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Flood Risk Perception and its Impact on Land Prices in Japan*

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Abstract

This paper estimates how flood risk perception affects land prices by making use of the granular geographical information of land prices, flood events collected in the Flood Statistics, and of flood risk captured in hazard maps in Japan. The estimates are conducted through two approaches, the hedonic approach and local projection, for the sampled sites that are selected from the viewpoint of avoiding potential omitted variable bias. Our main findings are threefold: (a) hazard map information affects land prices in a statistically significant manner. The effect is accompanied by a lag and its size varies depending on land use. (b) In addition to hazard map information, past flooding experiences affect land prices, suggesting the importance of the role played by the subjective flood risk perception formed through past flooding experiences. Indeed, in areas where large-scale flooding has occurred frequently in the past, hazard map information is reflected in the level of land prices to a greater degree and land prices are less susceptible to changes in hazard map information. (c) The estimated impact of flood risk on land prices based on the two approaches does not deviate significantly from the alternative measure of the impact of flood risk on land prices computed using the actual flood damage. However, the differences between the estimated impact and the alternative measure may become large for a certain type of flood risk and land use. Our results suggest that, in addition to the objective flood risk contained in, for example, hazard map, subjective perceptions of flood risk, such as those reflected in past flooding experiences, may also be important in land price formation.

JEL Classification: Q54; R30

Keywords: Flood; Hazard maps; Land price; Hedonic approach; Local projection

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1. Introduction

In recent years, many countries around the globe have witnessed an unprecedented size and frequency of large-scale natural disasters. As concerns over climate change are growing, an increasing number of research output about the impacts of natural disasters has been published by international organizations, national governments, and research institutes.[1] There is also growing interest in how firms' or households' perceptions of natural disaster risk affect economic activity.[2] Floods or landslides, for example, damage the physical assets in the affected areas and possibly reduce current and future income derived from the land there. If that happens in residential areas, there is even a risk of the loss of human lives. If the perception of flood risk of firms and households is updated as a result of, for example, the publication of new scientific findings such as those contained in hazard maps, land prices may change accordingly through changes in the expected value of holding or living off the land. As theoretical studies such as Kiyotaki and Moore (1997) and Iacoviello (2005) predict, once land prices change, this has important implications not only for households and firms that own the lands, but also for the financial and economic stability of the economy as a whole. Indeed, Bolton et al. (2020) (the so-called Green Swan Report) points out that the decline in asset prices, such as land prices triggered by extreme weather events or long-term alterations in climate patterns induced by climate change, could deteriorate households' and firms' balance sheets and depress economic and financial intermediation activities.

While the quantity and quality of scientific information on the risk of natural disasters associated with climate change increase year by year, it is still difficult to determine a priori to what extent and at what pace such information is incorporated into economic variables including real estate prices. This is because the risk perceptions, i.e., the probability and scale of natural disasters perceived by households and firms involved in real estate transactions, do not necessarily coincide with the latest scientific and objective risk information available at the time, due for example to issues regarding accessibility to the relevant information or the attention of firms and households. A large number of empirical studies have already been accumulated in this area, and there is nearly consensus on this point.

Against this backdrop, this paper empirically estimates how information on flood risk

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1 In response to climate change, not only studies on climate change but also international efforts to reduce greenhouse gas emissions are making progress. See, for example, Kurachi et al. (2022) for an overview of the data regarding Japan's transition to a decarbonized society.

2 Against the background of increasing concerns over the impact of natural disasters on economic activities, some countries have introduced policy initiatives that aim to quantify the scope and magnitude of natural disasters. In Japan, for example, the Building Lots and Buildings Transaction Business Act (enforced in 2020) was revised, making it mandatory for sellers of properties to explain to the buyers in advance of the transaction the location of the corresponding property on a flood hazard map.

is reflected in land prices by combining hazard maps and statistics on actual flood damage with official land prices in Japan. The sample period is from 2001 to 2020, and the number of analyzed sites is about 3,500. One of the reasons to focus on Japan is that, as Yamamoto and Naka (2021) point out, Japan has often experienced natural disasters, 70% of which are flood-related, categorized as inundation and sediment disaster, and more than 40% of the population and business offices face flood risks (Figure 1). Not surprisingly, therefore, there is rich flood-related data available, in both the time-series and cross-sectional dimensions. This paper employs two analytical methods -- the hedonic approach and local projection -- which are widely used in existing literature. The former estimates the effect of flood risk on the level of land prices, while the latter estimates the effect of updated flood risk on changes in land prices. The usage of the two methods allows us to understand the process of the transmission of flood risk to land prices from multiple perspectives, and also to secure the robustness of the estimation results. As described later, some existing literature points out that the hedonic approach might not be able to separate the impact on land prices of flood risk from that of the benefits (hereinafter referred to as "amenity") that the land brings, such as the utility derived from the landscape. For the purpose of accurately identifying the effect of flood risk, we use the data of the sites that are close to each other, so that attributes other than flood risk and flood damage are similar across sampled sites.

We first quantitatively assess the role of the objective flood risk in land price formation by estimating the impact of hazard map information, which we consider as capturing the objective and scientific size of flood risk, on land prices.[3] We then study the role of the subjective risk perceptions held by firms and/or households that are involved in land transactions in land price formation. Hallstrom and Smith (2005), Ortega and Taspinar (2018), and other empirical studies that mainly use United States data, often point out that a large-scale natural disaster depresses real estate prices, not only in the directly damaged areas, but also in neighboring areas that have the risk of being hit by similar natural disasters even when they are not directly damaged by the disaster. Along these lines, we study if how hazard map information affects land prices differs between prefectures that have been hit by large-scale floods frequently and those that have not. Lastly, following Hino and Burke (2020), we describe implications of our quantitative findings about how

[3] Flood risks (Expected Flood Inundation Area) represented in hazard maps are calculated by inundation analysis models under some presumptions regarding the amount of possible rainfall (e.g., once in 1,000 years) and information such as laser-surveyed ground elevation, operational status of drainage facilities, and the effect of raising the river's surface of bridges and other structures. Sediment disaster risk of areas (Sediment Disaster Alert Areas) is also designated based on the magnitude of, for example, the force of earth and rock movement calculated on the basis of height and slope. These risks indicated by hazard maps are scientifically measured and uniquely pinned down, and referred to in this paper as "objective risk." By contrast, although past flooding experiences, as described in section 2, may be related to the size of objective risks to some extent, the risk perceptions may be likely to differ from one entity to another, reflecting their experiences. In this paper, we refer to such risk perceptions as "subjective risk" from the perspective of distinguishing them from scientific measurements.

flood risk affects land prices. We construct a theoretical measure of land price discount due to flood risk using the actual flood damage data and compare it with the size of price discount that our estimate results imply.

Our main findings are threefold. First, in most cases, the objective flood risk indicated in hazard maps significantly depresses land prices. The degree to which the risks depress land prices differs depending on the land use, and the spillover of the risks takes place with a lag after the information is announced or revised. According to the estimate based on the hedonic approach, on average, the objective flood risk of, for example, an inundation depth of 1 meter that may occur every 1,000 years causes land prices to decline by 1.1% for residential land and by 4.7% for commercial land. According to the estimate based on local projection, announcements of changes in the objective flood risks in the form of a 1-meter increase in the inundation depth gradually depress commercial land prices by about 0.5% in the following year and by 2.5% cumulatively in the subsequent six years. These observations suggest the possibilities that the risk perception held by participants of land transactions may differ by land use or that there is informational friction that slows down the update of participants' risk perception. Second, in addition to the hazard map information, whether there have been past large-scale floods in the area matters to land price formation. In prefectures where large-scale floods have occurred frequently, the same size of objective risk affects land prices to a greater degree compared to other prefectures. By contrast, when the objective flood risk changes due to updates of hazard map information, land prices in prefectures experiencing large-scale floods frequently tend to see a smaller adjustment in land prices, possibly because the flood risk is already reflected in land prices. Third, the price discount rate implied from our empirical analysis is generally within the range of values of the theoretical discount rate that are alternatively calculated using the actual flood damage data, though the difference between the two rates may become large depending on the type of land use and the estimation method.

The rest of this paper is organized as follows. Section 2 reviews the existing studies on the effect of natural disaster risks, including flood risk on land prices, and describes the theoretical relationship between flood risk and land prices. Section 3 explains the estimation strategy and the data used in our analysis. Section 4 reports and describes the estimation results. Section 5 concludes.

2. Literature Review and Theoretical Model of Land Price Formation

2.1. Literature Review

Theoretically, land prices are equalized to the discounted present value of expected income, and thus they should decline when flooding probability rises or when expected damage from future flooding increases.[4] Empirically, however, while there is a good number of works documenting that higher objective flood risk indicated in scientific measures such as hazard maps depresses real estate prices, such works also point out that the magnitude of the price penalties does not necessarily coincide with what the theory predicts. For example, Hino and Burke (2020) estimate, using the U.S. data, that house prices in newly designated flood risk areas fall by -1.4% to -2.1% after such designation, and that this decline is smaller than what they call the efficient market discount that is alternatively computed using the insurance payments, arguing that there is little evidence that the objective flood risk is fully reflected in the actual real estate prices. Regarding works that use Japanese land prices, while works such as Sato et al. (2016), Saito (2005), and Kojima (2011) report a negative and statistically significant effect of the objective flood risk on real estate prices, Mori et al. (2016) document that there is no statistically significant relationship between the objective flood risk and land prices. Similarly, Teramoto et al. (2008) report that the objective flood risk is a statistically significant determinant of land prices in the Tokyo region but not in the Osaka region.

There have already been several candidate explanations proposed in existing studies regarding why objective and scientific risks are not automatically reflected in real estate prices. Muller and Hopkins (2019), Baldauf et al. (2019), Hino and Burke (2020), and Bernstein et al. (2019) stress the importance of differences in terms of the amount of related information or awareness held by transacting entities of the real estate. For example, Muller and Hopkins (2019) document that objective flood risk tends to have a larger negative impact on the real estate prices in communities with higher flood risk awareness even when the size of flood risk is the same.[5] Hino and Burke (2020) report that real estate prices are more likely to reflect flood risk when purchases are made by "commercial buyers," who are considered more experienced with such transactions, and in states with strict disclosure requirements for buyers regarding flood risk and flooding history.

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[4] In Japan, the "Real Estate Appraisal Standards," stipulated by the Ministry of Land, Infrastructure, Transport and Tourism, explicitly states that "the risk of floods, landslides and other disasters" should be reflected in land prices.

[5] Muller and Hopkins (2019) define a community as an area with a high public risk awareness if it is enrolled in flood awareness programs to provide information on flood risks offered by the National Flood Insurance Program in the U.S.

Recent studies also point out the importance of a channel through which the occurrence of some events, such as a large-scale natural disaster in a neighboring region, trigger changes in the risk perception held by the residents or potential participants in real estate transactions in the unaffected area. For example, Ortega and Taspinar (2018), studying the case of Hurricane Sandy in 2012, report that the severe flood event depressed the real estate prices in areas that were not flooded but were in close proximity to the flooded area and therefore at flood risk, pointing out the possibility that the disaster changed the subjective risk perceptions of residents or market participants in the area and affected real estate prices. Hallstrom and Smith (2005), Muller and Hopkins (2019), and Addoum et al. (2021) make similar observations for hurricanes in the U.S. In Japan, Iwahashi et al. (2006), Saito (2005), and Shinomura (2010) point out the importance of past flooding history on land prices. From a different but similar angle, Inoue et al. (2015) report that the impact of flood risk on land prices in the Kanda River area in Tokyo has increased since mid-2011, arguing that there may be a change in residents' risk awareness toward natural disasters after the Great East Japan Earthquake in March 2011.[6] As described later, changes in risk perception triggered by such events and resultant changes in real estate prices are studied on a theoretical basis by Bakkensen and Barrage (2021), as with other studies that exploit the framework of Bayesian updating.

Our analysis is close to the above literature, in that it conducts a quantitative assessment of the impact of flood risk on land prices.[7] In contrast to the existing studies, however, our paper is unique in that it examines not only the impact on land prices of objective flood risks, but also that of large-scale flooding experiences, which we view as capturing the size of subjective risk perception. In addition, we study the relationship between flood risk and land prices from various angles; for example, by comparing the effects of flood risk in hazard maps and those of actual flood damage, their effects on residential and commercial lands, or between different types of flood risk.

2.2. Theoretical Model of Land Price Formation

In this section, ahead of conducting an empirical analysis, we summarize the role of risk perception held by participants in real estate transactions in the formation of land prices.

[6] Similar points are made in the studies of transition risk. For example, Bolton and Kacperczyk (2021) examine stock price data of more than 10,000 firms in 77 countries and document that firms with higher CO_2 emission growth rate levels see higher premiums, and that these premiums were not observed before the Paris Protocol of 2015, arguing that this observation may be due to a change in investors' attitudes toward transition risk.

[7] Our paper is also related to two strands of literature in macroeconomics. The first strand is the studies on the implications of fluctuations in real estate prices to the business cycle and to financial intermediation activities. The second strand is studies on the implications of risk perceptions of households or firms with respect to disasters such as large-scale natural disasters, including floods and landslides, which occur infrequently but have a significant impact on economic activity once they occur. See, for example, Iacoviello (2005) for the former and Gourio (2012) for the latter.

