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Estimation of Nonlinear Functions Using Coarsely Discrete Measures in Panel Data: The Relationship Between Land Prices and Earthquake Risk in the Tokyo Metropolitan District

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Estimation of nonlinear functions using coarsely discrete measures in panel data: The relationship between land prices and earthquake risk in the Tokyo Metropolitan District[a] [b]

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Abstract: This paper proposes a simple method to estimate a nonlinear function using only coarsely discrete explanatory variables in panel data. The basic premise is to distinguish carefully between two types of discrete variables by assuming that if the variable changes between two points in time, it increases (decreases) marginally from near the upper (lower) bound one rank below (above). The dynamic pricing behavior at the boundary between two consecutive ranks is then properly approximated. Applying the proposed method, we estimate the nonlinear relationship between land prices and earthquake risk, with the latter being assessed over only five ranks. The panel datasets used comprise some two thousand fixed places over time in the Tokyo Metropolitan District. We interpret the estimated nonlinear land pricing functions using prospect theory from behavioral economics.

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1. Introduction

Nonlinearity matters in the field of behavioral economics generally and in the context of prospect theory more particularly. Estimating nonlinear functions, which frequently emerge from applications of prospect theory, requires explanatory variables to be densely continuous. However, the available variables are often coarsely discrete when using natural experiments. This paper presents a simple method to estimate the predicted nonlinear function by exploiting the panel data structure of the discrete measure concerned.

Our method carefully distinguishes between the two types of coarsely discrete explanatory variables by assuming that if the variable changes between two points in time, it increases (decreases) marginally from near the upper (lower) bound of the rank below (above). We can then properly approximate the dynamic behavior at the boundary between two consecutive ranks about both the lower bound of one rank above and the upper bound of one rank below. The resulting econometric specification displays the features of *nonlinear probability weighting*, *rank dependence*, and *asymmetry between gains and losses*, all of which are essential ingredients in prospect theory. As an application, we estimate the nonlinear relationship between land prices and earthquake risk using the proposed method when earthquake risk is assessed only on a scale of discrete measures. We then interpret the estimation results in terms of various dimensions of prospect theory.

According to the nonlinear probability weighting function (an inverted S-shaped function), frequently adopted as one of the major theoretical devices in prospect theory, including in Tversky and Kahneman (1992) and Prelec (1998), small-sized risks (measured in terms of the objective probability of disastrous events) tend to be overweighted in subjective risk assessment, but such overweighting quickly dissolves as risks approach near-zero. Conversely, medium-sized risks are likely to be underweighted. However, such underweighting also rapidly disappears as risks become large.

Let us employ a simple setup where land pricing is linearly decreasing in the *subjectively* evaluated earthquake risk, but this subjective risk is not observable. All we can observe is the objectively evaluated risk. Assuming that the objective probability is distorted by nonlinear probability weighting, we estimate a nonlinear relationship between land prices and the *objective* risk. More concretely, land prices increase rapidly when the overweighting of the underlying risk dissolves as the risk approaches near-zero. Conversely, land prices are more insensitive to the objective risk when medium-sized risk is underweighted, and land prices decrease quickly when underweighting of the underlying risk disappears as the risk becomes large. As depicted by the solid blue line in **Figure 1**, a nonlinear function consequently emerges concerning the relationship between land prices and objective earthquake risk.

Given the densely continuous risk measures available in cross-sectional datasets, it is quite possible to estimate this nonlinear relationship precisely. However, it is impossible to do this using only coarsely discrete risk measures at a particular point in time. Suppose that three intervals of the objective earthquake risk are represented by discrete indexes, 1 (least risky and safest), 2 (intermediate risk and safety), and 3 (most risky and least safe). We approximate the nonlinear function with the two thick dotted blue lines AB and BC in **Figure 1**, both of which connect the midpoints of each interval. However, this approximation is never able to capture precisely the nonlinear nature of the function in question. Line AB fails to approximate either the right derivative at point A or the left derivative at point B, while line BC fails in capturing either the right derivative at point B or the left derivative at point C.

The basic premise of our proposed estimation method is quite simple. We attempt to compensate for the absence of continuous risk measures in cross-sectional datasets by exploiting changes in coarsely discrete measures between two points in time in panel datasets. Here, we assume that if the discrete measure concerned changes over time, then it either decreases from near the lower bound of the rank above or increases from near the upper bound of the rank below. More concretely, we can exploit this assumption to approximate the right derivative at point A (B) indicated by the red arrow DA (EB) using risk-improving observations from Ranks 2 to 1 (3 to 2) at the border, and the left derivative at point B (C) illustrated by the black arrow DB (EC) using risk-deteriorating observations from Ranks 1 to 2 (2 to 3) at the border.

For this purpose, we have available a perfect environment for natural experiments from the Tokyo Metropolitan District (TMD). The Tokyo Metropolitan Government (TMG) evaluates objective earthquake risks using coarsely discrete indexes from throughout the TMD every five years (excluding those for its western mountainous region). More specifically, it ranks earthquake risk on a relative scale of one (safest) to five (riskiest) for every numbered subdivision (*cho-me* in Japanese) of all wards, cities, and towns in the TMD in 1998, 2002, 2008, 2013, and 2018. For its part, the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT) lists land prices appraised every new year for many fixed points of location in urban areas throughout Japan. For the TMD, the land prices of about two thousand or more fixed locations are appraised every new year.[1]

Given the above research environment, the earthquake risk measures, released publicly by the TMG and available for our study, are not cardinal/continuous, but ordinal/discrete. Thanks to the proposed econometric framework, however, we can still exploit the information associated with the continuous movement of unavailable, but cardinal risk measures at each border between two consecutive risk ranks. The current specification does not focus on how much earthquake risk differs among various points of location in a static context, but it considers in which direction the unobservable risk measure changed marginally at each boundary in a dynamic context. Combining the panel data of discrete earthquake risk ranks with that of land prices for each fixed place, we estimate a nonlinear relationship between land prices and earthquake risk. We then explore whether

[1] Using cross-sectional data not panel data from the same datasets, Nakagawa et al. (2009) estimate the linear relationship between earthquake risk and land prices.

the estimated nonlinear function is consistently interpretable considering prospect theory.

As pointed out by Barberis (2013a, 2013b), O'Donoghue and Sprenger (2018), and others, prospect theory is characterized by three components, comprising nonlinear probability weighting, rank dependence (reference dependence), and asymmetry between gains and losses (loss aversion and diminishing sensitivity), all of which result in a nonlinear relationship between the variables concerned. While these components are often explored empirically by conducting laboratory experiments or using questionnaires, they can also be examined using data from natural experiments, frequently combined with field experiments or questionnaires. The latter empirical research into nonlinear probability weighting has been carried out intensively in the field of finance and insurance.[2] For example, according to Barberis and Huang (2008), Boyer et al. (2010), and Bali et al. (2011), positively skewed securities are overpriced and earn low or even negative risk premiums (expected excess returns) as predicted by nonlinear probability weighting. Barseghyan et al. (2013) employ data on insurance deductions and reveal the overweighting of small probabilities and insensitivity to probability changes, both of which arise from nonlinear probability weighting. Botzen and van den Bergh (2009, 2012) also present evidence consistent with rank dependence and nonlinear probability weighting using flood insurance data. For instance, they find that the willingness-to-pay for flood insurance is higher than the expected loss but insensitive to changes in the underlying probabilities.

In the field of natural disaster risk, the three elements associated with prospect theory are typically examined using natural experiment data, combined with those from field experiments or questionnaires. For example, Iwasaki et al. (2019) provide evidence for reference dependence and loss aversion using the responses of residents to the Fukushima nuclear accident in Japan. Employing questionnaires about health conditions for those forced to relocate after the accident, they set the pre-accident situation as the reference point, and find a kinked relationship between health conditions and household characteristics. Page et al. (2014) present findings on risk-seeking attitudes following a loss by studying the risk-taking behavior of those experiencing the 2011 Australian floods, finding that flood victims would prefer a lottery to insurance. Botzen et al. (2015) also provide evidence consistent with nonlinear probability weighting by interviewing those residing in flood-prone areas in New York, revealing that those that incurred flood damage tend to overestimate flood risk.[3] Lastly, Holden and Quiggin (2017) conclude that farmers in Malawi were

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[2] In empirical finance, the implications of prospect theory are often examined in terms of the behavioral impacts of gain/loss asymmetry without any explicit consideration of nonlinear probability weighting. See Barberis et al. (2001) and Zhang and Semmler (2009), among others.

[3] Beron et al. (1997) find that while earthquake risk was initially overestimated, the hedonic price of earthquake risk fell after the 1989 Loma Prieta earthquake in central California. Gu et al. (2018), conclude that after a huge fault-driven earthquake (the Great Hanshin-Awaji earthquake) destroyed the Hanshin area in western Japan in January 1995, prices of land around the Uemachi fault line, which is adjacent to the fault line responsible for the 1995 earthquake, were heavily discounted. Naoi et al. (2009) show that homeowners and renters revised upward their subjective assessment of earthquake risks following large-scale earthquakes.

more likely to adopt drought-tolerant maize as they became more risk and loss averse through overestimating the risk of drought.

