residents' awareness of flood risk, which are different from areas in which floods are rare.

5. Concluding Remarks

This study analyzed the relationship between the occurrence of flood events and changes in real estate property transaction prices in flood-prone areas using the DID analysis method and turning time point detection.

Unlike previous research that used study areas that were not frequent flooded areas, the occurrence of floods did not affect the transaction prices of real estate properties located in flooded areas. Properties in flood hazard areas were confirmed as being less expensive than those in non-flood hazard areas. From these estimation results, flood risk can be explained as being reflected in transaction prices of real estate properties and are perceived by real estate market participants and local residents through flood event experiences in the target area.

Although the estimated parameters of the transaction price model were highly significant, the model's fitness is quite low. Transaction prices are affected by situation of the parties to a sale; their variance is very large and it is difficult to construct a model with high fitness. However, the low fitness model leads to the misspecification of parameters; therefore, building a model with improved goodness of fit is needed. Analyses at different sites are also necessary to check whether the results obtained by this study are robust. These tasks are left for future studies.

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