2.2.1. Impact of Changes in Risk Perception on Land Prices

Following Bakkensen and Barrage (2021), we consider an economy that consists of two types of land: land that does not face any flood risk and land that faces flood risk. For simplicity, we further assume that there are only two states of flooding: either flooding occurs or it does not. Holding land that faces flood risk can both yield profits (or utility flows) -- due, for example, to its associated living convenience or scenic beauty (amenity) -- and generate losses once flooding occurs. The model abstracts from changes in land supply, and therefore profits or utility flows from land holding are constant. In the model, the price of land without flood risk P_t and the price of land with flood risk P_t^{flood}, both in period t, are respectively described as follows:

$$P_t = \beta(\mathrm{R}_t + \mathrm{E}_t[P_{t+1}]) \tag{1}$$

$$P_t^{flood} = \beta\left(\mathrm{R}_t + \xi - \pi_t\delta + \mathrm{E}_t[P_{t+1}^{flood}]\right), \tag{2}$$

where $\beta \in (0,1)$ is the discount factor, E_t is the expectation operator in period t, R_t is the profits from holding the two types of land in period t, ξ is the additional profits (or utility flows) from holding land with flood risk, π_t is the probability of flooding in period t, and δ is the loss from flooding. For simplicity, we assume that all of the agents in the economy assign the same size of the probability π_t to the occurance of floods.

Using equations (1) and (2), the premium for holding land at flood risk can be expressed as:

$$\begin{aligned} \mathrm{PREM}_t^{flood} &\equiv P_t^{flood} - P_t \\ &= \beta(\xi - \pi_t\delta + \mathrm{E}_t[P_{t+1}^{flood} - P_{t+1}]) \\ &= \sum_{j=1}^{\infty} \beta^j \xi - \sum_{j=1}^{\infty} \beta^j E_t[\pi_{t+j-1}]\delta. \end{aligned} \tag{3}$$

Note that here we assume that equations (1) and (2) continue to hold forever and do not consider the explosive equilibrium. Equation (3) shows that this premium equals to the discounted present value of additional revenue from amenities and the expected loss due to flooding.[8] It also shows that an increase in the expected probability of flooding π_t (i.e., an increase in the flood risk) reduces the price of land facing flood risk through an increase in the expected loss due to flooding.

[8] As indicated by equation (3), the premium reflects the utility flow due to the amenities as well as flood risk. In order to isolate them empirically, in our estimation, we use samples that are physically close to each other, thereby reducing as much as possible the difference in amenity between locations and identifying the contribution of flood risk to land price differentials. On this point, see also appendix B1.

Let π_t^* be the objective and scientific flood risk represented, for example, by hazard maps. Theoretically, the publication of such objective information on flood risk should immediately affect land prices through changes in risk perception π_t held by transacting entities. However, as pointed out in the existing studies mentioned above, the risk perception of transacting entities is formed by factors other than the objective flood risks, such as the frequency of access to objective risk information or the degree of risk preference of the entities, and it is not guaranteed that π_t immediately and automatically converges to π_t^*. The objective flood risk π_t^* and the subjective risk π_t held by the transacting entities can differ from each other. Regarding the relationship between π_t^* and π_t, Bakkensen and Barrage (2021), for example, consider a model where the transacting entities form the subjective flood risk perception based on the objective flood risk and other factors, such as the entities' own experience of flooding. An example of such a model is as follows:

$$\pi_t = q_t\pi_t^* + (1 - q_t)\pi^L , \tag{4}$$

where $q_t \in [0,1]$ is the "probability that the objective risk π_t^* is correct" from the viewpoint of the transacting entities. π^L is a parameter that is specific to the entities.

In equation (4), the subjective risk perception of the probability of flooding is affected by the objective flood risk π_t^* as well as specific weight q_t, which represents the weight attached to the objective risk by the transacting entities. Assuming that variables and parameters such as q_t and π^L are determined independently from the objective flood risk, then the change in the subjective flood risk in response to the change in the objective flood risk is expressed as $\Delta\pi_t = q_t\Delta\pi_t^*$. If $q_t < (>)\ 1$ holds, a change in the objective risk is translated less (more) to the change in subjective risk perception.

2.2.2. Flooding Experiences and Subjective Risk Perceptions

Theoretical and empirical studies, such as Bakkensen and Barrage (2021) and Gallagher (2014), imply that the experience of past large-scale flooding may change the risk perception of the transacting entities and reduce property prices in the neighborhoods of the damaged areas, in addition to those in the actually damaged area. Using the setting described in equation (3) and (4) as an example, even when the subjective flood risk π_t is initially smaller than the objective risk π_t^*, if the subjective flood risk increases as the transacting entities experience a large-scale flood event, then through equation (3), land prices should fall.[9] To be more specific, let us consider the case where a transacting entity observes whether or not a flood occurs each period and updates q_t according to Bayes'

[9] This kind of learning process has been applied not only to natural disasters, but also in a wide range of fields, including household participation in capital markets (Malmendier and Nagel (2011)), disease risk (Davis (2004)), and game theory (Camerer and Ho (1999)).

theorem, as shown in the equation below:

$$(q_t|y_{t-1}=1)=\frac{\pi_{t-1}^{*}q_{t-1}}{\pi_{t-1}^{*}q_{t-1}+\pi^{L}\,(1-q_{t-1})} \tag{5}$$

$$(q_t|y_{t-1}=0)=\frac{(1-\pi_{t-1}^{*})q_{t-1}}{(1-\pi_{t-1}^{*})q_{t-1}+\left(1-\pi^{L}\right)(1-q_{t-1})}, \tag{6}$$

where y_t is a function that takes 1 when flooding occurs and 0 otherwise in period t. Given that $(q_t|y_{t-1}=1)-(q_t|y_{t-1}=0)>0$, under this assumption, a flood in period t increases the subjective flood risk π_t held by the entity, and from equation (3), land prices in period t decline.

Note that this implies that the number of past flooding experiences matters to land prices. Using equations (4) through (6), the subjective flood risk π_t can be expressed by the following equation:

$$(\pi_t|\{y_s\}_{s=0}^{t-1};I_{t-1})=\frac{1}{1+\left(\frac{\pi^{L}}{\pi^{*}}\right)^{n}\left(\frac{1-\pi^{L}}{1-\pi^{*}}\right)^{t-n-1}\left(\frac{1}{q_0}-1\right)}\left(\pi^{*}-\pi^{L}\right)+\pi^{L}, \tag{7}$$

where q_0 is the specific weight that transacting entities attach to the objective risk in the initial period 0, and $n\equiv\sum_{s=0}^{t-1}y_s$ represents the number of flooding experiences from period 0 to period t-1. Equation (7) indicates that, if $\pi^{L}<\pi^{*}$ holds, the greater the number of past flooding experiences, the higher the subjective flood risk π_t.

3. Empirical Model and Data

3.1. Empirical Model

For the purpose of understanding how flood risk is reflected in land prices from multiple perspectives, the analysis employs two methods widely used in related literature. We first describe two empirical models for estimating the impact of the objective flood risk on land prices (hereafter referred to as the “baseline model”).

The first method is the hedonic approach, which compares land prices at locations with higher and lower flood risk in the same time period, controlling various land-specific attributes such as distance from the nearest train or subway station. The hedonic approach assumes that the price of a good reflects the sum of utilities, each of which is generated by various attributes of the good, extracting the contribution of each attribute to the price.[10] This methodology has been widely used for quality adjustments of goods and services when compiling price indexes or for the analysis of real estate prices, including that on the relationship between flood risk and land prices (e.g., Witte et al. (1979), Miyata and Yasube (1991)).

As the objective flood risk is considered one of the determinants of land prices, following the empirical model employed in related studies such as Hino and Burke (2020), we use equation (7) below and estimate the contribution of flood risk to the level of land prices:

$$logP_i \times 100 = \beta_1 F.Risk_i + \beta_2 L.Risk_i + \sum_{k=1}^{n} \beta_k X_{k,i} + \delta_q + u_i, \tag{7}$$

where P_i is the price of land i, $F.Risk_i$ is the objective flood inundation risk, $L.Risk_i$ is the objective sediment disaster risk (e.g., landslide disaster), $X_{k,i}$ is other attributes specific to land i, δ_q is the fixed effect for prefecture q where land i is located, and u_i is the error term.[11] β_1 and β_2 are the parameters that represent the effect of flood risk on land prices. Details on the data for land prices, flood inundation risk, and sediment disaster risk are described later. Other attributes specific to land i are distance from the nearest train or subway station, dummy variables representing the availability of public utilities (gas, sewage, and waterworks), building coverage ratio, elevation, and per capita taxable income of the city where land i is located that represents the land's productivity.[12]

Another analytical approach is local projection, proposed by Jordà (2005). While the hedonic approach estimates the static impact of flood risk on the level of land prices, local projection estimates the dynamic response of land prices to changes in objective flood risk; for example, those reflected in updates to hazard maps. Because local projection allows more flexibility in formulating estimation equation, such as inclusion of cross terms, compared to the VAR model, it has recently been used not only in macroeconomics, but also in analyses of natural disasters, such as research by Tran and Wilson (2020) and Yamamoto and Naka (2021).

Specifically, with equation (8) below, we define the impulse response function of land prices in year t+h to changes in flood inundation risk and sediment disaster risk in year t ($\Delta F.Risk_{i,t}$ and $\Delta L.Risk_{i,t}$):

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[10] For more detail on the theoretical background of the hedonic approach, see Shimizu and Karato (2018).
[11] If fixed effects are set at the municipal level instead of at the prefectural level, accurately identifying the impact of flood risk is considered difficult, since flood risk is assigned to almost all sites in some municipalities. To avoid this, fixed effects are set at the prefectural level.
[12] To address the issue of possible endogeneity between land prices and income in the estimation equation, we use taxable income one year prior to the year of the land prices.

$$
\begin{aligned}
\frac{\partial logP_{i,t+h}}{\partial \Delta F.Risk_{i,t}} &\equiv E\left(logP_{i,t+h} \middle| \Delta F.Risk_{i,t} = 1; I_t\right) \\
&\quad - E\left(logP_{i,t+h} \middle| \Delta F.Risk_{i,t} = 0; I_t\right), \\
\frac{\partial logP_{i,t+h}}{\partial \Delta L.Risk_{i,t}} &\equiv E\left(logP_{i,t+h} \middle| \Delta L.Risk_{i,t} = 1; I_t\right) \\
&\quad - E\left(logP_{i,t+h} \middle| \Delta L.Risk_{i,t} = 0; I_t\right), \\
&\qquad h = 1, \dots, H.
\end{aligned}
\tag{8}
$$

where I_t represents the information set in year t. The impulse response function defined in equation (8) is estimated using equation (9) below:

$$
\begin{aligned}
&\left(logP_{i,t+h} - logP_{i,t}\right) \times 100 \\
&= \sum_{\tau=-3}^{h-1} \rho_\tau^h \Delta F.Risk_{i,t+\tau} + \sum_{\tau=-3}^{h-1} \eta_\tau^h \Delta L.Risk_{i,t+\tau} + \sum_{\tau=-3}^{h-1} \theta_\tau^h Damage_{c,t+\tau} \\
&+ \sum_{k=1}^{n} \delta_k^h \Delta X_{k,i,t} + \delta_i^h + \delta_t^h + \varepsilon_{i,t}^h,
\end{aligned}
\tag{9}
$$

where $Damage_{c,t}$ is the flood damage per capita in city c where land i is located, $\Delta X_{k,i,t}$ is the change in other attributes specific to land i,[13] δ_i^h is the fixed effect of land i, δ_t^h is the time fixed effect, and $\varepsilon_{i,t}^h$ is the error term.

Equation (9) implies that the cumulative change in land prices from year t to year t+h is determined by changes in the objective flood risk, as well as the flood damage per capita, changes in other land-specific attributes, the land-specific fixed effect, and the macroeconomic environment captured by the time fixed effect. The impulse response functions of land prices to changes in objective flood inundation risk and sediment disaster risk, defined in equation (8), can be estimated as ρ_0^h and η_0^h in equation (9), respectively.

One of the advantages of using panel data to analyze the relationship between flood risk and changes in land prices in the time-series dimension is that the effect of amenities (e.g., landscape) that are considered constant through time on land prices can be controlled. That is, as Hino and Burke (2020) and Bakkensen and Barrage (2021) point out, if high flood risk is associated with amenities that are inseparable from the characteristics of the land, the hedonic approach cannot identify the quantitative contribution of flood risk to land prices. For this reason, a growing number of studies,

[13] Specifically, the dummy variables represent those used in the hedonic approach, such as the change in availability of gas supply, the difference in the building coverage ratio, and the growth rate of taxable income per capita. For taxable income per capita, a one-period lag is used because of the possible endogeneity with land prices.

such as Hino and Burke (2020), use panel data to separate the effect of amenities from that of flood risk.

3.2. Data

Land prices used in the estimation are "official land prices," published by the Ministry of Land, Infrastructure and Transport (hereafter MLIT).[14] Official land prices are reported separately according to land use set by the MLIT, and for our analysis, residential land and commercial land are used.

As for objective flood inundation risk, the time series of expected inundation depths is constructed for each of the sites for which official land prices are reported, using the estimates reported in the "Expected Flood Inundation Area" together with the designation dates of the area published on the GIS homepage, both of which are provided by the MLIT. The year in which the newly expected inundation depths are reflected in the time series is set to the year six months after the date of designation as a flood inundation area, taking into account the lag time until it is reflected in hazard maps and made known to the public.[15] Note that while the expected inundation depths on the GIS homepage are reported in the form of intervals (e.g., between 3 meters and 5 meters), we only use the figures on the deeper side when constructing the time series. For objective sediment disaster risk, information on "Sediment Disaster Dangerous Site" and "Sediment Disaster Alert Areas" published on the GIS homepage is matched with each land location in the official land price.[16] Each sample has time-series data comprised of dummy variables that take a value of 1 if the sample is included in one of these sites or areas. In the same way as for objective flood inundation risk, the 6-month lag between the date of designation and the date of being made known is considered.