Our study differs from the extant literature in the following respects. First, any change in earthquake risk does not result from a particular large-scale earthquake event, but location-specific events, which have a potential impact on earthquake risk assessments. These include urban redevelopment, land improvement projects, deterioration of social and private structures, and newly revealed local damage. In the TMD, for instance, aging structures in urban and suburban areas, still heavily crowded by older and more fragile wooden houses, invite caution in terms of earthquake risk. Second, our estimation concerns not dependence on a single reference point, but on multiple ranks. Accordingly, the entire shape of the (inverted S-shaped) probability weighting function can be recovered through our estimations. Third, we employ a 20-year dataset of land prices and earthquake risk, not just interval datasets from a few years before and after a particular disaster. In the dataset compiled by the TMG, earthquake risk was assessed systematically every five years from 1998 through 2018. Finally, we do not rely on questionnaires of individual subjective assessments of earthquake risk, but instead, assume that these subjective assessments are reflected in land pricing. That is, we use only publicly available datasets, consisting of objective earthquake risks and observable land prices.

The remainder of the paper is organized as follows. Section 2 presents the econometric specifications used to capture nonlinear probability weighting, rank dependence, and the asymmetry between gains and losses, all essential features of prospect theory. Section 3 describes the datasets of earthquake risk and land prices for the TMD and Section 4 reports the estimation results. Section 5 discusses the results and provides some brief concluding remarks.

2. Econometric specification

Let us present a simple land pricing model in the presence of earthquake risk. In a standard setup, land prices are discounted by expected earthquake damage qD, where q and D denote the objective event probability and the damage from an earthquake, respectively.[4] However, in prospect theory, the subjective not the objective probability is employed. As discussed, the objective probability is distorted according to the nonlinear probability weighting function $\pi(q)$, which is

[4] More rigorously, in the presence of risk aversion on the consumer's side, the expected damage should be further adjusted by the marginal rate of substitution between the current safe state and a forthcoming disastrous state. Suppose that wealth is equal to W in the current safe state, and W declines by uninsured damage Z with an earthquake. Given that the utility function U is increasing, concave, and differentiable, the expected damage qD should be adjusted by $\frac{U'(W-Z)}{U'(W)}$. Here, we assume that the curvature of U is quite small, as for the equity premium puzzle (Mehra and Prescott, 1985). Accordingly, $\frac{U'(W-Z)}{U'(W)}$ is close to one. Thus, we ignore risk aversion in the current specification.

depicted as an inverted S-shape by the solid blue line in **Figure 2** (Tversky and Kahneman, 1992; Prelec, 1998). A small objective probability is overweighted, but such overweighting dissolves as the probability approaches zero. In contrast, a middle-sized objective probability is underweighted, but such underweighting disappears as the probability becomes larger.

We slightly modify the above setup of prospect theory. The weighting function π is still applied to the event probability q. Thus, the expected damage is under or overestimated according to $\pi(q)D$. Then, $\ln[\pi(q)D]$ is subtracted from the logarithmic land price ($\ln P$) after adjustment by other important factors in land pricing. Accordingly, the nonlinear land pricing function of the objectively expected damage ($\ln(qD)$) is depicted by the solid blue line in **Figure 3**, which is a mirror image of **Figure 2** in a vertical direction.

However, we do not have any continuous measure of earthquake risk, $\ln(qD)$. Instead, all we have is a discrete measure of earthquake risk on a scale from one (safest) to five (riskiest). We assume that a smaller (larger) q accompanies a smaller (larger) D, and that the ranks of q and D correspond to that of qD.

Fortunately, we have panel datasets of this discrete risk rank for every numbered subdivision of all wards, cities, and towns in the TMD. We also have available land price panel data for more than two thousand fixed points of location in the TMD. By exploiting these panel datasets of earthquake risk and land prices, we propose use of the following econometric specification to estimate the nonlinear land pricing function.

As assumed, the ranks of q and $\ln D$ correspond with that of $\ln(qD)$. Then, $-[\ln[\pi(q)] + \ln D]$ is specified in a *rank-dependent* manner. To begin, we formulate a stepping function of the discrete risk rank $\sum_{i=2}^{r_{n,t}} a_{i,t}$, where $r_{n,t}$ denotes the discrete risk rank, 2, 3, 4, or 5, and $a_{i,t}$ represents the risk sensitivity for each rank of earthquake risk. We then approximate the logarithmic land price of location n in year t ($\ln P_{n,t}$) using this stepping function together with other explanatory variables for land prices:

$$\ln P_{n,t} = p_t\left(r_{n,t}, x_{j,n,t}, f_n\right) = \sum_{i=2}^{r_{n,t}} a_{i,t} + \sum_{j=1}^{J} b_j x_{j,n,t} + f_n + const_t, \qquad (1)$$

where $x_{j,n,t}$ represents a time-varying factor and f_n denotes a fixed factor for location n. Along with the earthquake risk factor, $x_{j,n,t}$ and f_n play important roles in determining land prices.

We further introduce *gain/loss asymmetry* into equation (1) as follows. If a land price in logarithm ($\ln P_t$) is decreasing in land risks ($r_{n,t}$), then $a_{i,t} < 0$ for $i = 2, 3, 4,$ and 5. As discussed, the interpretation of parameter $a_{i,t}$ in the step function is quite subtle. For example, $a_{2,t}$ cannot be interpreted as either the right derivative for Rank 1 or the left derivative for Rank 2. This is because without densely continuous risk measures for $r_{n,t}$, it is impossible properly to estimate the derivatives at different points using cross-sectional data only. However, it is possible to approximate the two derivatives separately by distinguishing between risk-improving, -deteriorating, and -

invariant observations when using panel data. In other words, the panel data structure allows us to not only eliminate fixed effects (f_n) as is usual but also to differentiate between the two derivatives.

For this purpose, equation (1) is further specified as

$$p_t^+(r_{n,t}, x_{j,n,t}, f_n) = \sum_{i=2}^{r_{n,t}-1} a_{i,t} + a_{r_{n,t},t}^+ + \sum_{j=1}^{J} b_{j,t} x_{j,n,t} + f_n + const_t^+, \tag{2}$$

for risk-deteriorating observations (from $r_{n,t} - 1$ to $r_{n,t}$) that are assumed to deteriorate from near the upper bound of the rank below. On the other hand, equation (1) is specified as

$$p_t^-(r_{n,t}, x_{j,n,t}, f_n) = \sum_{i=2}^{r_{n,t}+1} a_{i,t} - a_{r_{n,t}+1,t}^- + \sum_{j=1}^{J} b_{j,t} x_{j,n,t} + f_n + const_t^-, \tag{3}$$

for risk-improving observations (from $r_{n,t} + 1$ to $r_{n,t}$) which we assume improve from near the lower bound of the rank above. Using the above specifications, we can interpret $a_{r_{n,t},t}^+$ ($a_{r_{n,t},t}^-$) as an approximation for the left (right) derivative. Finally, equation (1) is specified as

$$p_t^0(r_{n,t}, x_{j,n,t}, f_n) = \sum_{i=2}^{r_{n,t}} a_{i,t} + \sum_{j=1}^{J} b_{j,t} x_{j,n,t} + f_n + const_t \ , \tag{4}$$

for risk-invariant observations. Note how equations (2) and (3) are specified in the same gain/loss asymmetric manner as the probability weight in cumulative prospect theory (Tversky and Kahneman, 1992).[5]

To incorporate equations (2), (3), and (4) in a panel data setup, we assume that the risk sensitivity $a_{i,t}$ may change from time t_0 and t_1 in a restrictive manner as follows:

$$a_{i,t_1} = a_{i,t_0} + c. \tag{5}$$

That is, overall risk sensitivity may change over time for equations (2), (3), and (4).[6]

Let us assume that the land pricing function at time t_0 follows equation (4) for risk-improving,

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[5] Using equations (2) and (3), the change in the land price, $\Delta P_{n,t}$, from a change in the risk index is determined by the increment in the probability weighting $-\Delta[\ln[\pi(q)] + \ln D]$. In turn, $-\Delta[\ln[\pi(q)] + \ln D]$ depends on whether the underlying risk worsens or improves. For a risk deterioration from $r_{n,t} - 1$ to $r_{n,t}$, $\Delta P_{n,t} = \sum_{i=2}^{r_{n,t}} a_{i,t}^+ - \sum_{i=2}^{r_{n,t}-1} a_{i,t}^+ = \sum_{i=r_{n,t}}^{5} a_{i,t}^+ - \sum_{i=r_{n,t}+1}^{5} a_{i,t}^+ = a_{r_{n,t},t}^+$, and for a risk improvement from $r_{n,t} + 1$ to $r_{n,t}$, $\Delta P_{n,t} = -\left(\sum_{i=2}^{r_{n,t}+1} a_{i,t}^- - \sum_{i=2}^{r_{n,t}} a_{i,t}^-\right) = -a_{r_{n,t}+1,t}^-$. By comparison, in cumulative prospect theory, the probability weight ω_i is defined by the change in the weighting function, $\Delta\pi(q)$. In turn, $\Delta\pi(q)$ depends on whether outcome x_i, paired with probability q_i, increases or decreases. Suppose $x_1 < \cdots < x_{\bar{n}} < r < x_{\bar{n}+1} < \cdots < x_N$. For outcome gains from a reference point r, $\omega_n = \pi^+\left(\sum_{i=n}^{N} q_i\right) - \pi^+\left(\sum_{i=n+1}^{N} q_i\right)$, and for outcome losses from r, $\omega_n = \pi^-\left(\sum_{i=1}^{n} q_i\right) - \pi^-\left(\sum_{i=1}^{n-1} q_i\right)$.