[14] Official land prices have been published annually since 1970 as the price per unit area of standard sites (approximately 26,000 sites in 2020) as of January 1 of each year, based on the Land Market Value Publication Act. These prices are based on appraisals by two or more real estate appraisers designated by the Land Appraisal Committee of the MLIT. Public land prices are not actual transaction data like the "Real Estate Transaction Price Information," which is also published by the MLIT, but include detailed address information and long-time price data in every appraised year that are not available in the "Real Estate Transaction Price Information." In fact, official land prices have been used in many related studies in Japan and are also widely used in financial institutions' practices, such as collateral valuation by regional banks (Figure 2).

[15] Hazard maps are compiled by overlaying other information such as evacuation sites and then delivered to the residents and firms by the local government after the national or prefectural governments responsible for managing rivers designate the Expected Flood Inundation Area. Therefore, there is often a lag time between the date of designation and the publication of hazard maps.

[16] While the designation of Sediment Disaster Alert Areas has progressed in response to the "Act on Sediment Disaster Countermeasures for Sediment Disaster Alert Areas" enacted in 2000, the Sediment Disaster Dangerous Site, which has been designated since the 1960s, has not been updated since 2010 up to the time of writing. In this paper, information on both Sediment Disaster Alert Areas and the Sediment Disaster Dangerous Site are used considering the fact that some municipalities have not completed assessment of Sediment Disaster Alert Areas, due to the wider survey areas compared to those of the Sediment Disaster Dangerous Site.

For land-specific attributes other than flood risks, the distance from the nearest train or subway station, a dummy variable indicating the availability of public utilities (gas, sewage, and waterworks), and the building coverage ratio are obtained from information attached to the official land price.[17] The elevation selected as a variable describing convenience of the land is constructed using the average elevation of a 250 square meter area obtained from the National Land Survey Data. Taxable income per capita by municipality is calculated using the "Survey of Municipal Taxation Status" (the Ministry of Internal Affairs and Communications; hereafter MIC).

Flood damage per capita by municipality is calculated by dividing the amount of damage to general assets (excluding crops) in the "Flood Statistics" (the MLIT) by population in the "Survey of Population, Demographics and Households Based on the Basic Resident Ledger" (the MIC). The municipal code is adjusted to the most recent area in order to reflect municipal mergers, and then matched to the municipality to which the land in the official land price belongs.

The estimation period is from 2001, when the Flood Prevention Act was revised and the designation of the Expected Flood Inundation Area began, to 2020.[18] In order to accurately identify the relationship between flood risks and land prices, we use samples for which attributes other than flood risk, such as amenities, are considered to be as similar as possible. Specifically, the estimation sample consists of land with the objective flood risk (treatment group) and land without the objective flood risk that is located within 1 km of the former samples (control group).[19] Even with this distance restriction, the total number of sites is about 3,500 across all prefectures and the sample size is about 60,000, ensuring a large enough sample size. The summary statistics for each variable are shown in Table 1.

4. Estimation Results and Their Evaluation

The following section consists of three analyses.[20] First, a baseline model is estimated to

[17] Some previous studies using public land prices employ the floor-area ratio (e.g., Sato et al. (2016)) or the width of the front road (e.g., Mori (2016)) as a potential determinant of land prices. Since the floor-area ratio is mainly determined by the width of the front road, we check the robustness of our results by incorporating the width of the front road as an additional explanatory variable in our estimation equation and find that the results are little changed.

[18] Because the most recent survey year for the Flood Statistics at the time of our analysis is 2019, public land prices up to 2020, which are considered to reflect information through December 31, 2019, are used.

[19] In their analysis of the impact of the 2013 Thames flooding on real estate prices, Garbarino and Guin (2020) use propensity score matching to select a control group with attributes that are similar to actually damaged real estate. Our strategy regarding choosing sample sites is similar to theirs, as it selects sites physically nearby as the control group that can be considered to have similar attributes.

[20] The results of the robustness check regarding the estimation period and distance restrictions on sampled sites are reported in Appendix B.

capture the contribution of the objective flood risk to land prices. Second, the extended model is introduced to examine the impact of the experience of past large-scale floods on land prices, which is considered to play an important role in shaping the subjective flood risk perceptions in the related literature. Lastly, following Hino and Burke (2020), whether the empirically estimated impact of flood risk is larger than the price decline that is alternatively computed using objective flood risks and flood damage is studied.

4.1. Baseline Model Estimation Results

Table 2 shows the estimated results for land prices in 2020 using the hedonic approach.[21] Column (a) shows the results for residential land and (b) shows the results for commercial land. First, the flood inundation risk has a statistically significant and negative impact on both residential and commercial land, depressing residential land prices by 1.1% and commercial land prices by 4.7% for the risk of inundation depth of 1 meter.[22,23] In addition, the sediment disaster risk has a significantly negative impact on both residential and commercial land. Quantitatively, similar to flood inundation risk, it exerts stronger downward pressure on commercial land: -11.9% for residential land and -18.9% for commercial land. Note that the control variables for locational attributes and regional economic attributes satisfy the expected sign condition and are generally significant for both residential and commercial land.

Figure 3 and Table 3 show the impulse response functions of residential and commercial land to an increase in the objective flood risk using local projections.[24,25] First, looking at the response to an increase in flood inundation risk, residential land shows no significant response after the update of flood inundation risk while the commercial land price shows a significant negative response up to 6 years after the update.

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[21] To address possible heteroskedasticity, a robust standard error is used for computing the standard errors.

[22] Note that in our estimation equation, the dependent variable is the logarithmic value of land prices multiplied by 100. For computing the impact of flood risk on the percentage change in land price rather than that on the log percentage change in land prices, therefore, the estimated coefficient β is converted by the equation $\exp(\beta/100) - 1$.

[23] The negative coefficients are consistent with the findings reported in research by Shinomura (2010) and Teramoto et al. (2008), who report that the objective flood risk significantly depresses land prices.

[24] The "Expected Flood Inundation Area," based on which our measure of objective flood inundation risk is constructed, started to be made public with the 2001 revision of the Flood Prevention Act, and the number of rivers that are covered was expanded in its revision in 2005. The assumed rainfall specified in the 2001 amendment to the law was set consistent with flood control projects (e.g., once in 100 years), but the assumed rainfall specified in the 2015 amendment to the law was raised to the maximum possible rainfall (e.g., once in 1,000 years). The "change" in objective flood inundation risk in our local projection mainly represents the event that an area is newly designated as the Expected Flood Inundation Area after 2001 and the event that the expected inundation depth has changed, reflecting the changes in the assumed rainfall to the maximum possible rainfall after 2015. The "change" in sediment disaster risk refers to the cases in which a site is newly designated as a "Sediment Disaster Dangerous Site" or part of "Sediment Disaster Alert Areas." Note that the responses of land prices to the change in objective flood inundation risk does not differ significantly when the effect of changes in objective flood inundation risk due to the new designation and that of changes due to other reasons are separately estimated.

[25] To address possible serial correlation, a standard error clustered at cross-section is used.

Quantitatively, when the expected inundation depth is increased by 1 meter, land prices of commercial land cumulatively fall by 2.6% in 6 years.[26] Second, in response to an increase in the sediment disaster risk, both residential and commercial land prices are significantly depressed. However, while the impact on residential land becomes insignificant after five years, commercial land prices remain depressed significantly beyond five years. Quantitatively, residential and commercial land prices fall by 2.3% at the end of 3 years and by 14% at the end of 6 years after the designation, respectively, when the area is designated as a hazardous area of sediment disaster.[27]

The response of land prices to the actual flood damage is also estimated using this setting.[28] As in the case of changes in objective flood risks, we see that both residential and commercial land prices decrease significantly after the occurrence of flood damage, and that commercial land prices respond more than residential land prices. Quantitatively, when flood damage that is equivalent to the 99th percentile value of the entire sample happens, land prices in that municipality decline, on average, by 0.6% in residential land and by 1.7% in commercial land 3 years after the flood event.[29] However, unlike the change in the objective flood risk, the land prices almost recover to pre-flood levels after 5 years. This indicates that the impact of actual flood damage on land prices may be less persistent than the impact of change in the objective flood risk, partly due to the recovery of the local economy after the disaster. The observation that the impact of actual flooding events is less persistent than the impact of changes in risk perception is consistent with existing studies -- for example, in Ortega and Taspinar (2018) -- that document the emergence of persistent price penalties for properties in undamaged zones and the gradual restoration of prices of damaged properties following Hurricane Sandy.

The estimation results of the baseline model suggest that the objective flood risk described in hazard maps may have a statistically significant negative effect on land prices, which is consistent with previous studies in Japan and other countries. However, the estimation results also indicate that the objective flood risk is not immediately and uniformly reflected in land prices. For example, as some studies focusing on other countries point out, there is a lag in the spillover of flood risk information to land prices,

[26] Regarding objective flood inundation risk, Shinomura (2010) for residential land in Tokyo indicates that the effect of publication of hazard maps on land prices is not significant, which is consistent with the response of residential land prices estimated in this paper.

[27] Similarly, Yoshinaga (2014), using land prices in seven prefectures including Fukui Prefecture, analyzes the impact of designation of Sediment Disaster Alert Areas, and finds that designation reduces land prices by 2.8%. This result is similar to our results of the estimated decline in residential land prices over the next three years after the designation. Yoshinaga (2014) also reports that designation as Sediment Disaster Special Alert Areas, which are considered to have higher risk than Sediment Disaster Alert Areas, results in a 9.1% decline in land prices.

[28] In equation (9), the impact of flood damage on land prices is estimated as θ_0^h.

[29] 41,000 yen/person. This is equivalent, for example, to the amount of damage in Yuki City, Ibaraki Prefecture, which suffered large-scale flooding above the ground level due to Typhoon No. 19 in 2019.

and the degree of price decline varies depending on land use. As described in section 2, this suggests that factors that are specific to transacting entities, such as frictions associated with accessibility to information or the relative importance of the information in shaping risk perceptions, play some role in the process by which the dissemination of information about objective risk affects the risk perceptions of transacting entities. For example, with regard to the difference in the impact of flood risk on commercial and residential land, "commercial buyers" may have incorporated objective flood risk into prices to a greater extent than individual or household buyers do, as pointed out in Hino and Burke (2020), possibly because they are more experienced in real estate transactions and have sufficient managerial resources to access sufficient information on objective flood risk.[30] In fact, Hino and Burke (2020) report that the housing price decline due to flood risk is about 6.9% when purchases are made by commercial buyers compared to 1.8% when made by noncommercial buyers. The background to the lag in the land price response may reflect the frequency of access to information and the psychological momentum of the entities. The existence of such lags has been noted in U.S. studies, such as Ortega and Taspinar (2018).

4.2. Impact of Past Flooding Experience on Land Prices

In this section, we introduce what we refer to as the "extended model" to examine the extent to which the subjective flood risk, in addition to the objective flood risk, affects land prices. As a proxy indicator for the subjective flood risk, we use the number of past large-scale flooding experiences in a neighborhood.

First, we extend the baseline model of the hedonic approach as shown in equation (10) below, incorporating the number of past flooding experiences $N.Flood$ as an additional explanatory variable in the estimation equation:

$$\begin{aligned} logP_i \times 100 = \beta_1 F.Risk_i + \beta_1^S F.Risk_i \times N.Flood_q \\ + \beta_2 L.Risk_i + \beta_2^S L.Risk_i \times N.Flood_q \\ + \sum_{k=1}^{n} \beta_k X_{k,i} + \delta_q + u_i. \end{aligned} \quad (10)$$

The second and fourth terms capture the effects of the objective flood risk on land prices considering the past flooding experiences, which change the subjective perceptions of flood risk. On the other hand, the first and third terms capture the effects of the objective flood risk on land prices other than other factors.

[30] Comparing residential and commercial land, related regulations as well as the use and transaction behavior of owners are different, and these factors may have an impact on land price formation.

The explanatory variable $N.Flood_q$ is the number of relatively large-scale floods experienced in prefecture q, where land i is located, over the past 10 years.[31] "Relatively large-scale floods" are defined as flood damage per capita exceeding the 75th percentile value for all prefectures in the past 10 years. The "Flood Statistics" are an almost exhaustive survey of flood events that take place in Japan, and thus include data on extremely minor flood damage, such as damage per capita of less than 1 yen, implying that flood damage occurs in almost all prefectures every year. In constructing this explanatory variable, we set a threshold for the amount of flood damage and implicitly consider that the formation of risk perception is affected by flood events in the same prefecture but not those in other prefectures, assuming that transacting entities revise their subjective risk perception only when a large flood event occurs in the neighboring areas.[32] In equation (10), β_1^S and β_2^S capture the degree to which the effect of objective flood inundation risk and sediment disaster risk is amplified or suppressed by the number of past flooding experiences, respectively.

Table 4 shows the estimation results of equation (10). Columns (a) and (b) represent results for residential and commercial land prices, respectively. First, as for flood inundation risk, the additional impact of the number of past flooding experiences is negative at a statistically significant level for both residential and commercial land prices. Quantitatively, the results suggest that, as of 2020, one additional flooding experience in the past 10 years pushes down the price of residential and commercial land by 1% and 4.5% per 1-meter expected inundation depth, respectively. Under this model, the parameter β_1, which represents the impact of solely the objective flood risk excluding the impact of the number of past flooding experiences, is no longer statistically significant, suggesting that the subjective risk perception through past flooding experiences may play a more important role in land prices formation.

As for sediment disaster risk, first, the parameter β_2, which represents the impact of the objective flood risk excluding the impact of the number of past flooding experiences, is negative at a statistically significant level for commercial land prices and is insignificant for residential land prices. On the other hand, the parameter β_1^S, which in our preferred interpretation represents the impact of subjective risk, is conversely negative at a statistically significant level for residential land prices while not significant for commercial land prices. Quantitatively, for residential land, designation as a hazardous site of sediment disaster discounts the price by 4.4% per one additional large-

[31] Figure 4 shows a histogram of the number of flooding experiences for the entire sample (47 prefectures times 26 years). The median, 75th percentile, and 90th percentile number of times experienced is 2, 3, and 4, respectively.

[32] Gallagher (2014) analyzes the impact of flood risk on flood insurance take-up and finds that even in areas not actually affected by flooding, flood insurance take-up tends to increase when the area is covered by the same TV media network as the damaged area.

scale flooding experience in the past 10 years. These differences may suggest a possibility that the role of objective flood risk differs across types of transacting entities and that a subjective risk perception plays a larger role among transacting entities of residential land while the objective flood risk plays a larger role among transacting entities of commercial land.

Next, we use local projection to estimate the response of land prices to the changes in objective risk, considering the role played by subjective risk perceptions. Specifically, we estimate the following equation (11), which adds the number of past flooding experiences to the explanatory variables in equation (9):

$$
\begin{aligned}
&\left(logP_{i,t+h} - logP_{i,t}\right) \times 100 \\
&= N.Flood_{p,t}\left(\rho_t^{h,S} \Delta F.Risk_{i,t} + \eta_t^{h,S} \Delta L.Risk_{i,t} + \theta_t^{h,S} Damage_{c,t}\right) \\
&= \sum_{\tau=-3}^{h-1} \rho_\tau^h \Delta F.Risk_{i,t+\tau} + \sum_{\tau=-3}^{h-1} \eta_\tau^h \Delta L.Risk_{i,t+\tau} + \sum_{\tau=-3}^{h-1} \theta_\tau^h Damage_{c,t+\tau} \\
&+ \sum_{k=1}^{n} \delta_k^h \Delta X_{k,i,t} + \delta_i^h + \delta_t^h + \varepsilon_{i,t}^h.
\end{aligned} \qquad (11)
$$

Here, $\rho_t^{h,S}$ and $\eta_t^{h,S}$ are the parameters that capture the additional impact of the number of past flooding experiences on land prices.

Figure 5 shows the impulse response of land prices to increases in the objective flood risk for residential and commercial land and Table 5 shows the corresponding estimated coefficients of the explanatory variables. In Figure 5, the shadows indicate periods in which the number of flooding experiences has no statistically significant effect. First, as for the residential land prices, the number of flooding experiences has no significant effect on the response to changes in sediment disaster risk. Looking at flood inundation risk, for residential land prices, the effect of the number of experiences is significant in the first year and becomes non-significant for 2-6 years after the update. For commercial land prices, there is a statistically significant effect of the flooding experiences for the entire six years.[33] In addition, the larger the number of past flooding experiences, the smaller the decline in land prices in response to an increase in the objective flood risk. Note also that ρ_τ^h remains negative at a statistically significant level, suggesting that updating information on the objective flood risk has a significant impact on land prices, even if there were no past flooding experiences.

Lastly, as for the impact of flood damage, Figure 5 and Table 5 show that the greater the number of past flooding experiences, the less responsive the impulse of both

[33] We drop the second explanatory variable from equation (11) in the estimates for commercial land prices as the variables are almost collinear.

residential and commercial land prices at a statistically significant level. As Yamamoto and Naka (2021) point out, if an area has experienced more flooding in the past, it is possible that firms and households are more prepared and thus the indirect effects on the local economy may become more limited for a given size of direct effects, or that flood risk may already be reflected in subjective risk perceptions and therefore land prices to a greater extent in these areas, making land prices less susceptible to additional flood events.

4.3. Evaluation of the Estimated Flood Risk Impact

As mentioned earlier, under the premise that flood risk reflected in land prices represents a subjectively formed perception of flood risk of transacting entities, its magnitude does not necessarily coincide with the objective flood risk. Against this backdrop, we compute the alternative measure of price discount due to the objective flood risk (hereinafter referred to as the Efficient Discount Rate; EDR) using the data of the actual damage by flood events, following Hino and Burke (2020). By comparing the EDR with the actual price discount rate, which is empirically estimated in sections above, we attempt to evaluate whether the subjective flood risk is fully reflected in land prices, or in other words, to what extent the objective risk is reflected in land prices.[34]

Following Hino and Burke (2020), EDR_l is calculated using equation (12) below. Note that the time dimension is annual.

$$\mathrm{EDR}_l = -\frac{\sum_{t=0}^{\infty} \frac{\pi_l \delta_l}{(1+r)^t}}{P}, \quad \text{where } \delta_l \equiv \sum_{j=1}^{n} L_{j,l} V_j + \sum_{k=1}^{m} O_k. \tag{12}$$

P is the land price, the subscript l represents certain flood damage, such as subfloor flooding, π_l is the possibility of flooding, r is the discount rate, $L_{j,l}$ is the damage rate of asset j at the time of flooding, V_j is the value of asset j, and O_k is the amount of expense k, such as cleaning expenses and loss due to business shutdowns. Equation (12) shows that EDR_l is equal to the ratio of the discounted present value of the expected loss that a house or retail store built on the land suffers to the land value.[35] By comparing EDR_l obtained from equation (12) with the estimated actual price discount rate, it is possible to evaluate whether the flood risk incorporated in the actual land price is greater

[34] Hino and Burke (2020) argue that flood risk is not fully reflected in real estate prices, based on the comparison between the empirically estimated impact of flood risk on real estate prices and the EDR calculated by flood insurance premiums.

[35] Equation (12) can be derived in the theoretical model of section 2 with an additional assumption that the amenity ξ is zero.

than the objective flood risk.

The main parameters used to calculate EDR_l are set as follows.[36] First, the discount rate r is set to 1% or 5%, as it is considered to have a range depending on, for example, the financing cost and the characteristics of the property. The probability of flooding is assumed to be 0.1% for flood inundation and 0.15% for sediment disaster.[37] The damage rate, one of the parameters used to determine the amount of damage in the event of flooding, is taken from the Flood Control Economic Study Manual (FCESM) published by the MLIT. Other expenses are determined following the FCESM, including household alternative activity expenses and cleaning expenses for residential land, as well as loss due to business shutdowns and emergency expenses for commercial land, for each type of flood damage.[38] The value of parameters used to calculate the value of underlying assets and their sources are summarized in Table 6. For residential land, the land and house values are calculated using the average area of a custom-built house with land (published by the Japan Housing Finance Agency) and the per-area value (obtained from the FCESM and official land prices). For commercial land, asset values are calculated assuming a typical retail store, using the assessed value per the floor area of building and depreciable assets from the FCESM, the floor area per building from the Economic Census, and the commercial land price from the official land price.

Figure 6 shows the value of EDR_l estimated in the case of a 1% discount rate r. For residential land, the price discount by subfloor flooding and sediment accumulation (less than 50 cm) is 1.4% and 20.5%, respectively. Damage to household utilities and houses contribute significantly, but cleaning expenses and alternative activity expenses also account for considerable shares. Meanwhile, for commercial land, the price discount due to subfloor flooding and sediment deposition (less than 50 cm) is 2.6% and 31%, respectively. The price discount for commercial land is more negative than for residential land because damage to depreciable and inventory assets and loss due to business shutdowns are greater for commercial land. In addition, reflecting the higher damage rate, the price discount is more negative for sediment accumulation (less than 50 cm) than for inundation under the floor.

[36] Hino and Burke (2020) use U.S. data to calculate the EDR based on the assumption that the expected loss is equal to the insurance premium. In Japan, on the other hand, unlike the U.S., flood insurance premiums are generally set on a prefectural basis, and the price may not necessarily reflect the precise magnitude of risk at individual locations within a prefecture. For this reason, we instead use the FCESM and the Economic Census, rather than insurance premium data, in calculating expected losses and the EDR.

[37] We set the probability of flood events as the inundation depth after the revision of the Flood Prevention Act in 2015 has been calculated for once-in-1,000-year heavy rainfall. For sediment disaster risk, we follow Matsuda and Nakatani (2020), which estimates that the probability of such a disaster occurring more than once in 100 years is about 15% at sites designated as Sediment Disaster Alert Areas.

[38] Damage rates and other expenses in the FCESM are constructed from various sources including information from the Flood Damage Survey and reports from property insurance companies and house builders.

Next, using the results of the empirical analysis in the previous section, we calculate the actual price discount rate. Specifically, we use the coefficients for flood risk estimated in equations (10) for the hedonic approach and (11) for local projection, respectively.[39] The corresponding depth for subfloor flooding is set at 0.45 meter,[40] and the sediment accumulation (less than 50 cm) corresponds to the dummy variable for the sediment disaster risk of 1. The effect of the number of past flooding experiences on land prices is considered for the cases where it takes a value of between 1 and 3 (corresponding to the 25th, 50th, and 75th percentile values of the whole sample, respectively), since the number of flooding experiences differs depending on the prefecture.

Figure 7 compares EDR_l, which is shown as a range between cases of a discount rate r of 1% and 5%, with the actual price discount rate. Note that EDR_l is calculated using national basis data, while the actual price discount rate considers heterogeneity of past flooding experiences. First, looking at residential land, some of the actual price discount rates fall within the range of EDR_l, while others are above the upper limit of EDR_l, suggesting that the objective flood risk may not be fully reflected in land prices. This trend is particularly pronounced for price discounts derived from the estimation results of local projections, both for the risk of subfloor flooding and for the risk of sediment deposition (less than 50 cm). For commercial land, the actual price discount rates are within the range of EDR_l for many cases. However, in the hedonic approach for cases with the number of flooding experiences at 3, the actual price discount rate exceeds EDR_l, suggesting that flood risk may be over-reflected in land prices or may reflect the probability that frequency or damage of flood events will increase in the future.

5. Conclusion

As the risks of climate change to the real economy have gained international attention, there has also been growing interest in how objective and scientific information about these risks, such as that reflected in hazard maps, is translated to asset prices, including land prices. In this paper, we estimate the impact of flood inundation risk and sediment disaster risk represented by hazard maps on the level and changes of land prices in Japan, using two analytical methods: the hedonic approach and local projection. In addition to the objective information reflected in hazard maps, we study the role of a number of past large-scale flooding experiences that are considered to have affected subjective risk perception formed by entities that transact land.

[39] To capture long-term effects, for the estimated results, we use the cumulative effect through the sixth years.
[40] This is based on the fact that the Building Standard Law in Japan requires that the height from the ground to the floor be at least 45 cm.

The results of our analysis are summarized as follows. First, objective flood risks depress land price levels, and when such flood risks increase, land prices also fall. However, the quantitative impact differs across land use and does not come at once. When comparing residential and commercial land prices, the impact of objective flood risk tends to be larger for commercial land, suggesting that the subjective risk perception of entities involved in land transactions may differ between the residential and commercial land buyers. In addition, there is a lag in the process by which updates of objective flood risk are reflected in land prices, suggesting the existence of information friction. Second, the number of past experiences of large-scale flooding also affects land prices; for certain types of flood risks or land uses, the number seems to play a larger role in shaping land prices than the objective flood risk itself. For example, even if the objective flood risk indicated by hazard maps is identical, the magnitude of the objective flood risk to the land price level tends to be larger in areas where large-scale flooding has often occurred in the past compared to areas where it has occurred less frequently. In addition, in such areas, land prices respond less to changes in objective flood risks, possibly because such objective flood risks have already been incorporated in the land prices to a reasonable extent. Third, the estimated degree to which objective flood risks are reflected in land prices differs from the alternative measure of price discount that is constructed from flood damage data for most cases. The two measures, however, disagree for some flood risks or land use, suggesting that risk perception of transacting entities may be formed not only by objective risks but also by other factors, such as their own experience.

There are mainly two research agenda that are not covered in the current study and left for the future. The first is a more detailed study of the impact of flood risk on land prices. For example, whether the differences between commercial and residential land prices, such as the difference in responses to changes in hazard maps information, reflect differences in the amount of information held by transacting entities, as pointed out by previous studies such as Hino and Burke (2020), or whether other factors matter is outside the scope of this analysis. In the analysis based on local projection, it is observed that land prices respond with a lag after changes in the objective flood risk and flood damage, but the background to the lag is not analyzed, such as whether it reflects the speed of information diffusion or inertia in the change in entities' risk perception. In order to examine the impact of climate change and political measures on the economy, it is important to deepen our knowledge on these points, not just the relationship between the risk perception and land prices. This requires more granular data on the nature of the information set faced by the entity at the time of the transaction.

The second issue is an analysis on the relationship between land prices and the financial system. As mentioned in section 1, existing studies have pointed out that a decline in land prices as a result of climate change could substantially damage the balance sheets of households and firms, which could spill over to the financial system via downward pressure on economic activity and financial intermediation activities. Conversely, if some policy measures to deal with climate change go successfully and the risks associated with climate change are reduced, that could have a favorable effect on the financial system through higher land prices. The impact of climate change on the financial system through changes in land prices is an important topic from the perspective of financial stability, and further analysis is required.