[6] An alternative specification is (a) $a_{i,t_1} = a_{i,t_0}$ for $i = 2,3,4$, and 5, or (b) $a_{i,t_1} = a_{i,t_0} + c$ for $i = 3$ and 4, and $a_{i,t_1} = a_{i,t_0}$ for $i = 2$ and 5. However, estimation results do not depend that much on which specification is adopted.

deteriorating, and invariant observations. Thus, for an observation whose risk rank increases from r_{n,t_0} to r_{n,t_1} with one rank, the first difference in land prices is expressed as

$$\ln P^{+}_{n,t_1} - \ln P^{0}_{n,t_0} = \sum_{i=2}^{r_{n,t_1}-1} \left(a_{i,t_1} - a_{i,t_0}\right) + a^{+}_{r_{n,t_1},t_1} + \left(\sum_{j=1}^{J} b_{j,t_1} x_{j,n,t_1} - \sum_{j=1}^{J} b_{j,t_0} x_{j,n,t_0}\right) + \left(const^{+}_{t_1} - const_{t_0}\right)$$

$$= c\left(r_{n,t_1} - 2\right) + a^{+}_{r_{n,t_1},t_1} + \textstyle\sum_{j=1}^{J}\left(b_{j,t_1} - b_{j,t_0}\right)x_{j,n,t_1} + \sum_{j=1}^{J} b_{j,t_0}\left(x_{j,n,t_1} - x_{j,n,t_0}\right) + \left(const^{+}_{t_1} - const_{t_0}\right). \qquad (6)$$

For an observation whose risk rank decreases from r_{n,t_0} to r_{n,t_1} with one rank,

$$\ln P^{-}_{n,t_1} - \ln P^{0}_{n,t_0} = \sum_{i=2}^{r_{n,t_1}+1} \left(a_{i,t_1} - a_{i,t_0}\right) - a^{-}_{r_{n,t_1}+1,t_1} + \left(\sum_{j=1}^{J} b_{j,t_1} x_{j,n,t_1} - \sum_{j=1}^{J} b_{j,t_0} x_{j,n,t_0}\right) + \left(const^{-}_{t_1} - const_{t_0}\right)$$

$$= c r_{n,t_1} - a^{-}_{r_{n,t_1}+1,t_1} + \textstyle\sum_{j=1}^{J}\left(b_{j,t_1} - b_{j,t_0}\right)x_{j,n,t_1} + \sum_{j=1}^{J} b_{j,t_0}\left(x_{j,n,t_1} - x_{j,n,t_0}\right) + \left(const^{-}_{t_1} - const_{t_0}\right). \quad (7)$$

Lastly, for an observation without any change in the risk rank,

$$\ln P^{0}_{n,t_1} - \ln P^{0}_{n,t_0} = \sum_{i=2}^{r_{n,t_1}} \left(a_{i,t_1} - a_{i,t_0}\right) + \left(\sum_{j=1}^{J} b_{j,t_1} x_{j,n,t_1} - \sum_{j=1}^{J} b_{j,t_0} x_{j,n,t_0}\right) + \left(const_{t_1} - const_{t_0}\right)$$

$$= c\left(r_{n,t_1} - 1\right) + \textstyle\sum_{j=1}^{J}\left(b_{j,t_1} - b_{j,t_0}\right)x_{j,n,t_1} + \sum_{j=1}^{J} b_{j,t_0}\left(x_{j,n,t_1} - x_{j,n,t_0}\right) + \left(const_{t_1} - const_{t_0}\right). \ (8)$$

Combining equations (6), (7), and (8), the empirical specification takes the following form for observation n where the risk rank changes from r_{n,t_0} by one rank in year t_1, or never changes.

$$\begin{aligned} \ln P_{n,t_1} - \ln P_{n,t_0} = {} & \mathrm{c}\left(r_{n,t_1} - 2\right)D^{+} + \mathrm{c}\left(r_{n,t_1} - 1\right)D^{0} + \mathrm{c}r_{n,t_1}D^{-} + a^{+}_{r_{n,t_1},t_1}D^{+} - a^{-}_{r_{n,t_1}+1,t_1}D^{-} \\ & + \textstyle\sum_{j=1}^{J}\left(b_{j,t_1} - b_{j,t_0}\right)x_{j,n,t_1} + \sum_{j=1}^{J} b_{j,t_0}\left(x_{j,n,t_1} - x_{j,n,t_0}\right) + const, \qquad (9) \end{aligned}$$

where D^{+} (D^{-}, D^{0}) is a dummy variable denoting a deteriorating (improving, invariant) observation.[7] Note that a negative sign appears in front of $a^{-}_{r_{n,t_1}+1,t_1}D^{-}$. We exclude observations whose risk index changes by more than one rank from the estimation.

The above econometric specification shares the features of *nonlinear probability weighting*, *rank dependence*, and *gain/loss asymmetry*, all of which are essential parts of prospect theory. The specification can be described graphically using **Figure 3**, where the nonlinear land pricing function at time t_1 is depicted by the solid blue line. Equation (6) for risk-deteriorating observations is then

[7] It is assumed that $const^{+}_{t_1} - const_{t_0}$ in equation (6), $const^{-}_{t_1} - const_{t_0}$ in equation (7), and $const_{t_1} - const_{t_0}$ in equation (8) are equal to one another. Once a difference among the three constant terms is admitted, some of $a^{+}_{r_{n,t_1},t_1}$ and $a^{-}_{r_{n,t_1},t_1}$ are unidentifiable because of strong multi-collinearity of D^{+}, D^{-}, or D^{0} with these constant terms.

represented by the black arrow, while equation (7) for risk-improving observations is depicted by the red arrow. From this, we anticipate the following findings:

i. If strong nonlinearity exists at Ranks 2 and 4, then $a^{-}_{2,t_1} < a^{+}_{2,t_1}$, and $a^{-}_{5,t_1} > a^{+}_{5,t_1}$ are predicted. If nonlinearity is weak except between Ranks 1 and 2 and between Ranks 4 and 5, then $a^{-}_{3,t_1} \approx a^{+}_{3,t_1}$ and $a^{-}_{4,t_1} \approx a^{+}_{4,t_1}$ are likely to hold.

ii. If strong nonlinearity exists at Ranks 3 and 4, then the result changes to $a^{-}_{3,t_1} < a^{+}_{3,t_1}$ and $a^{-}_{5,t_1} > a^{+}_{5,t_1}$. In addition, $a^{-}_{2,t_1} \approx a^{+}_{2,t_1}$ and $a^{-}_{4,t_1} \approx a^{+}_{4,t_1}$ tend to hold for weakly nonlinear sections.

iii. If strong nonlinearity exists at Ranks 2 and 3, then the result is revised as $a^{-}_{2,t_1} < a^{+}_{2,t_1}$ and $a^{-}_{4,t_1} > a^{+}_{4,t_1}$. In addition, $a^{-}_{3,t_1} \approx a^{+}_{3,t_1}$ and $a^{-}_{5,t_1} \approx a^{+}_{5,t_1}$ tend to hold for weakly nonlinear sections.

We impose $a^{+}_{2,t_1} = a^{-}_{3,t_1}$, $a^{+}_{3,t_1} = a^{-}_{4,t_1}$, and $a^{+}_{4,t_1} = a^{-}_{5,t_1}$ as additional restrictions. These restrictions imply that within the same rank (r_{n,t_1}), the marginal effect from the lower bound ($a^{+}_{r_{n,t_1},t_1}$) is the same as that from the upper bound ($a^{-}_{r_{n,t_1+1},t_1}$). Thanks to these restrictions, the black and red arrows connect at the boundaries between Ranks 1 and 2, Ranks 2 and 3, Ranks 3 and 4, and Ranks 4 and 5.

We make a final remark on the above econometric framework. As explained in Section 3, the earthquake risk rank, which is released publicly by the TMG, is not cardinal/continuous, but ordinal/discrete. But we still exploit the information associated with the continuous movement of the cardinal risk measure, unavailable for researchers, at each border between the two consecutive risk ranks. That is, the current specification does not focus on how much earthquake risk differs among various points of location in a static context, but it considers in which direction the unobservable measure changes marginally at the risk boundary in a dynamic context. For this reason, we can identify the estimates of $a^{-}_{i,t}$ and $a^{+}_{i,t}$, or two-way risk sensitivities from the identical boundary between Ranks $i-1$ and i ($i = 2, 3, 4,$ and 5).

3. Data

3.1. On the Community Earthquake Risk Assessment Study conducted by the TMG

In this section, we describe the two major datasets employed, that is, the Community Earthquake Risk Assessment Study (CERAS) released by the TMG, and the land prices listed by the MLIT. The TMG initiated the CERAS in 1975 and releases it about every five years. In the first three editions, the areas covered and how subdivisions are defined differ substantially,[8] but the most

[8] In the 1st and 2nd editions, the Tokyo 23 wards (the eastern urban areas) and the Tama area (the western suburban areas) were assessed separately. In the 1st (2nd) edition, the former was assessed in 1975 (1984) and the latter in 1980 (1987). Up until the 3rd edition (the 1993 CERAS), each division

recent five editions starting from 1998 are more consistent, systematically expanding coverage to every numbered subdivision (*cho-me* in Japanese) of all wards, cities, and towns in the TMD, except in its western mountainous region. We thus employ the five most recent editions of the CERAS in this study (Bureau of Urban Development, TMG, 1998, 2002,[9] 2008, 2013, and 2018).

The CERAS evaluates earthquake risk for each numbered subdivision in terms of building collapse (BC) risk and fire risk. We choose the former measure for this analysis because it is a more direct measure of geological and construction vulnerability to earthquake hazards. The CERAS does not assume any earthquake occurring at any specific location. It instead assesses earthquake risk on the assumption that a hypothetical earthquake occurs at the same seismic intensity throughout the TMD.