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A. Changes in the Impact of Flood Risk over Time

In addition to the number of large-scale flooding experiences in the neighboring areas analyzed in this paper, there are other factors that affect subjective risk perceptions of transacting entities but that are not necessarily related to the geographical location of lands that are transacted. For example, the global growing concern over occurrence of natural disasters and climate change may have a significant impact on the formation of subjective risk perceptions globally. Along these lines, Inoue et al. (2015), for example, analyze the relationship between land prices in the Kanda River area in Tokyo and flood risks measured based on historical flood damage, and estimate that the quantitative impact of flood risk on land prices changed after the Great East Japan Earthquake in March 2011, arguing that the earthquake may have triggered a change in people's risk perceptions against natural disasters, regardless of the fact that the areas under their analysis were not those hit worst by the earthquake.

Against this backdrop, we use a hedonic approach to estimate the impact of flood risk on land prices in different years. Columns (a) through (d) in Table A1 present the estimation results of the baseline model for years 2020, 2017, 2014, and 2011, respectively. The overall results do not differ from those in the main text, in that increases in objective flood inundation risk and sediment disaster risk depress land prices, and that, given the certain level of the objective flood risk, commercial land prices tend to be depressed to a greater level than residential land prices. However, the results also reveal that the degree of the impact of the objective flood risk on land prices differs from year to year and there is a tendency toward the impacts becoming larger in recent years. First, for residential land prices, the coefficient on objective flood inundation risk, which is not statistically significant until 2014, becomes significant in 2017 and 2020. Also, the absolute value of the coefficient on sediment disaster risk has increased in recent years. Second, for commercial land, the impact of flood inundation risk on land prices is statistically significant in all of the four sample years, while the absolute value of the coefficient has increased in recent years. The coefficient on sediment disaster risk is statistically significant only in 2017 and 2020, and was not significant in 2011 and 2014. These estimates may suggest that the subjective risk perceptions change, reflecting not only factors that are specific to the areas for which the transactions are executed but also factors beyond those areas, including global factors.

B. Robustness Check

B1. Changes in Distance Restrictions of Sampled Sites

In the analysis in the main text, in order to isolate as much as possible the effects of omitted attributes that cannot be captured by the explanatory variables, or those of amenities that are correlated with objective flood risks, we choose sampled sites that are assigned with nonzero flood risks and sites without flood risks but located within 1 km of the former site. Under the assumption that attributes (including amenities) between sampled sites are more homogeneous if they are located close to each other, imposing such distance restrictions would make it statistically easier to extract the contribution of objective flood risks to land prices. In this section, we study how the estimation results may change depending on the degree of this distance restriction.

Table B1-1 shows the estimation results of the baseline model of the hedonic approach with various degrees of the distance restriction. For both residential and commercial land prices, columns (a), (b), and (c) are the cases where the distance restriction is set to 1 km or less, 2 km or less, and where all locations are pooled together, respectively. First, when looking at the estimation results for column (b), the coefficient for objective flood inundation risk is qualitatively unchanged from the baseline; namely, it is negative at a statistically significant level for both residential and commercial land prices and the absolute value of the coefficient is larger for commercial land prices than for residential land prices. On the other hand, column (c) shows that the coefficient for objective flood inundation risk is positive at a statistically significant level for residential land prices, suggesting the possibility that it cannot separate the impact of amenities from that of flood risk. Similarly, for commercial land, the coefficient is positive, although not statistically significant.

Table B1-2 shows the estimation results for the extended model of hedonic approach, which takes into account the number of past flooding experiences, again with various degrees of the distance restriction shown in columns (a) to (c). For residential land prices, as column (b) and (c) show, the impact of the objective flood risk on land prices increases as the number of past flooding experiences increases, similar to what is shown for column (a). Also, for commercial land prices, the result that objective flood inundation risk is reflected in land prices to a larger degree at locations with a greater number of past flooding experiences still holds. On the other hand, as shown in (c), the coefficient for the objective flood risk is positive at a statistically significant level for both residential and commercial land prices, suggesting that flood risk may not be extracted due to amenities, similar to those obtained in Table B1-1.

B2. Changes in the Threshold Value for Counting the Number of Large-scale Flooding Experiences

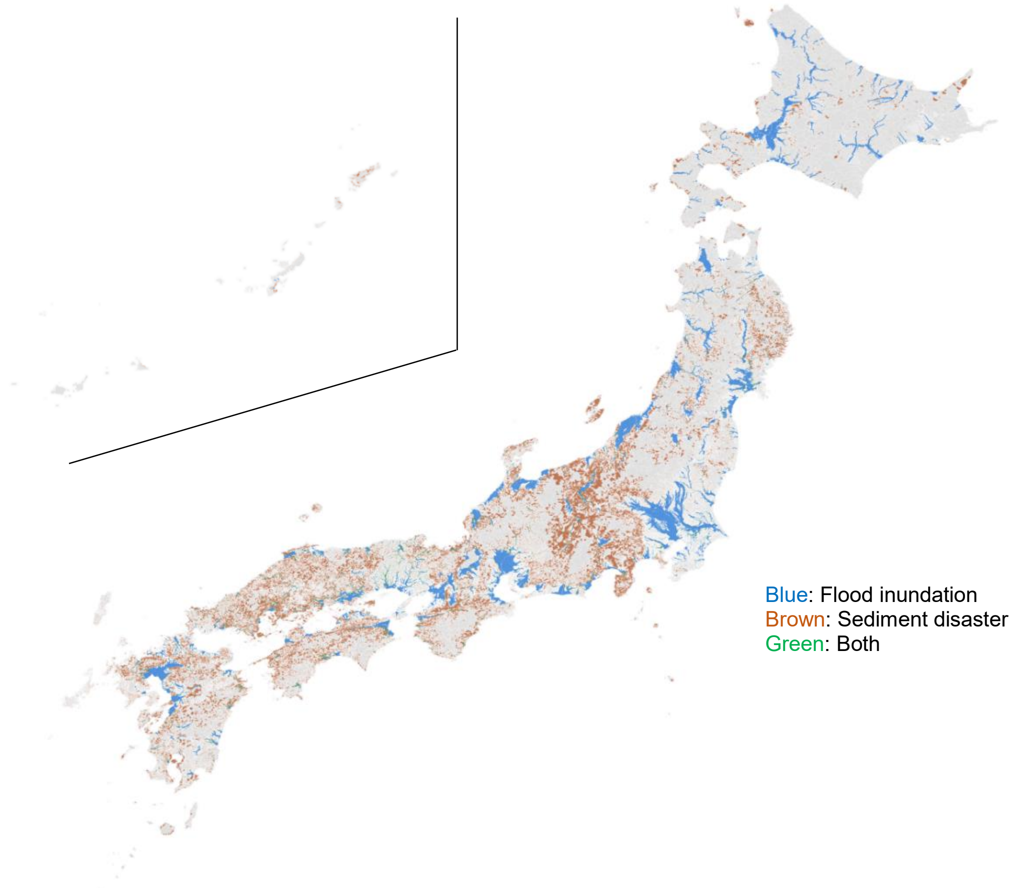
Lastly, we check the robustness of the estimation results with respect to the threshold value of flood damage size used in counting the "number of past large-scale flooding experiences." In the main text, we first aggregate the amount of annual flood damage at the prefectural level, pool that for prefectures (47 prefectures) and years (10 years), and define the occurrence of "large-scale flood damage" as that exceeding the 75th percentile value of flood damage per capita of the pool. For any sampled site, the number of years in which the amount of annual flood damage per capita of the prefecture where the site is located exceeds the 75th percentile value is defined as the number of floods experienced in the past. In this section, we study whether the estimation results change if the 50th percentile value is used instead of the 75th percentile value for defining large-scale flooding experience.

Columns (a) and (b) in Table B2-1 compare the estimation results for residential and commercial land prices when the threshold is set at the 75th and 50th percentile values, respectively. In general, the results suggest that the number of flooding experiences depresses land prices through changes in subjective risk perceptions. As for residential land prices, when the threshold value of the 50th percentile is applied, while not significant, the sign of the coefficient of the intersection term between objective flood risk and number of flooding experiences remains negative. For objective sediment disaster risk, the coefficient of the intersection term between objective flood risks and the number of experiences remains negative at a statistically significant level. As for commercial land prices, the cross term between either of the objective flood risks or the objective sediment disaster risk and the number of flooding experiences is also negative at a statistically significant level.

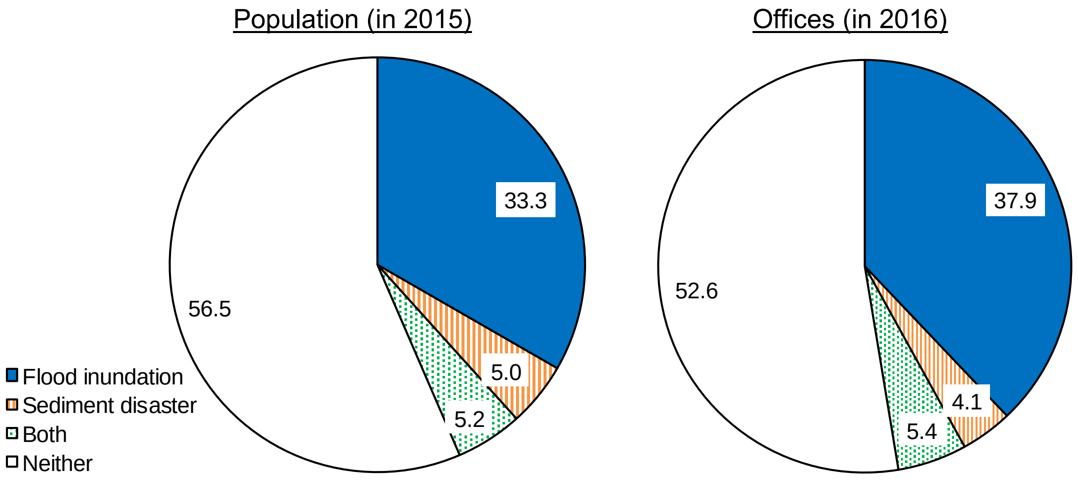
Table B2-2 shows the estimation results of local projection when the 50th percentile value is used as the threshold. The results show that the larger number of flooding experiences is associated with the mitigated responses in land prices to changes in hazard map information or to the occurrence of flood damage, similar to the case when the 75th percentile value is used as the threshold. For example, regarding residential land prices, as shown in column (a), the cross term between flood risk and the number of flooding experiences is positive at a statistically significant level for several years with h=1,...,5, confirming the results reported in the main text. For commercial land prices, as shown in column (b), the cross term between objective flood risk and the number of flooding experiences and the cross term between objective flood risk and flood damage are positive at a statistically significant level for several years.

Figure 1. Flood risk in Japan

(a) Geographical distribution of flood risk



(b) Share of population and offices at flood risk

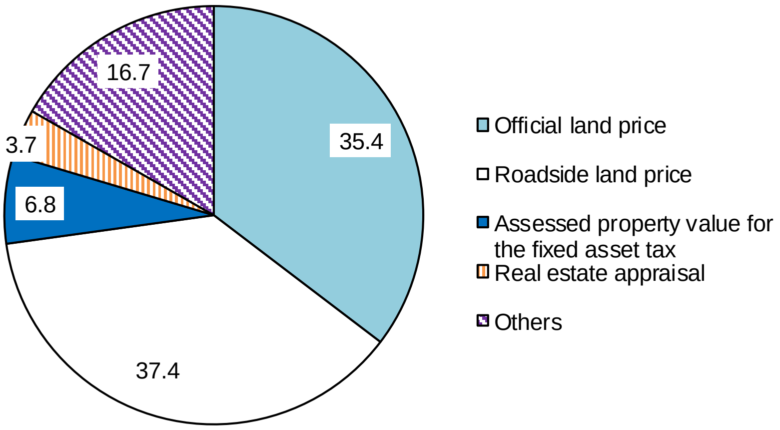


Note: 1. In panel (a), the blue, brown, and green sections represent areas with a large percentage of sites with flood inundation risk, sediment disaster risk, or both within 500 square meters. The sites with flood inundation risk correspond to "Expected Flood Inundation Area" and the river itself, whereas the areas with sediment disaster risk represent "Sediment Disaster Dangerous Site" and "Sediment Disaster Alert Areas." "Both" represents the case where the 500 square meter area faces both flood inundation and sediment disaster risk. Data are compiled using GIS data published on the "GIS Homepage" at the end of May 2021.

2. Panel (b) is constructed by multiplying the population or the number of offices in each 500 square meter area by the corresponding share shown in panel (a).

Source: MLIT; Ministry of Public Management, Home Affairs, Posts and Telecommunications.

Figure 2. Data used by regional banks for evaluating collateral (in fiscal 2019)

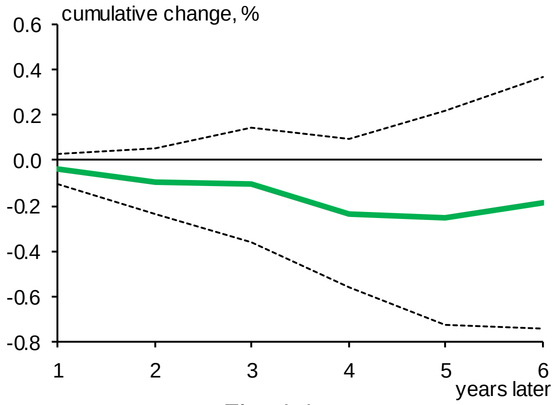


Note: The numbers are based on the survey asking banks the most common evaluation method for collateralized property. Note that "Roadside land price" and "Assessed property value for the fixed asset tax" are discounted to about 80% and 70% of "Official land price," respectively.
Source: BOJ.