The BC risk is evaluated for each numbered subdivision as follows. First, the number of buildings (not the number of housing units) are tallied according to structural type, building date, and the number of floors. Second, the topographical and geological conditions are assessed across 12 categories. Third, the CERAS computes how many buildings would collapse because of the occurrence of the hypothetical earthquake. For this purpose, shaking at the ground surface, the impacts of liquefaction, and differences between filling and cutting sites are particularly taken into consideration. Fourth, the number of buildings that would collapse is standardized per hectare for each subdivision. Fifth, the number of collapsed buildings per hectare for each subdivision is ordered from high to low. Finally, the ranking is determined by rating the first 1.6% of all subdivisions as Rank 5, the next 5.6% as Rank 4, the next 15.8% as Rank 3, the next 31.8% as Rank 2, and the final 45.2% as Rank 1.

For land prices, the MLIT lists the land prices appraised each new year for many fixed points of location in mostly urban areas throughout Japan. For the TMD, the land prices of more than two thousand fixed places are appraised each year, with 2,917 location points in 1999, 3,254 in 2004, 2,853 in 2009, 2,162 in 2014, and 2,602 in 2019.

We combine the assessed land prices with the earthquake risk rank reported by the CERAS by assuming that the earthquake risk rank compiled by the CERAS is reflected in land prices listed one year after its release. That is, the 1998 (2003, 2008, 2013, and 2018) editions of the CERAS are paired with the land prices listed in 1999 (2004, 2009, 2014, and 2019), respectively. We use only fixed points of location, in which (1) the land prices were listed at both ends of the interval 1999–2004, 2004–2009, 2009–2014, and 2014–2019,[10] and (2) the risk rank changed by only one rank. Under these conditions, we obtain 2,586, 2,653, 1,835, and 1,962 fixed places across the four intervals

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was defined in terms of a 500-meter mesh unit not the numbered subdivision.

[9] The 4th, 5th, 6th, 7th, and 8th editions were released in March 1998, December 2002, February 2008, September 2013, and February 2018, respectively. In the main text, however, the 5th edition is referred to as the 2003 CERAS to maintain a five-year interval among the five editions.

[10] Because the panel of the fixed points of location rotated irregularly, the number of fixed places for which listed land prices are available at both ends of the interval is less than for all points of location in which land prices are listed each year.

1999–2004, 2004–2009, 2009–2014, and 2014–2019, respectively.[11] As shown in **Table 1**, the earthquake risk rank improved or deteriorated for 32.3% of the fixed places in the interval 1999–2004, 24.3% in 2004–2009, 15.1% in 2009–2014, and 10.8% in 2014–2019. Given the nature of relative ranking with a fixed share of each rank, the number of fixed points exhibiting a risk improvement is almost equal to that of those showing a risk deterioration.

Any change in the CERAS earthquake risk rank is driven by three main factors. First, the BC risk reduced because of an improvement in the urban environment. For example, in the urban parts of the TMD, many urban reconstruction plans were implemented in the 2000s. In 2002, the Japanese Government enacted its Act on Special Measures concerning Urban Reconstruction (Urban Reconstruction Act). This allowed the TMG to deregulate restrictions in terms of urban reconstruction, including relaxed floor area ratios together with strict building coverage ratios, private initiatives for urban planning, financial aid, and tax reductions for private urban reconstruction projects. Under the large-scale private projects supported by this act, older more fragile buildings and houses were replaced by newer more resilient buildings in both commercial and residential areas in central and western parts of the Tokyo 23 wards (the eastern urban area in the TMD). Consequently, the BC risk diminished in these areas during the 2000s and 2010s. While the cardinal BC risk measures are not released publicly, a change in the measure, driven by the above factor, is expected to be not discontinuous, but continuous, when only a part of a numbered subdivision is reconstructed by such private projects.

Second, the BC risk increased in areas where many buildings and houses deteriorated, particularly in western parts of the Tama area (the western suburban area in the TMD) as well as eastern parts of the Tokyo 23 wards.[12] In the former where transportation was inconvenient, aging houses and condominiums were seldom reconstructed. In the latter, the area was congested heavily by aging wooden houses, which served as rental houses for low-income earners. However, the TMG developed reconstruction projects for disaster prevention in them.[13] Such public projects, though often small-scale, contributed to a decrease in the BC risk in these risky areas.

Third, the assessment of BC risk is influenced by revisions in the information associated with earthquake risk. In particular, the following revisions in earthquake risk information were

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[11] Given that the land price was listed at both ends of the interval, the risk measure changed by more than one rank for nine of 2,595 subdivisions in the interval 1994–2004, and for seven of 1,842 subdivisions in the interval 2009–2014.

[12] According to the Housing and Land Survey conducted by the Statistics Bureau of Japan, average building/house age decreased by 1.7 years in the Tokyo 23 wards in the interval 1998–2008 and by 4.6 years in its central part (Chiyoda, Chuo, Minato, Shinjuku, and Shibuya). In contrast, the average building/house age increased by 0.2 years in the Tama area during the same interval. However, after most areas with quite old buildings and houses were renovated under large-scale urban projects in the 2010s, the average ages increased by 2.3 years, even in the Tokyo 23 wards, in the interval 2008–2018. However, they increased by more than 4.0 years in the Tama area over the same interval.

[13] These public projects were established under the Act on Promotion of Improvement of Disaster Control in Populated Urban Districts, which was enacted in 2003, and amended majorly in 2003.

incorporated into the 2013 CERAS in light of information newly made available by the Great Hanshin-Awaji earthquake in January 1995, the Chuetsu-oki earthquake in July 2007, and especially the Great East Japan earthquake in March 2011. In particular, the earthquake risks associated with shaking at the ground surface, liquefaction, the age of buildings and houses, and aseismic retrofit treatments were thoroughly revised.

However, note that changes in the urban environment and every risk revision do not necessarily appear as changes in the BC risk rank. For example, if such changes and revisions alter the order of the number of collapsed buildings per hectare only among the numbered subdivisions belonging to the same rank, then the change in rank never shows up in the BC risk compiled by the CERAS. Only if a risk improvement is around the lower bound of a particular rank (other than Rank 1), or risk deterioration is around the upper bound of a specific rank (except Rank 5), does a rank-down or rank-up arise in BC risk. Among the subdivisions whose BC risk is similar at the boundary between the two consecutive ranks, some subdivisions with a risk improvement at a higher rank trade ranks with other subdivisions maintaining the *status quo* at a lower rank. Or, some subdivisions with a risk deterioration at a lower rank swap ranks with other subdivisions maintaining the *status quo* at a higher rank. Consequently, subdivisions with rank-down experience exhibit either a decrease or no change in BC risk, while those with rank-up experience reveal either an increase or no change in BC risk. Here, notice that the declining tendency of BC risk between two points in time among the five ranks is excluded as aggregate effects.

None of the various CERAS editions report the full dataset of BC risk, as measured for every numbered subdivision in terms of the number of collapsed buildings per hectare. But the 2018 CERAS does report some useful statistics. On average, BC risk declined from 3.51 in 2013 to 2.79 in 2018 across the TMD, from 4.97 to 3.85 in the Tokyo 23 wards, and from 1.22 to 1.15 in the Tama area. On this basis, earthquake risk tended to improve more in the Tokyo 23 wards than in the Tama area. Of the 5,128 subdivisions, BC risk changed within +0.1 and −2.0 in 4,245 subdivisions, increased by more than 0.1 in 362 subdivisions, and decreased by more than 2.0 in 521 subdivisions. Thus, after adjusted by overall improvement in BC risk, changes in ranks include both rank-down changes driven by risk improvement, and rank-up changes driven by risk deterioration.

Given the nature of the CERAS, we make the following assumptions on the cardinal BC risk measures, which are not released publicly by the TMG. First, the BC risk measure, assessed for every numbered subdivision, changes only continuously and never jumps within five years partly because not the entire subdivision, but only its part is reconstructed by private and public urban development, and partly because buildings, houses, and social infrastructures deteriorate slowly. Second, the BC risk measure changes marginally at the same border by similar magnitudes in either direction of risk improvement or deterioration.

3.2. How did the discrete risk index change in the CERAS?

Let us look more closely at how the BC risk index changed across the four intervals, 1998–2003, 2003–2008, 2008–2013, and 2013–2018. In Figures 4–5, the borders of the Tokyo 23 wards, as opposed to the Tama area, are drawn using a bold black line. Numbered subdivisions where the risk index decreased (increased) in each 5-year interval are marked by a blue (red) polygon. Crosses (risk deterioration) and black circles (risk improvement) identify the points of location for which officially listed land prices are available at both ends of the intervals 1999–2004, 2004–2009, 2009–2014, and 2014–2019.

Figures 4-A–4-D depict how the BC risk index changed between Ranks 1 and 2 across the four intervals. In the interval 1998–2003 (**Figure 4-A**), the risk rank decreased from Rank 2 to Rank 1 in the western part of the Tokyo 23 wards (Nerima, Suginami, and Setagaya) as well as Fuchu city in the Tama area, primarily from private urban reconstruction in the former and residential development in the latter. In the interval 2003–2008 (**Figure 4-B**), rank change from Rank 2 to Rank 1 took place in the central part of the Tokyo 23 wards (Chiyoda, Minato, and Shinjuku) following enactment of the Act on Special Measures concerning Urban Reconstruction in 2002. Conversely, the risk rank increased from Rank 1 to Rank 2 in the western suburban area, reflecting the increase in older houses and buildings. In the interval 2013–2018 (**Figure 4-D**), the risk rank decreased from Rank 2 to Rank 1 in the central and western parts of the Tokyo 23 wards because of private urban reconstruction. However, the numbered subdivisions with rank-downs contracted substantially, probably because urban reconstructions were initiated in areas that had already been classified as Rank 1. In this interval, suburban areas were also subject to rank-ups (risk deterioration).

In the interval 2008–2013 (**Figure 4-C**), urban reconstruction and suburban deterioration continued as in the intervals 1996–2003, 2003–2008, and 2013–2018. Nevertheless, how the risk rank changed between Ranks 1 and 2 differs during this interval from the other three. That is, rank-downs were often observed in the Tama area, whereas rank-ups were more frequent in the Tokyo 23 wards. A major reason for this is that as mentioned, the 2013 CERAS included a revised risk assessment criterion given information newly available from the Great Hanshin-Awaji earthquake in January 1995, the Chuetsu-oki earthquake in July 2007, and the Great East Japan earthquake in March 2011. In particular, serious consideration of liquefaction risks acted against coastal and riverside urban areas in the Tokyo 23 wards but worked in favor of hilly suburban parts of the Tama area.

How the risk index changed between Ranks 2 and 3 across the four intervals almost follows the same pattern as those for Ranks 1 and 2. Thus, we move to explore how the risk rank changed among Ranks 3, 4, and 5 across the four intervals. **Figure 5** depicts how the BC risk changed in the interval 1998–2003. As shown, a change in the risk index among the lower three ranks took place in the eastern part of the Tokyo 23 wards. As mentioned, many blocks in these areas were heavily congested by aging wooden houses. Therefore, BC risk increased with further building/house deterioration and decreased through public reconstruction projects for disaster control. The same pattern as the interval 1998–2003 is observed in the three intervals that follow.

4. Estimation results

4.1. Choice of dependent and explanatory variables

For estimation purposes, we respecify equation (9) as follows:

$$\ln P_{n,t_1} - \ln P_{n,t_0} = \mathrm{c}(r_{n,t_1} - 2)D^+ + \mathrm{c}(r_{n,t_1} - 1)D^0 + \mathrm{c}r_{n,t_1}D^- + \sum_{i=2}^{5} a^+_{i,t_1} D^+_{i-1,i} - \sum_{i=2}^{5} a^-_{i,t_1} D^-_{i,i-1}$$
$$+ \sum_{j=1}^{J}(b_{j,t_1} - b_{j,t_0})x_{j,n,t_1} + \sum_{j=1}^{J} b_{j,t_0}(x_{j,n,t_1} - x_{j,n,t_0}) + +const + \varepsilon_n, \qquad (11)$$

where $D^+_{i-1,i}$ takes a value of one if the risk rank increases from Rank $i-1$ by one rank, zero otherwise. Similarly, $D^-_{i,i-1}$ takes a value of one if the risk rank decreases from Rank i by one rank, zero otherwise. ε_n is the error term. In addition, equation (11) is estimated under alternative restrictions on coefficients, including the set of $a^+_{2,t_1} = a^-_{3,t_1}$, $a^+_{3,t_1} = a^-_{4,t_1}$, and $a^+_{4,t_1} = a^-_{5,t_1}$.

In the estimation, $\ln P_{n,t_1}$ and $\ln P_{n,t_0}$ are adjusted by the yearly average. Thus, the dependent variable in equation (11) denotes a relative not absolute change in land prices. The time-varying variable $x_{j,n,t}$ includes population density for $j = 1$, the distance to the nearest railway station for $j = 2$, and the floor area ratio for $j = 3$. Here, $x_{1,n,t}$ is available as a 1-kilometer mesh from the 2000, 2005, 2010, and 2015 digital versions of the population census,[14] while both $x_{2,n,t}$ and $x_{3,n,t}$ are obtainable from the dataset of listed land prices. We assume that other potentially important variables are incorporated as fixed effects, an assumption requiring some qualification in Section 4.3.

As described in Section 3, the TMG released earthquake risk ranks for every numbered subdivision of all wards, cities, and towns in the TMD in 1998, 2003, 2008, 2013, and 2018. The appraised land prices for the approximately two thousand fixed points of location in the TMD as listed by the MLIT are for the new year. Thus, a change in relative land prices in the period 1999 to 2004 is associated with a change in the BC risk rank in the period 1998 to 2003. A similar pair is constructed for changes in relative land prices between 2004 and 2009, 2009 and 2014, and 2014 and 2019.

The number of observations in which the land prices are available at both ends of the interval is 2,595 in 1999–2004, 2,653 in 2004–2009, 1,842 in 2009–2014, and 1,962 in 2014–2019. We exclude observations where the BC risk rank changes by two or more ranks (nine observations in 1999–2004 and seven observations in 2009–2014). In addition, the number of observations employed for the estimation further reduces because population density data are not available for some listed points adjacent to the coast (five points in 1999–2004, two in 2004–2009, and one in 2009–2014). **Table 1**

[14] The 2020 digital version of the population census was unavailable at the time of this research.

reports descriptive statistics for the changes in relative land prices, given the changes in the BC risk ranks, and **Table 2** provides descriptive statistics for the changes in the explanatory variables during each interval and at the end of each interval.

4.2. Estimation results under alternative restrictions on coefficients

Table 3-1 provides ordinary least squares estimation results for equation (11) without any restrictions on the coefficients. Heteroskedasticity-robust standard deviations are in parentheses. Let us first explore the nonlinearity predicted by prospect theory at the lower tails of the BC risk ranks. In the intervals 1999–2004 and 2004–2009, we detect nonlinearity between Ranks 1 and 2. As implied by $a^{-}_{2,t_0} < a^{+}_{2,t_0}$, the regression slope is steeper moving from Rank 2 to 1 and less downward moving from Rank 1 to 2. More precisely, a^{-}_{2,t_0} is negative in both intervals. However, a^{+}_{2,t_0} is significantly positive in the interval 1999–2004, whereas $a^{+}_{2,t_0} = 0$ cannot be rejected for the interval 2004–2009. In the interval 2014–2019, we identify nonlinearity between not Ranks 1 and 2 ($a^{-}_{2,t_0} \approx a^{+}_{2,t_0} < 0$), but Ranks 2 and 3 ($a^{-}_{3,t_0} < 0 < a^{+}_{3,t_0}$).

Moving to the upper tail of the BC risk ranks, we identify nonlinearity between Ranks 4 and 5 in the intervals 1999–2004 and 2014–2019. As implied by $a^{-}_{5,t_0} > a^{+}_{5,t_0}$, the regression slope is less downward from Ranks 5 to 4 and steeper from Ranks 4 to 5. More precisely, a^{+}_{5,t_0} is significantly negative in both intervals, whereas $a^{-}_{5,t_0} = 0$ cannot be rejected in the interval 1999–2004, and a^{-}_{5,t_0} is significantly positive in the interval 2014–2019. As implied by $a^{-}_{4,t_0} > a^{+}_{4,t_0}$, we detect nonlinearity between Ranks 3 and 4 in the interval 2004–2009. In these three intervals (1999–2004, 2004–2009, and 2014–2019), risk sensitivity is sometimes estimated to be not negative, but positive among Ranks 2, 3, and 4. One interpretation is that the inverse S-shaped probability weighting function may be slightly downward- not slightly upward-sloping at intermediate levels of risk.

What is puzzling is that no theoretically consistent nonlinearity is detected in the interval 2009–2014. That is, we can identify neither $a^{-}_{2,t_0} < a^{+}_{2,t_0}$ nor $a^{-}_{5,t_0} > a^{+}_{5,t_0}$. An obvious explanation is that the 2013 CERAS substantially revised the criteria for risk assessment. As discussed in Section 3.2, BC risk increased in coastal and riverside urban parts of the Tokyo 23 wards but decreased in hilly suburban parts in the Tama area. However, such changes in earthquake risks might have already been reflected in the appraisal of the listed land prices.

Let us then examine the estimated coefficients for the other explanatory variables. The significantly positive c for the intervals 1999–2004, 2004–2009, and 2014–2019 suggests that overall risk sensitivity is becoming smaller over time. As shown by the estimations of b_{1,t_0} and $b_{1,t_1} - b_{1,t_0}$, the impact of population density on land prices is more positive in the interval 1999–2004, remains positive in 2004–2009, and becomes negative in 2009–2014. Note that population density data are not available for the interval 2014–2019. As implied by the negative b_{2,t_0}, although not necessarily significant, land prices rise as the distance to the nearest station becomes shorter. As the significantly negative $b_{2,t_1} - b_{2,t_0}$ suggests, this tendency becomes stronger over time. The impact of the floor area ratio (b_{3,t_0}) is mixed. In the interval 1999–2004, land prices increase with the floor area ratio, but in the remaining three intervals, land prices are fairly insensitive to the floor area ratio. As for the estimation of $b_{3,t_1} - b_{3,t_0}$, b_{3,t_0} increases in the intervals 2004–2009 and 2014–2019 but decreases in the interval 2009–2014. According to the estimated coefficient on a dummy variable of residential land use, land prices increase more for observations of residential use in all intervals except 2009–2014.

We now impose parameter restrictions on equation (11) to make the estimation results more visual. First, **Table 3-2** reports estimation results with parameter restrictions $a^{+}_{2,t_1} = a^{-}_{3,t_1}$, $a^{+}_{3,t_1} = a^{-}_{4,t_1}$, and $a^{+}_{4,t_1} = a^{-}_{5,t_1}$. Given these restrictions, the land pricing function connects between Ranks 2 and 3 and Ranks 3 and 4. According to **Figure 6-1**, nonlinearity appears between Ranks 1 and 2 and between Ranks 3 and 4 in the interval 1999–2004, between Ranks 1 and 2 and Ranks 3 and 4 in 2004–2009, and between Ranks 2 and 3 and Ranks 4 and 5 in 2014–2019. However, in the interval 2009–2014, no theoretically consistent nonlinearity appears.