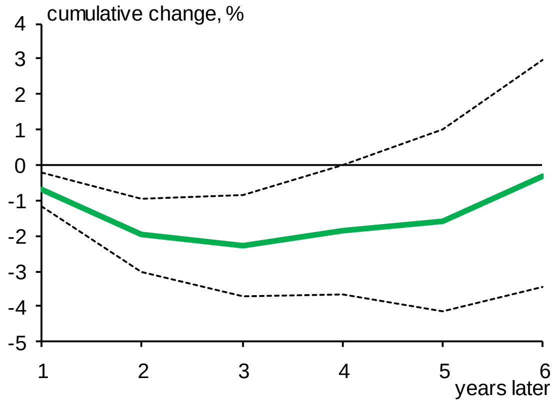
Figure 3. Impulse response of land price (baseline model)

(a) Residential land prices

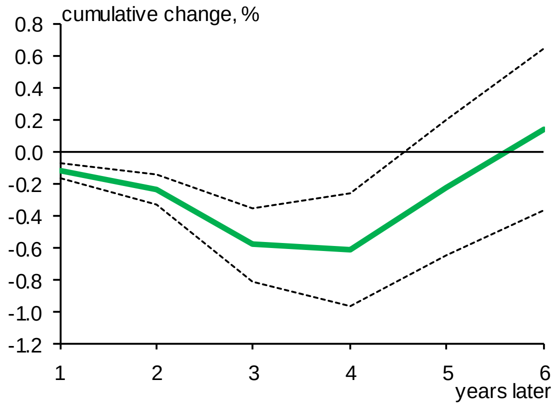
Flood inundation risk



Sediment disaster risk

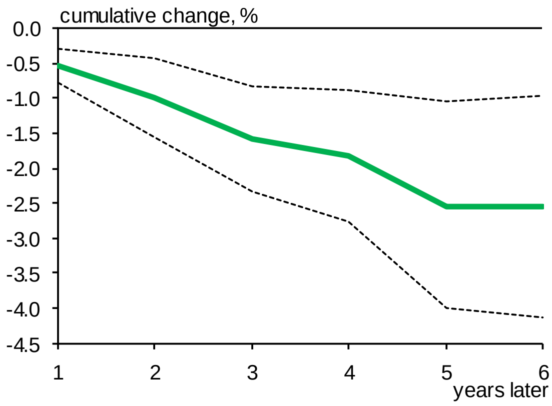


Flood damage

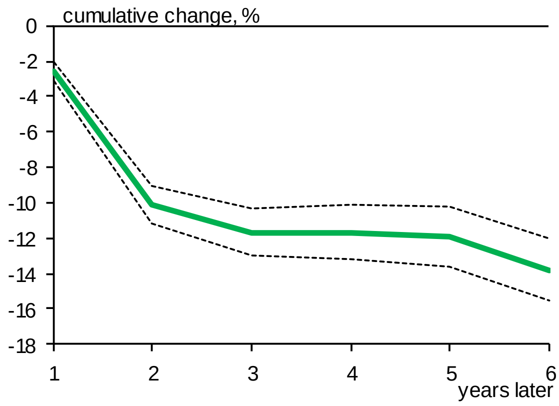


(b) Commercial land prices

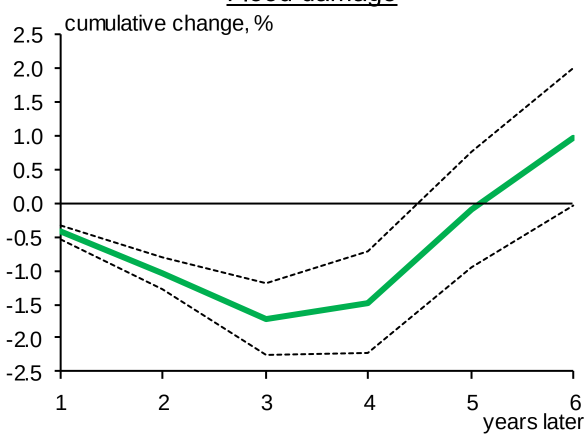
Flood inundation risk



Sediment disaster risk

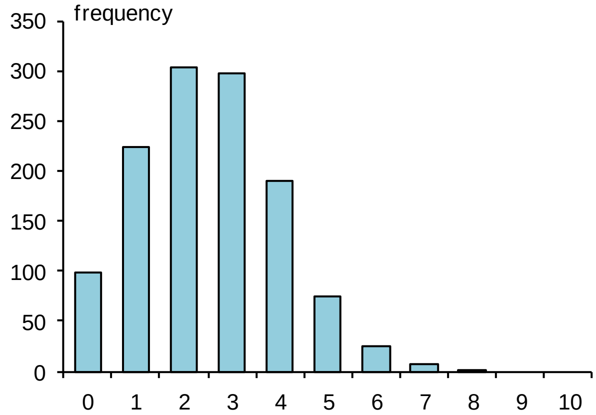


Flood damage



Note: "Flood inundation risk," "Sediment disaster risk," and "Flood damage" represent the cumulative response of land prices to a 1-meter rise in the estimated depth of inundation, designation as sediment disaster alert areas, and an actual flood event with damage equivalent to the 99th percentile value of the whole flood damage sample, respectively. Dashed lines indicate a 90% confidence interval. See also Table 3 for detailed estimation results.

Figure 4. Number of flooding experiences in the past 10 years

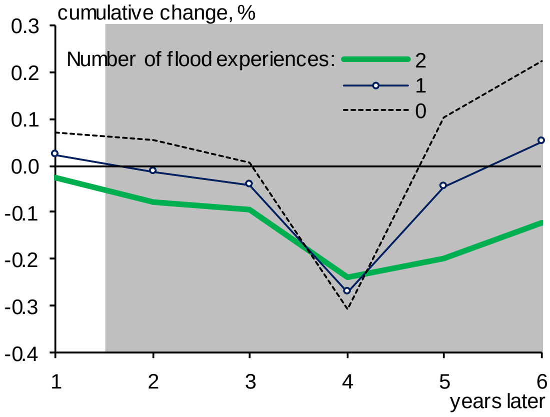


Note: The figures represent the distribution of the number of the relatively large-scale flooding experiences over the last 10 years for each prefecture. "Relatively large-scale floods" is defined as floods where damage per capita exceeds the 75th percentile value of the entire pooled sample for the last 10 years. The number of observations is 1,222 (i.e., 47 prefecture × 26 years <1995-2000>).

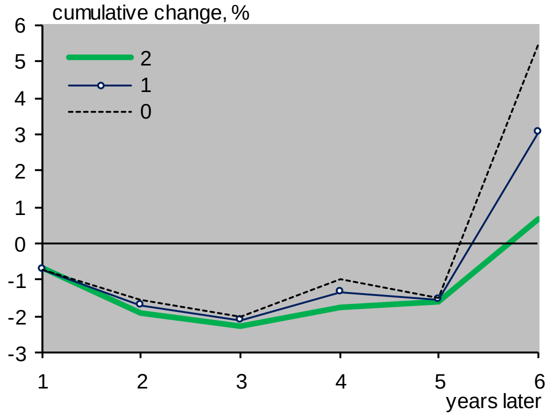
Figure 5. Impulse response of the land price (extended model)

(a) Residential land prices

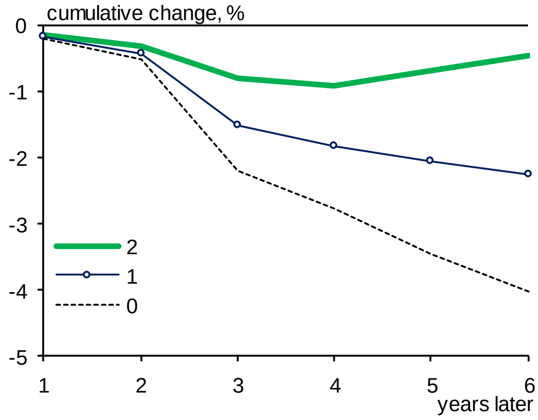
Flood inundation risk



Sediment disaster risk

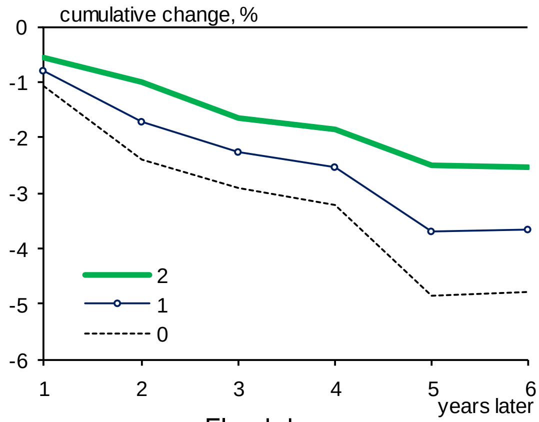


Flood damage

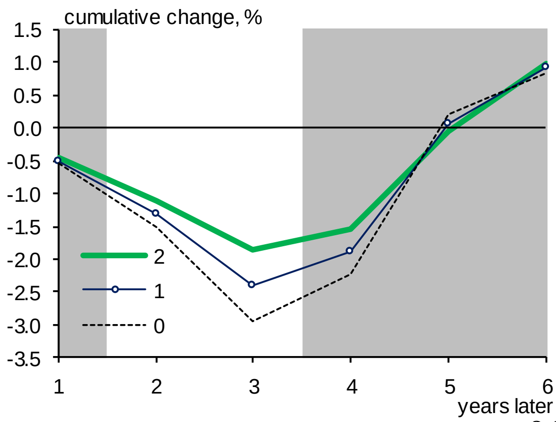


(b) Commercial land prices

Flood inundation risk



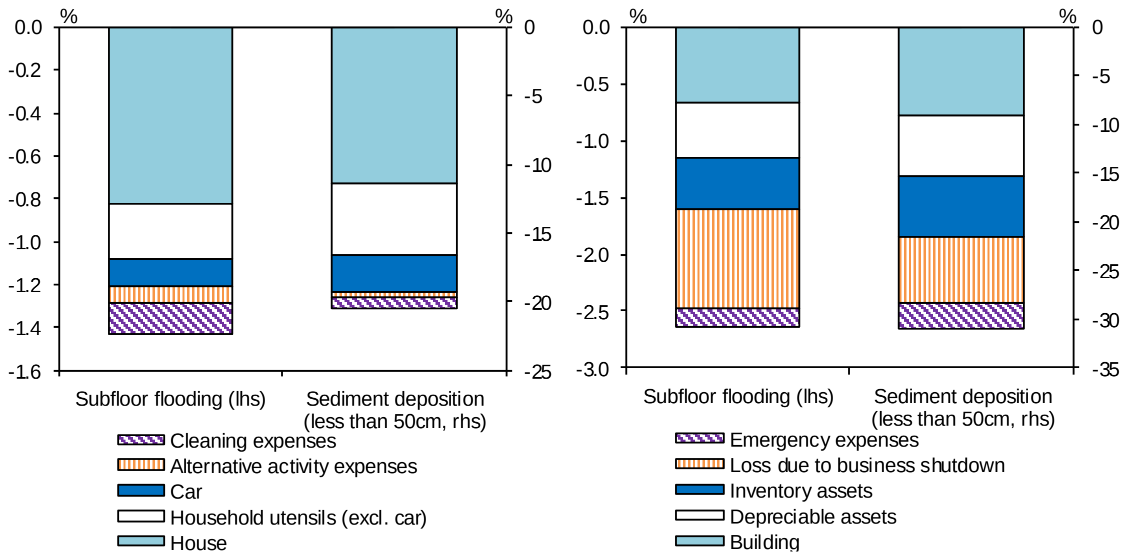
Flood damage



Note: 1. "Flood inundation risk," "Sediment disaster risk," and "Flood damage" represent the cumulative response of land prices to a 1-meter rise in the estimated depth of inundation, designation as sediment disaster alert areas, and an actual flood event with damage equivalent to the 99th percentile value of the whole flood damage sample, respectively. See also Table 5 for detailed estimation results.

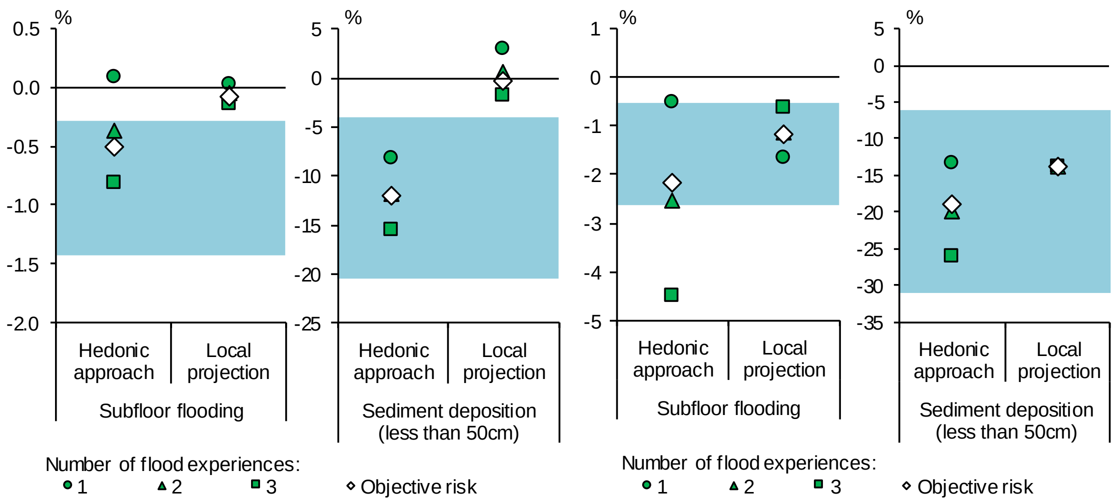
2. The gray shaded area represents periods when the difference in the number of relatively large-scale flooding experiences over the last 10 years does not have statistically significant effects on the impulse response.