The estimation results with two sets of more severe parameter restrictions are reported except for the interval 2009–2014 in **Table 3-3**. **Figure 6-2** plots the land pricing function where $a^{+}_{2,t_1} = a^{-}_{3,t_1} = a^{+}_{3,t_1} = a^{-}_{4,t_1} = a^{+}_{4,t_1} = a^{-}_{5,t_1}$ in Spec. A in Table 3-3. In this case, nonlinearity is imposed between Ranks 1 and 2, and between Ranks 4 and 5. In **Figure 6-3** based on Spec. B in Table 3-3, nonlinearity is imposed between Ranks 1 and 2 and between Ranks 3 and 4 in the intervals 1999–2004 and 2004–2009 ($a^{+}_{2,t_1} = a^{-}_{3,t_1} = a^{+}_{3,t_1} = a^{-}_{4,t_1}$ and $a^{+}_{4,t_1} = a^{-}_{5,t_1}$), and between Ranks 2 and 3 and Ranks 4 and 5 in 2014–2019 ($a^{+}_{2,t_1} = a^{-}_{3,t_1}$ and $a^{+}_{3,t_1} = a^{-}_{4,t_1} = a^{+}_{4,t_1} = a^{-}_{5,t_1}$).

4.3. On the potential correlation between the BC risk measure and economic activity

One potential problem associated with the above econometric exercise is that the BC risk measure may be correlated with economic activity and that the estimations of risk sensitivity a^{-}_{i,t_1} and a^{+}_{i,t_1} are then likely to be biased, depending on whether proxies for economic activity are included as explanatory variables. For example, people and firms may move into (out of) earthquake risk-improved (-deteriorated) areas. Accordingly, the BC risk measure is correlated negatively with regional population density and community income in terms of both levels at a particular point in time and changes between two points in time.

However, the current estimation results are almost free from possible missing-variable bias. Here, population density as an explanatory variable x_{1,n,t_1} is expected to be correlated with the cardinal BC risk measure, although the latter is never fully disclosed in any edition of the CERAS. However, the estimation of risk sensitivity a^{-}_{i,t_1} and a^{+}_{i,t_1} scarcely changes, even if both x_{1,n,t_1} and $x_{1,n,t_1} - x_{1,n,t_0}$ are omitted from the explanatory variables in the three intervals. For example, **Figure 6-4** compares estimation results between with and without population density following the econometric specification used in Table 3-2. According to this figure, excluding population density has no impact on the basic pattern of risk sensitivity in the intervals 1999–2004, 2004–2009 and 2009–2014.

Two reasons may be responsible for the absence of missing-variable bias. First, the current estimation focuses on not all, but some of the listed points of location, for which the BC risk measure changes over time at the border between the two consecutive ranks. In only 32.3% (24.3%, 15.1%, and 10.8%) of all points was the BC risk rank revised at the border in the interval 1999–2004 (2004–2009, 2009–2014, and 2014–2019). The correlation between the BC risk measure and population density may then be strong among observations in the same rank, but weak among observations at the border between the two consecutive ranks. Second, the BC risk measure may be correlated with population density strongly at levels, but weakly in changes. Population increases (decreases) may not immediately follow risk improvement (deterioration). Overall, because of our focus on dynamic not static behavior, the estimation results appear free from missing-variable bias.

5. Conclusion

Using the newly proposed econometric framework, this paper addresses land pricing behavior at the border between the two consecutive risk ranks over a five-year interval and reveals a nonlinear relationship in the changes between land prices and earthquake risk. This framework employs only the available ordinal risk measure in panel data, but it allows us to exploit the information associated with the continuous movement of the unavailable cardinal risk measure at the border between the two consecutive risk ranks. The empirical findings, in particular the risk improvement/deterioration asymmetry, are consistent with the implications of prospect theory. In all intervals except for 2009–2014, risk improvement was reflected in a substantial increase in land prices at the border between Ranks 1 and 2 and Ranks 2 and 3, but risk deterioration was less evident in a decrease in land prices at the same borders. In contrast, risk deterioration appeared as a noticeable decrease in land prices at the borders between Ranks 4 and 5 and Ranks 3 and 4, but risk improvement did not result in a considerable increase in land prices at the same borders.

The finding of the improvement/deterioration asymmetry suggests several policy implications. First, earthquake risk is improved by urban/suburban development and reconstruction in safer areas (those in Ranks 1 and 2), and this manifests itself as marked increases in land prices. For this reason, private projects drive regional development in safer areas. Thus, even large-scale property projects in the central part of the Tokyo 23 wards and transportation-convenient parts of the Tama area could be left to private initiatives or market mechanisms.

Second, earthquake risk deterioration through aging buildings, houses, and social infrastructure is reflected in only minor decreases in land prices in safer areas, but quite substantial decreases in riskier areas (those in Ranks 5 and 4). For these riskier areas, private developers would not expect any benefits from reconstruction-induced increases in land prices. Consequently, without public intervention, risky areas, particularly those heavily congested with aging wooden houses in the eastern part of the Tokyo 23 wards, could suffer from a serious decline in land prices. In extreme cases, these areas could become slums. The reconstruction projects for disaster control initiated by the TMG, though often small-scale, indeed prevented land prices from slumping sharply in these areas.

Finally, a proper combination of private development projects in safer areas and public reconstruction projects in riskier areas could contribute to both promoting urban/suburban intensification and preventing more fragile urban areas from collapsing into slums and being severely segregated. In the gentrification process in risky areas, however, the central and local governments need to provide largish housing allowances for low-income earners who cannot live in expensive rental houses.[15]

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[15] Even with urban development in safe areas, low-income earners and older households are often crowded out from safe, but expensive, rental apartments.

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Table 1: Descriptive statistics of changes in relative land prices dependent on changes in risk rank

		# of obs.	Mean	Std. Dev.	Min	Max
1999→2004	1→1	893	-0.3354	0.1662	-1.3981	0.1916
	2→1	270	-0.2379	0.1166	-0.6508	-0.0547
	1→2	205	-0.2711	0.1768	-0.8566	0.1153
	2→2	531	-0.2082	0.1204	-0.8048	0.1238
	3→2	136	-0.2284	0.1378	-0.7465	-0.0604
	2→3	114	-0.2211	0.1141	-0.5266	0.0564
	3→3	241	-0.2418	0.1113	-0.5359	-0.0327
	4→3	37	-0.2718	0.1342	-0.5165	-0.0555
	3→4	50	-0.2643	0.0903	-0.5117	-0.0718
	4→4	63	-0.2395	0.0944	-0.4737	-0.0348
	5→4	8	-0.2292	0.0997	-0.3784	-0.1234
	4→5	15	-0.2530	0.1030	-0.5151	-0.0993
	5→5	23	-0.2136	0.0867	-0.4252	-0.0880
	total	2586				
	risk improvement	451	17.4%			
	risk deterioration	384	14.8%			
	changes in risk	835	32.3%			

		Obs	Mean	Std. Dev.	Min	Max
2004→2009	1→1	958	-0.2670	0.1095	-1.1064	0.2306
	2→1	159	-0.0383	0.2006	-0.4248	0.5621
	1→2	165	-0.2395	0.0630	-0.3870	-0.0282
	2→2	675	-0.1575	0.1343	-0.3797	0.6624
	3→2	117	-0.1359	0.1164	-0.2886	0.4439
	2→3	111	-0.1621	0.1095	-0.3560	0.0951
	3→3	266	-0.1616	0.0953	-0.3209	0.1721
	4→3	37	-0.1689	0.0850	-0.3044	-0.0021
	3→4	38	-0.1690	0.0858	-0.2932	-0.0008
	4→4	81	-0.1886	0.0774	-0.3097	0.0254
	5→4	10	-0.2024	0.0755	-0.2557	-0.0015
	4→5	9	-0.1993	0.0999	-0.3595	-0.0505
	5→5	27	-0.1921	0.0765	-0.2862	-0.0432
	total	2653				
	risk improvement	323	12.2%			
	risk deterioration	323	12.2%			
	changes in risk	646	24.3%			

		Obs	Mean	Std. Dev.	Min	Max
2009→2014	1→1	723	-0.0348	0.0535	-0.3802	0.0685
	2→1	65	-0.0544	0.0730	-0.3511	0.0652
	1→2	65	-0.0320	0.0441	-0.1971	0.0265
	2→2	549	-0.0385	0.0541	-0.3683	0.0887
	3→2	54	-0.0328	0.0336	-0.1279	0.0300
	2→3	46	-0.0564	0.0567	-0.2887	0.0006
	3→3	207	-0.0367	0.0477	-0.2365	0.1404
	4→3	19	-0.0579	0.0357	-0.1369	0.0035
	3→4	22	-0.0087	0.0565	-0.1310	0.1013
	4→4	56	-0.0212	0.0448	-0.1108	0.1375
	5→4	1	-0.0925	.	-0.0925	-0.0925
	4→5	6	-0.0164	0.0205	-0.0411	0.0102
	5→5	22	-0.0321	0.0333	-0.1007	0.0284
	total	1835				
	risk improvement	139	7.6%			
	risk deterioration	139	7.6%			
	changes in risk	278	15.1%			

		Obs	Mean	Std. Dev.	Min	Max
2014→2019	1→1	802	-0.1697	0.1210	-0.4135	0.2992
	2→1	58	-0.0799	0.1026	-0.2634	0.1597
	1→2	65	-0.1964	0.0805	-0.4026	0.1077
	2→2	627	-0.0984	0.1106	-0.3610	0.5374
	3→2	29	-0.0150	0.1016	-0.1430	0.4185
	2→3	25	-0.0954	0.0809	-0.2259	0.1026
	3→3	231	-0.0820	0.0847	-0.2244	0.1404
	4→3	10	-0.0629	0.0533	-0.1583	0.0249
	3→4	14	-0.0698	0.1074	-0.1874	0.1728
	4→4	66	-0.0832	0.1065	-0.2066	0.3982
	5→4	6	-0.0682	0.0841	-0.1651	0.0473
	4→5	5	-0.1181	0.0808	-0.1853	-0.0047
	5→5	24	-0.0808	0.0553	-0.1734	0.0019
	total	1962				
	risk improvement	103	5.2%			
	risk deterioration	109	5.6%			
	changes in risk	212	10.8%			

Table 2: Basic statistics of time-varying explanatory variables

1999-2004 change and 2004 level	Obs	Mean	Std. Dev.	Min	Max
Δpopulation density (thousand)	2,581	0.540	0.882	-1.576	5.309
population density (thousand)	2,581	13.245	6.067	0.004	31.123
Δdistance to the nearest station (km)	2,581	-0.010	0.131	-1.650	2.480
distance to the nearest station (km)	2,581	0.969	0.995	0.000	10.600
residential use (0 or 1)	2,581	0.683			
Δfloor area ratio (%)	2,581	0.9%	14.7%	-20.0%	400.0%
floor area ratio (%)	2,581	229.8%	172.5%	0.0%	1000.0%
2004-2009 change and 2009 level					
Δpopulation density (thousand)	2,651	0.649	0.903	-1.933	7.607
population density (thousand)	2,651	13.916	6.513	0.002	32.079
Δdistance to the nearest station (km)	2,651	-0.028	0.231	-6.000	1.300
distance to the nearest station (km)	2,651	0.873	0.950	0.000	10.600
residential use (0 or 1)	2,651				
Δfloor area ratio (%)	2,651	0.9%	15.9%	-320.0%	300.0%
floor area ratio (%)	2,651	260.2%	193.7%	0.0%	1300.0%
2009-2014 change and 2014 level					
Δpopulation density (thousand)	1,834	0.498	0.942	-5.046	5.330
population density (thousand)	1,834	14.237	6.832	0.144	31.203
Δdistance to the nearest station (km)	1,834	-0.005	0.137	-3.600	2.800
distance to the nearest station (km)	1,834	0.830	0.911	0.000	8.000
residential use (0 or 1)	1,834				
Δfloor area ratio (%)	1,834	0.1%	3.3%	0.0%	100.0%
floor area ratio (%)	1,834	279.7%	203.2%	50.0%	1300.0%
2014-2019 change and 2019 level					
Δdistance to the nearest station (km)	1,962	-0.001	0.055	-0.560	0.500
distance to the nearest station (km)	1,962	0.838	0.909	0.000	7.900
residential use (0 or 1)	1,962				
Δfloor area ratio (%)	1,962	0.1%	2.6%	0.0%	100.0%
floor area ratio (%)	1,962	276.4%	202.7%	50.0%	1300.0%

Note

1. The floor area ratio is set at zero in urbanization control areas.

Table 3-1: Estimation results without parameter restrictions

	1999 to 2004	2004 to 2009	2009 to 2014	2014 to 2019
Coefficient on risk rank at the end year, $r_{n,t_1}-2$, $r_{n,t_1}-1$, or r_{n,t_1} (c)	0.017*** (0.004)	0.011*** (0.002)	-0.001 (0.001)	0.013*** (0.002)
Risk sensitivity, a^-_{2,t_1}	-0.010 (0.007)	-0.095*** (0.014)	0.008 (0.007)	-0.022** (0.009)
a^-_{3,t_1}	0.020* (0.011)	-0.023** (0.011)	-0.004 (0.004)	-0.031** (0.013)
a^-_{4,t_1}	0.082*** (0.020)	0.033** (0.013)	0.016*** (0.006)	0.045*** (0.010)
a^-_{5,t_1}	0.034 (0.036)	0.084*** (0.015)	0.064*** (0.005)	0.042*** (0.012)
Risk sensitivity, a^+_{2,t_1}	0.048*** (0.010)	0.003 (0.005)	0.001 (0.004)	-0.026*** (0.009)
a^+_{3,t_1}	0.037*** (0.009)	0.004 (0.007)	-0.022*** (0.005)	0.023** (0.010)
a^+_{4,t_1}	-0.033** (0.014)	-0.035*** (0.012)	0.032*** (0.011)	0.001 (0.013)
a^+_{5,t_1}	-0.065** (0.028)	-0.024 (0.023)	0.021** (0.009)	-0.036** (0.018)
Coefficient on a change in logarithmic population density, $x_{1,n,t_1}-x_{1,n,t_0}$ (b_{1,t_0})	0.035 (0.043)	0.051 (0.039)	-0.099*** (0.020)	
Coefficient on logarithmic population density at the end year, x_{1,n,t_1} $(b_{1,t_1}-b_{1,t_0})$	0.065*** (0.011)	0.003 (0.005)	0.026*** (0.003)	
Coefficient on a change in distance to the nearest station, $x_{2,n,t_1}-x_{2,n,t_0}$ (b_{2,t_0})	-0.006 (0.023)	-0.045** (0.018)	0.000 (0.004)	-0.011 (0.027)
Coefficient on distance to the nearest station at the end year, x_{2,n,t_1} $(b_{2,t_1}-b_{2,t_0})$	-0.065*** (0.004)	-0.033*** (0.002)	-0.005*** (0.001)	-0.026*** (0.002)
Coefficient on a change in a floor area ratio, $x_{3,n,t_1}-x_{3,n,t_0}$ (b_{3,t_0})	0.118*** (0.028)	-0.020* (0.012)	-0.005 (0.005)	-0.002 (0.021)
Coefficient on a floor area ratio at the end year, x_{3,n,t_1} $(b_{3,t_1}-b_{3,t_0})$	0.003 (0.003)	0.044*** (0.002)	-0.014*** (0.001)	0.040*** (0.002)
Coefficient on a dummy of residential use, $x_{4,n}$	0.100*** (0.009)	0.057*** (0.007)	0.000 (0.003)	0.017*** (0.006)
Constant term $(const)$	-0.912*** (0.103)	-0.365*** (0.046)	-0.231*** (0.025)	-0.235*** (0.009)
Number of observations	2,581	2,651	1,834	1,962
R-squared	0.394	0.531	0.391	0.626

Notes:

1. Heteroskedasticity-robust standard errors in parentheses.
2. ***, **, and * denote p-values less than .01, .05, and .10, respectively.

Table 3-2: Estimation results with parameter restrictions ($a^{+}_{2,t_1} = a^{-}_{3,t_1}$, $a^{+}_{3,t_1} = a^{-}_{4,t_1}$, and $a^{+}_{4,t_1} = a^{-}_{5,t_1}$)

	1999 to 2004	2004 to 2009	2009 to 2014	2014 to 2019
Coefficient on risk rank at the end year, $r_{n,t_1}-2$, $r_{n,t_1}-1$, or r_{n,t_1} (c)	0.014*** (0.004)	0.007*** (0.002)	-0.002 (0.001)	0.013*** (0.002)
Risk sensitivity, a^{-}_{2,t_1}	-0.010 (0.007)	-0.096*** (0.014)	0.007 (0.007)	-0.022** (0.009)
$a^{+}_{2,t_1} = a^{-}_{3,t_1}$	0.034*** (0.008)	-0.011* (0.006)	-0.002 (0.003)	-0.028*** (0.007)
$a^{+}_{3,t_1} = a^{-}_{4,t_1}$	0.046*** (0.009)	0.010 (0.006)	-0.011** (0.005)	0.029*** (0.008)
$a^{+}_{4,t_1} = a^{-}_{5,t_1}$	-0.023* (0.013)	-0.009 (0.012)	0.035*** (0.010)	0.013 (0.010)
a^{+}_{5,t_1}	-0.059** (0.028)	-0.018 (0.023)	0.024*** (0.009)	-0.035* (0.018)
Coefficient on a change in logarithmic population density, $x_{1,n,t_1} - x_{1,n,t_0}$ (b_{1,t_0})	0.036 (0.043)	0.048 (0.039)	-0.100*** (0.019)	
Coefficient on logarithmic population density at the end year, x_{1,n,t_1} $(b_{1,t_1} - b_{1,t_0})$	0.067*** (0.011)	0.004 (0.005)	0.026*** (0.003)	
Coefficient on a change in distance to the nearest station, $x_{2,n,t_1} - x_{2,n,t_0}$ (b_{2,t_0})	-0.004 (0.023)	-0.045** (0.018)	-0.000 (0.004)	-0.012 (0.026)
Coefficient on distance to the nearest station at the end year, x_{2,n,t_1} $(b_{2,t_1} - b_{2,t_0})$	-0.065*** (0.004)	-0.034*** (0.002)	-0.005*** (0.001)	-0.026*** (0.002)
Coefficient on a change in a floor area ratio, $x_{3,n,t_1} - x_{3,n,t_0}$ (b_{3,t_0})	0.117*** (0.028)	-0.020* (0.012)	-0.003 (0.005)	-0.001 (0.022)
Coefficient on a floor area ratio at the end year, x_{3,n,t_1} $(b_{3,t_1} - b_{3,t_0})$	0.004 (0.003)	0.044*** (0.002)	-0.014*** (0.001)	0.040*** (0.002)
Coefficient on a dummy of residential use, $x_{4,n}$	0.101*** (0.009)	0.057*** (0.007)	0.000 (0.003)	0.017*** (0.006)
Constant term $(const)$	-0.922*** (0.103)	-0.373*** (0.046)	-0.231*** (0.025)	-0.234*** (0.009)
Number of observations	2,581	2,651	1,834	1,962

Notes:
1. Heteroskedasticity-robust standard errors in parentheses.
2. ***, **, and * denote p-values less than .01, .05, and .10, respectively.