Figure 6. Decomposition of the EDR



Note: The EDR is defined as the percentage share over land prices of the expected loss of assets and expenses for 1 year. In the figure, a 1% discount rate is used. The commercial land is assumed to be used for a retail store.

Figure 7. Comparison of the EDRs and estimated coefficients



Note: 1. The markers indicate effects of the "Subfloor flooding" and "Sediment deposition (less than 50cm)" on land prices estimated by the hedonic approach (Tables 2 and 4) and the local projection (Tables 3 and 5), respectively. The white markers (objective risk, ◇) are estimates based on the baseline model, while green markers (○, △, □) are estimates based on the extended model considering the number of flooding experiences in the last 10 years. Green markers are calculated separately for three different numbers of flooding experiences in the last 10 years (1, 2, and 3).

2. The blue shading represents the range of the values of EDR when the discount rate r changes from 1% to 5%.

Table 1. Summary statistics

Land use	Variable	Obs.	Mean	Std. dev.	Min	Max
Residential	Land price (yen)	44,084	140,109	137,959	3,200	4,050,000
	Utilities: gas	43,951	0.79	0.40	0	1
	Utilities: sewage	43,951	0.91	0.28	0	1
	Utilities: waterworks	43,951	1.00	0.04	0	1
	Distance from the nearest station (m)	43,951	1,602	2,164	0	48,000
	Building coverage ratio (%)	43,951	54.93	12.01	0	80
	Elevation (m)	53,400	40.23	54.83	-0.60	590.30
	Taxable income per capita (mil. yen)	50,730	3.52	0.62	2.20	12.67
	Flood inundation risk (estimated depth, m)	53,400	0.39	1.11	0.00	10.00
	Sediment disaster risk	53,400	0.17	0.38	0	1
	Flood damages per capita (thousand yen)	50,560	1.60	16.26	0.00	612.17
Commercial	Land price (yen)	14,915	1,273,879	3,154,197	17,700	42,700,000
	Utilities: gas	14,861	0.95	0.22	0	1
	Utilities: sewage	14,861	0.98	0.14	0	1
	Utilities: waterworks	14,861	1.00	0.00	1	1
	Distance from the nearest station (m)	14,861	569	649	0	6,500
	Building coverage ratio (%)	14,861	70.53	25.02	0	80
	Elevation (m)	18,880	24.85	59.66	-0.30	771.40
	Taxable income per capita (mil. yen)	17,936	4.05	1.72	2.17	12.67
	Flood inundation risk (estimated depth, m)	18,880	0.46	0.97	0.00	10.00
	Sediment disaster risk	18,880	0.05	0.21	0	1
	Flood damages per capita (thousand yen)	17,926	2.38	24.34	0.00	657.34

Note: Data period is between 2001 and 2020.

Table 2. Estimation results based on the hedonic approach (baseline model)

Explanatory variable / Dependent variable	log(Land price)×100 (a) Residential land		(b) Commercial land	
Flood risk				
Flood inundation risk	-1.1	**	-4.8	**
	[0.6]		[2.2]	
Sediment disaster risk	-12.7	***	-21.0	*
	[2.6]		[11.0]	
Locational attributes				
Utilities: gas	53.0	***	80.7	***
	[3.0]		[14.0]	
Utilities: sewage	35.4	***	44.3	**
	[4.6]		[19.3]	
Utilities: waterworks	21.2		-	
	[34.3]			
Distance from the nearest station (logarithm)	-20.1	***	-17.6	***
	[1.4]		[2.4]	
Building coverage ratio	0.5	***	0.6	
	[0.1]		[0.6]	
Elevation	-0.3	***	-0.5	***
	[0.0]		[0.1]	
Regional economic attributes				
Taxable income per capita	38.9	***	9.4	***
	[3.9]		[2.1]	
Fixed effect	Prefecture		Prefecture	
Sample size	2,640		922	
R-squared	0.75		0.73	
Estimation period	2020		2020	

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in [ ] represent the standard error of the coefficient.

Table 3. Estimation results based on the local projection

(baseline model)

(a) Residential land prices

Explanatory variable / Dependent variable	$[\log(\text{Land price})_{i,t+h} - \log(\text{Land price})_{i,t}]\times 100$ Lag h					
	1	2	3	4	5	6
Flood risk						
Flood inundation risk	-0.04	-0.09	-0.11	-0.24	-0.25	-0.19
	[0.04]	[0.09]	[0.15]	[0.20]	[0.29]	[0.34]
Sediment disaster risk	-0.70 **	-2.00 ***	-2.31 ***	-1.87 *	-1.59	-0.31
	[0.30]	[0.64]	[0.89]	[1.12]	[1.60]	[1.97]
Flood damage	-0.003 ***	-0.006 ***	-0.014 ***	-0.015 ***	-0.006	0.004
	[0.001]	[0.002]	[0.004]	[0.005]	[0.006]	[0.008]
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.66	0.70	0.72	0.73	0.74	0.76
Number of sites	2,593	2,593	2,569	2,525	2,321	2,295
Sample size	38,414	38,400	35,795	33,212	30,674	28,353
Estimation periods	2001 - 2020					

(b) Commercial land prices

Explanatory variable / Dependent variable	$[\log(\text{Land price})_{i,t+h} - \log(\text{Land price})_{i,t}]\times 100$ Lag h					
	1	2	3	4	5	6
Flood risk						
Flood inundation risk	-0.54 ***	-0.99 ***	-1.60 ***	-1.83 ***	-2.57 ***	-2.58 ***
	[0.15]	[0.35]	[0.47]	[0.58]	[0.92]	[0.99]
Sediment disaster risk	-2.63 ***	-10.66 ***	-12.43 ***	-12.39 ***	-12.68 ***	-14.86 ***
	[0.32]	[0.72]	[0.92]	[1.04]	[1.19]	[1.26]
Flood damage	-0.011 ***	-0.026 ***	-0.043 ***	-0.037 ***	-0.002	0.024
	[0.002]	[0.004]	[0.008]	[0.012]	[0.013]	[0.015]
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.69	0.72	0.73	0.74	0.74	0.76
Number of sites	907	907	889	847	798	782
Sample size	12,987	12,985	12,077	11,187	10,339	9,542
Estimation periods	2001 - 2020					

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
The numbers in [ ] represent the standard error of the coefficient.

Table 4. Estimation results based on the hedonic approach
(extended model)

Explanatory variable / Dependent variable	log(Land price)×100 (a) Residential land	log(Land price)×100 (b) Commercial land
Flood risk		
Flood inundation risk	1.2	3.4
	[1.0]	[4.6]
Flood inundation risk × number of flood experiences	-1.0 **	-4.6 **
	[0.4]	[2.0]
Sediment disaster risk	-4.5	-38.2 *
	[4.4]	[21.0]
Sediment disaster risk × number of flood experiences	-4.1 **	7.9
	[1.9]	[7.0]
Locational attributes		
Utilities: gas	53.0 ***	81.3 ***
	[3.0]	[14.2]
Utilities: sewage	35.2 ***	47.4 **
	[4.5]	[21.6]
Utilities: waterworks	17.8	-
	[32.7]	
Distance from the nearest station (logarithm)	-20.1 ***	-17.5 ***
	[1.4]	[2.4]
Building coverage ratio	0.5 ***	0.6
	[0.1]	[0.6]
Elevation	-0.3 ***	-0.5 ***
	[0.0]	[0.1]
Regional economic attributes		
Taxable income per capita	38.8 ***	9.3 ***
	[3.9]	[2.1]
Fixed effect	Prefecture	Prefecture
Sample size	2,640	922
R-squared	0.75	0.73
Estimation period	2020	2020

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in [ ] represent the standard error of the coefficient.

Table 5. Estimation results based on the local projection
(extended model)

(a) Residential land prices

Explanatory variable / Dependent variable	$[\log(\text{Land price})_{i,t+h} - \log(\text{Land price})_{i,t}]\times100$ Lag h					
	1	2	3	4	5	6
Flood risk						
Flood inundation risk	0.07	0.06	0.01	-0.31	0.10	0.22
	[0.07]	[0.14]	[0.22]	[0.31]	[0.40]	[0.44]
Flood inundation risk × number of flood experiences	-0.05 *	-0.07	-0.05	0.03	-0.15	-0.17
	[0.03]	[0.05]	[0.07]	[0.11]	[0.11]	[0.12]
Sediment disaster risk	-0.74 *	-1.55 *	-2.05	-0.99	-1.53	5.32
	[0.42]	[0.88]	[1.46]	[2.35]	[3.38]	[3.42]
Sediment disaster risk × number of flood experiences	0.02	-0.19	-0.12	-0.38	-0.04	-2.33
	[0.20]	[0.43]	[0.62]	[0.92]	[1.26]	[1.43]
Flood damage	-0.005 **	-0.013 ***	-0.055 ***	-0.069 ***	-0.087 ***	-0.102 ***
	[0.002]	[0.003]	[0.011]	[0.014]	[0.016]	[0.018]
Flood damage × number of flood experiences	0.001	0.002 ***	0.018 ***	0.023 ***	0.035 ***	0.045 ***
	[0.001]	[0.001]	[0.005]	[0.006]	[0.007]	[0.008]
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.66	0.70	0.72	0.73	0.75	0.76
Number of sites	2,593	2,593	2,569	2,525	2,321	2,295
Sample size	38,414	38,400	35,795	33,212	30,674	28,353
Estimation periods	2001 - 2020					

(b) Commercial land prices

Explanatory variable / Dependent variable	$[\log(\text{Land price})_{i,t+h} - \log(\text{Land price})_{i,t}]\times100$ Lag h					
	1	2	3	4	5	6
Flood risk						
Flood inundation risk	-1.07 ***	-2.44 ***	-2.94 ***	-3.25 ***	-4.99 ***	-4.90 ***
	[0.27]	[0.62]	[0.91]	[1.10]	[1.74]	[1.83]
Flood inundation risk × number of flood experiences	0.27 ***	0.73 ***	0.64 **	0.69 **	1.23 **	1.18 **
	[0.09]	[0.20]	[0.27]	[0.32]	[0.51]	[0.55]
Sediment disaster risk	-2.66 ***	-10.74 ***	-12.51 ***	-12.46 ***	-12.81 ***	-14.99 ***
	[0.32]	[0.72]	[0.91]	[1.04]	[1.20]	[1.26]
Sediment disaster risk × number of flood experiences	-	-	-	-	-	-
Flood damage	-0.014 ***	-0.037 ***	-0.074 ***	-0.056 **	0.005	0.021
	[0.004]	[0.009]	[0.014]	[0.022]	[0.025]	[0.029]
Flood damage × number of flood experiences	0.001	0.005 *	0.014 ***	0.009	-0.003	0.002
	[0.002]	[0.003]	[0.004]	[0.008]	[0.008]	[0.010]
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.69	0.72	0.73	0.74	0.74	0.76
Number of sites	907	907	889	847	798	782
Sample size	12,987	12,985	12,077	11,187	10,339	9,542
Estimation periods	2001 - 2020					

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
The numbers in [ ] represent the standard error of the coefficient.

Table 6. Summary of parameters used for constructing the EDR

Land use	Assets	Value	Unit	Source
Residential	House	222.3	1,000 yen /m^2	Weighted average of prefectural values in the Flood Control and Economic Survey Manual, weighted by the number of households of each prefecture.
		111.1	m^2	Japan Housing Finance Agency (average value for custom-built home with land).
	Household articles (excl. car)	9,801	1,000 yen /household	Flood Control and Economic Research Manual.
	Car	3,441	1,000 yen /household	Flood Control and Economic Research Manual.
	Land	72.0	1,000 yen /m^2	Official Land Prices of the residential land (median value excluding area at flood risks).
		195.2	m^2	Japan Housing Finance Agency (average value for custom-built home with land).
Commercial	Number of employees	7.7	/office	Calculated from Economic Census (2016).
	Building	216	1,000 yen /m^2	Weighted average of prefectural values in the Flood Control and Economic Survey Manual, weighted by the number of retailers' offices of each prefecture in the Economic Census.
		164	m^2	Sum of the sales area calculated from Economic Census (2016) and other areas including office spaces assumed to be 20% of the sales area.
	Depreciable assets	2,437	1,000 yen /employee	Flood Control and Economic Research Manual.
	Inventory assets	2,800	1,000 yen /employee	Flood Control and Economic Research Manual.
	Land	122	1,000 yen /m^2	Official Land Prices of the commercial land (median value excluding area at flood risks).
		205	m^2	Building area divided by the building coverage ratio in the Official Land Prices of the commercial land (median value).

Table A1. Estimation results based on the hedonic approach (baseline model) with various sample periods

Explanatory variable / Dependent variable	log(Land price)×100							
	Residential land				Commercial land			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Flood risk								
Flood inundation risk	-1.1 **	-1.1 **	-0.9	-0.8	-4.8 **	-5.9 ***	-4.3 **	-4.1 **
	[0.6]	[0.6]	[0.7]	[0.7]	[2.2]	[2.0]	[1.9]	[1.8]
Sediment disaster risk	-12.7 ***	-11.9 ***	-11.5 ***	-9.2 ***	-21.0 *	-20.9 **	-8.8	-3.8
	[2.6]	[2.4]	[2.4]	[2.5]	[11.0]	[10.5]	[11.2]	[11.2]
Locational attributes								
Utilities: gas	53.0 ***	48.4 ***	40.6 ***	36.4 ***	80.7 ***	66.7 ***	47.6 ***	52.0 ***
	[3.0]	[2.8]	[2.9]	[2.9]	[14.0]	[10.9]	[12.5]	[14.8]
Utilities: sewage	35.4 ***	30.7 ***	25.7 ***	27.7 ***	44.3 **	34.7 *	41.8 **	35.7 *
	[4.6]	[4.1]	[4.1]	[4.1]	[19.3]	[20.5]	[20.8]	[19.8]
Utilities: waterworks	21.2	22.2	-10.3	-0.4	-	-	-	-
	[34.3]	[33.8]	[11.5]	[14.2]				
Distance from the nearest station (logarithm)	-20.1 ***	-17.1 ***	-15.9 ***	-14.3 ***	-17.6 ***	-15.5 ***	-14.9 ***	-15.6 ***
	[1.4]	[1.3]	[1.3]	[1.3]	[2.4]	[2.2]	[1.9]	[2.0]
Building coverage ratio	0.5 ***	0.5 ***	0.8 ***	0.8 ***	0.6	1.0 *	0.6	0.7
	[0.1]	[0.1]	[0.1]	[0.2]	[0.6]	[0.6]	[0.7]	[0.8]
Elevation	-0.3 ***	-0.3 ***	-0.3 ***	-0.3 ***	-0.5 ***	-0.5 ***	-0.0	-0.2
	[0.0]	[0.0]	[0.0]	[0.0]	[0.1]	[0.1]	[0.1]	[0.2]
Regional economic attributes								
Taxable income per capita	38.9 ***	40.6 ***	70.7 ***	68.6 ***	9.4 ***	8.6 ***	14.0 ***	10.0 ***
	[3.9]	[3.9]	[3.5]	[3.9]	[2.1]	[2.6]	[3.5]	[3.1]
Fixed effect	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture
Sample size	2,640	2,474	1,981	1,666	922	838	641	593
R-squared	0.75	0.77	0.79	0.77	0.73	0.73	0.74	0.74
Estimation period	2020	2017	2014	2011	2020	2017	2014	2011

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in [ ] represent the standard error of the coefficient.

Table B1-1. Estimation results based on the hedonic approach (baseline model) with various distance restrictions

Explanatory variable / Dependent variable	log(Land price)×100 Residential land (a)	(b)	(c)	Commercial land (a)	(b)	(c)
Flood risk						
Flood inundation risk	-1.1 **	-1.8 ***	1.2 ***	-4.8 **	-3.8 *	0.7
	[0.6]	[0.5]	[0.2]	[2.2]	[2.0]	[0.4]
Sediment disaster risk	-12.7 ***	-14.8 ***	-16.1 ***	-21.0 *	-18.7 *	-23.3 ***
	[2.6]	[2.5]	[1.4]	[11.0]	[10.6]	[4.0]
Locational attributes						
Utilities: gas	53.0 ***	52.3 ***	66.5 ***	80.7 ***	77.7 ***	81.7 ***
	[3.0]	[2.6]	[1.1]	[14.0]	[12.0]	[2.0]
Utilities: sewage	35.4 ***	33.3 ***	36.4 ***	44.3 **	40.9 **	26.5 ***
	[4.6]	[3.7]	[1.3]	[19.3]	[18.4]	[3.4]
Utilities: waterworks	21.2	20.1	40.6 ***	-	-	-
	[34.3]	[28.3]	[9.0]			
Distance from the nearest station (logarithm)	-20.1 ***	-20.0 ***	-17.8 ***	-17.6 ***	-18.5 ***	-10.8 ***
	[1.4]	[1.2]	[0.5]	[2.4]	[1.9]	[0.7]
Building coverage ratio	0.5 ***	0.6 ***	0.1 **	0.6	0.8	1.2 ***
	[0.1]	[0.1]	[0.1]	[0.6]	[0.5]	[0.1]
Elevation	-0.3 ***	-0.3 ***	-0.1 ***	-0.5 ***	-0.5 ***	-0.1 ***
	[0.0]	[0.0]	[0.0]	[0.1]	[0.1]	[0.0]
Regional economic attributes						
Taxable income per capita	38.9 ***	42.3 ***	46.4 ***	9.4 ***	10.5 ***	34.2 ***
	[3.9]	[4.2]	[1.8]	[2.1]	[1.7]	[1.3]
Fixed effect	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture
Sampling distance	1KM	2KM	inf.	1KM	2KM	inf.
Sample size	2,640	3,534	18,160	922	1,220	6,404
R-squared	0.75	0.76	0.80	0.73	0.73	0.73
Estimation period		2020			2020	

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in [ ] represent the standard error of the coefficient.

Table B1-2. Estimation results based on the hedonic approach (extended model) with various distance restrictions

Explanatory variable / Dependent variable	log(Land price)×100					
	Residential land			Commercial land		
	(a)	(b)	(c)	(a)	(b)	(c)
Flood risk						
Flood inundation risk	1.2	0.0	3.5 ***	3.4	3.9	3.4 ***
	[1.0]	[0.9]	[0.4]	[4.6]	[4.4]	[1.0]
Flood inundation risk × number of flood experiences	-1.0 ***	-0.8 **	-0.9 ***	-4.6 **	-4.2 **	-1.1 ***
	[0.4]	[0.4]	[0.1]	[2.0]	[2.0]	[0.4]
Sediment disaster risk	-4.5	-8.0 *	-11.6 ***	-38.2 *	-26.0	-20.1 ***
	[4.4]	[4.2]	[2.7]	[21.0]	[20.4]	[7.7]
Sediment disaster risk × number of flood experiences	-4.1 **	-3.4 *	-1.8 *	7.9	3.5	-0.6
	[1.9]	[1.8]	[1.0]	[7.0]	[6.8]	[2.6]
Locational attributes						
Utilities: gas	53.0 ***	52.2 ***	65.8 ***	81.3 ***	78.3 ***	79.5 ***
	[3.0]	[2.6]	[1.1]	[14.2]	[12.2]	[2.0]
Utilities: sewage	35.2 ***	33.2 ***	36.1 ***	47.4 **	38.9 *	25.6 ***
	[4.5]	[3.7]	[1.3]	[21.6]	[20.2]	[3.4]
Utilities: waterworks	17.8	17.5	41.2 ***	—	—	—
	[32.7]	[27.1]	[9.0]			
Distance from the nearest station (logarithm)	-20.1 ***	-20.0 ***	-17.7 ***	-17.5 ***	-18.5 ***	-10.7 ***
	[1.4]	[1.2]	[0.5]	[2.4]	[1.9]	[0.7]
Building coverage ratio	0.5 ***	0.6 ***	0.1 *	0.6	0.8	1.1 ***
	[0.1]	[0.1]	[0.1]	[0.6]	[0.5]	[0.1]
Elevation	-0.3 ***	-0.3 ***	0.0 ***	-0.5 ***	-0.5 ***	0.0 ***
	[0.0]	[0.0]	[0.0]	[0.1]	[0.1]	[0.0]
Regional economic attributes						
Taxable income per capita	38.8 ***	42.3 ***	46.3 ***	9.3 ***	10.5 ***	34.4 ***
	[3.9]	[4.2]	[1.8]	[2.1]	[1.7]	[1.3]
Fixed effect	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture
Sampling distance	1KM	2KM	inf.	1KM	2KM	inf.
Sample size	2,640	3,534	18,160	922	1,220	6,404
R-squared	0.75	0.76	0.80	0.73	0.74	0.74
Estimation period		2020			2020	

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in [ ] represent the standard error of the coefficient.

Table B2-1. Estimation results based on the hedonic approach (extended model) with an alternative threshold value to count the number of flooding experiences

Explanatory variable / Dependent variable	log(Land price)×100			
	Residential land		Commercial land	
	(a)	(b)	(a)	(b)
Flood risk				
Flood inundation risk	1.2	0.7	3.4	9.4
	[1.0]	[1.5]	[4.6]	[6.1]
Flood inundation risk × number of flood experiences	-1.0 **	-0.4	-4.6 **	-3.1 **
	[0.4]	[0.3]	[2.0]	[1.3]
Sediment disaster risk	-4.5	4.2	-38.2 *	6.3
	[4.4]	[6.3]	[21.0]	[44.3]
Sediment disaster risk × number of flood experiences	-4.1 **	-3.8 **	7.9	-5.1
	[1.9]	[1.5]	[7.0]	[7.7]
Locational attributes				
Utilities: gas	53.0 ***	52.9 ***	81.3 ***	80.4 ***
	[3.0]	[3.0]	[14.2]	[14.0]
Utilities: sewage	35.2 ***	35.6 ***	47.4 **	43.2 **
	[4.5]	[4.6]	[21.6]	[20.7]
Utilities: waterworks	17.8	20.8	-	-
	[32.7]	[33.8]		
Distance from the nearest station (logarithm)	-20.1 ***	-20.1 ***	-17.5 ***	-17.7 ***
	[1.4]	[1.4]	[2.4]	[2.4]
Building coverage ratio	0.5 ***	0.5 ***	0.6	0.7
	[0.1]	[0.1]	[0.6]	[0.6]
Elevation	-0.3 ***	-0.3 ***	-0.5 ***	-0.5 ***
	[0.0]	[0.0]	[0.1]	[0.1]
Regional economic attributes				
Taxable income per capita	38.8 ***	38.9 ***	9.3 ***	8.8 ***
	[3.9]	[3.9]	[2.1]	[2.1]
Fixed effect	Prefecture	Prefecture	Prefecture	Prefecture
Sample size	2,640	2,640	922	922
R-squared	0.75	0.75	0.73	0.73
Percentile values for threshold	75%	50%	75%	50%
Estimation period	2020		2020	

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
The numbers in [ ] represent the standard error of the coefficient.

Table B2-2. Estimation results based on the local projection (extended model)

with an alternative threshold value to count the number of flooding experiences

(a) Residential land prices

Explanatory variable / Dependent variable	$[\log(\text{Land price})_{i,t+h} - \log(\text{Land price})_{i,t}]\times 100$ Lag h					
	1	2	3	4	5	6
Flood risk						
Flood inundation risk	-0.18	-0.59 ***	-0.78 **	-0.78 *	-0.41	-0.25
	[0.12]	[0.22]	[0.32]	[0.45]	[0.66]	[0.77]
Flood inundation risk × number of flood experiences	0.03	0.11 ***	0.15 **	0.12	0.04	0.02
	[0.02]	[0.04]	[0.06]	[0.08]	[0.12]	[0.14]
Sediment disaster risk	-1.01 **	-3.42 ***	-4.43 ***	-4.37 **	-5.83 **	-4.71
	[0.50]	[0.98]	[1.27]	[1.70]	[2.31]	[3.18]
Sediment disaster risk × number of flood experiences	0.08	0.37 **	0.56 ***	0.65 **	1.15 ***	1.17 *
	[0.10]	[0.16]	[0.19]	[0.26]	[0.43]	[0.66]
Flood damage	-0.001	-0.013 **	-0.042 ***	-0.077 ***	-0.083 ***	-0.088 ***
	[0.003]	[0.006]	[0.010]	[0.014]	[0.014]	[0.016]
Flood damage × number of flood experiences	-0.000	0.001	0.006 ***	0.013 ***	0.016 ***	0.020 ***
	[0.001]	[0.001]	[0.002]	[0.003]	[0.003]	[0.003]
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.66	0.70	0.72	0.73	0.74	0.76
Number of sites	2,593	2,593	2,569	2,525	2,321	2,295
Sample size	38,414	38,400	35,795	33,212	30,674	28,353
Estimation periods	2001 - 2020					

(b) Commercial land prices

Explanatory variable / Dependent variable	$[\log(\text{Land price})_{i,t+h} - \log(\text{Land price})_{i,t}]\times 100$ Lag h					
	1	2	3	4	5	6
Flood risk						
Flood inundation risk	-2.01 ***	-4.50 ***	-5.38 ***	-3.96 ***	-5.32 **	-4.08 *
	[0.33]	[0.73]	[1.16]	[1.43]	[2.11]	[2.21]
Flood inundation risk × number of flood experiences	0.31 ***	0.74 ***	0.76 ***	0.43 **	0.57 *	0.31
	[0.06]	[0.12]	[0.18]	[0.22]	[0.30]	[0.32]
Sediment disaster risk	-2.65 ***	-10.70 ***	-12.48 ***	-12.38 ***	-12.70 ***	-14.86 ***
	[0.30]	[0.67]	[0.87]	[0.97]	[1.10]	[1.16]
Sediment disaster risk × number of flood experiences	-	-	-	-	-	-
Flood damage	-0.013 ***	-0.033 ***	-0.080 ***	-0.108 ***	-0.062 **	-0.054
	[0.005]	[0.009]	[0.011]	[0.021]	[0.030]	[0.045]
Flood damage × number of flood experiences	0.000	0.002	0.009 ***	0.017 ***	0.014 *	0.018
	[0.001]	[0.002]	[0.002]	[0.006]	[0.008]	[0.014]
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.69	0.72	0.73	0.74	0.74	0.76
Number of sites	907	907	889	847	798	782
Sample size	12,987	12,985	12,077	11,187	10,339	9,542
Estimation periods	2001 - 2020					

Note: ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in [ ] represent the standard error of the coefficient.