Table 3-3: Estimation results for alternative parameter restrictions

	1999 to 2004		2004 to 2009		2014 to 2019	
	Spec. A	Spec. B	Spec. A	Spec. B	Spec. A	Spec. B
Coefficient on risk rank at the end year, $r_{n,t_1}-2$, $r_{n,t_1}-1$, or r_{n,t_1} (c)	0.012***	0.015***	0.008***	0.008***	0.013***	0.013***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Risk sensitivity, a^{-}_{2,t_1}	-0.011	-0.010	-0.095***	-0.095***	-0.022**	-0.022**
	(0.007)	(0.007)	(0.014)	(0.014)	(0.009)	(0.009)
$a^{+}_{2,t_1}=a^{-}_{3,t_1}=a^{+}_{3,t_1}=a^{-}_{4,t_1}=a^{+}_{4,t_1}=a^{-}_{5,t_1}$	0.030***		-0.004		-0.008	
	(0.006)		(0.004)		(0.006)	
$a^{+}_{2,t_1}=a^{-}_{3,t_1}=a^{+}_{3,t_1}=a^{-}_{4,t_1}$		0.038***		-0.003		
		(0.006)		(0.004)		
$a^{+}_{4,t_1}=a^{-}_{5,t_1}$		-0.023*		-0.010		
		(0.013)		(0.012)		
$a^{+}_{2,t_1}=a^{-}_{3,t_1}$						-0.028***
						(0.007)
$a^{+}_{3,t_1}=a^{-}_{4,t_1}=a^{+}_{4,t_1}=a^{-}_{5,t_1}$						0.023***
						(0.006)
a^{+}_{5,t_1}	-0.054**	-0.060**	-0.018	-0.019	-0.036**	-0.034*
	(0.028)	(0.028)	(0.023)	(0.023)	(0.018)	(0.018)
On a change in logarithmic population density, $x_{1,n,t_1}-x_{1,n,t_0}$ (b_{1,t_0})	0.037	0.036	0.050	0.050		
	(0.043)	(0.043)	(0.039)	(0.039)		
On logarithmic population density at the end year, x_{1,n,t_1} $(b_{1,t_1}-b_{1,t_0})$	0.067***	0.067***	0.004	0.004		
	(0.011)	(0.011)	(0.005)	(0.005)		
On a change in distance to the nearest station, $x_{2,n,t_1}-x_{2,n,t_0}$ (b_{2,t_0})	-0.005	-0.004	-0.046***	-0.046**	-0.017	-0.012
	(0.023)	(0.023)	(0.018)	(0.018)	(0.026)	(0.026)
On a distance to the nearest station at the end year, x_{2,n,t_1} $(b_{2,t_1}-b_{2,t_0})$	-0.065***	-0.065***	-0.033***	-0.033***	-0.027***	-0.026***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
On a change in a floor area ratio, $x_{3,n,t_1}-x_{3,n,t_0}$ (b_{3,t_0})	0.117***	0.118***	-0.020	-0.020	-0.002	-0.001
	(0.028)	(0.028)	(0.012)	(0.012)	(0.022)	(0.022)
On a floor area ratio at the end year, x_{3,n,t_1} $(b_{3,t_1}-b_{3,t_0})$	0.004	0.003	0.045***	0.045***	0.040***	0.040***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
On a dummy of residential use, $x_{4,n}$	0.101***	0.101***	0.057***	0.057***	0.016***	0.017***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)
Constant term $(const)$	-0.927***	-0.925***	-0.376***	-0.376***	-0.234***	-0.234***
	(0.103)	(0.103)	(0.045)	(0.045)	(0.009)	(0.009)
Number of observations	2,581		2,651		1,962	

Notes:

1. Heteroskedasticity-robust standard errors in parentheses.
2. ***, **, and * denote p-values less than .01, .05, and .10, respectively.

Figure 1: A nonlinear relationship between land prices and objective earthquake risk

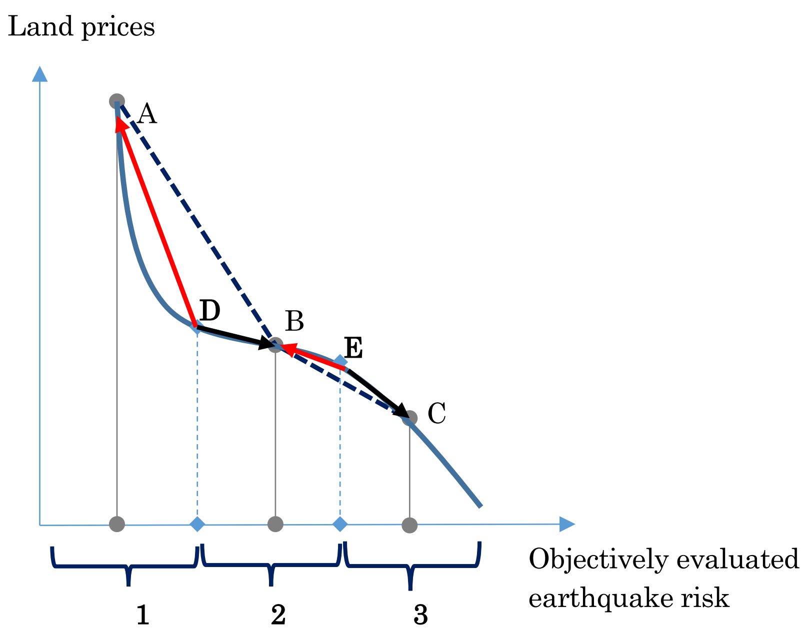

Figure 2: An inverted S-shape of the probability weighting function

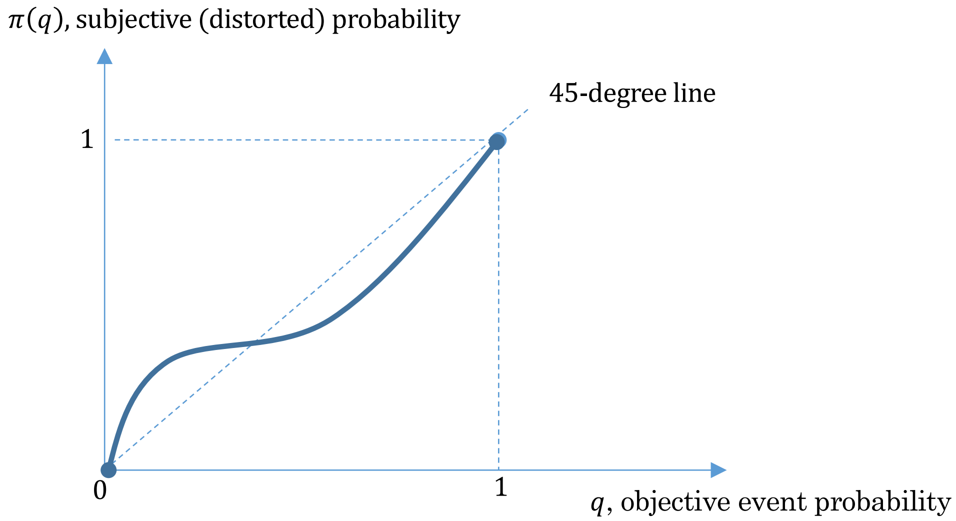

Figure 3: Estimation of a nonlinear land pricing function by discrete earthquake risk measures

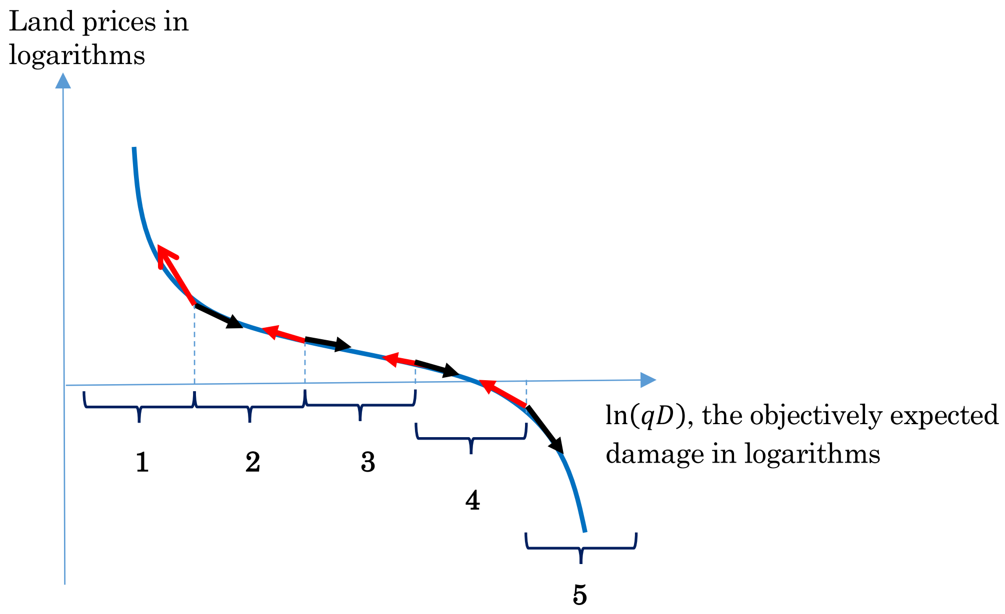

Figure 4-A: Numbered subdivisions and officially appraised points of location, where the risk rank changed between Rank 1 and Rank 2 in the period 1998–2003

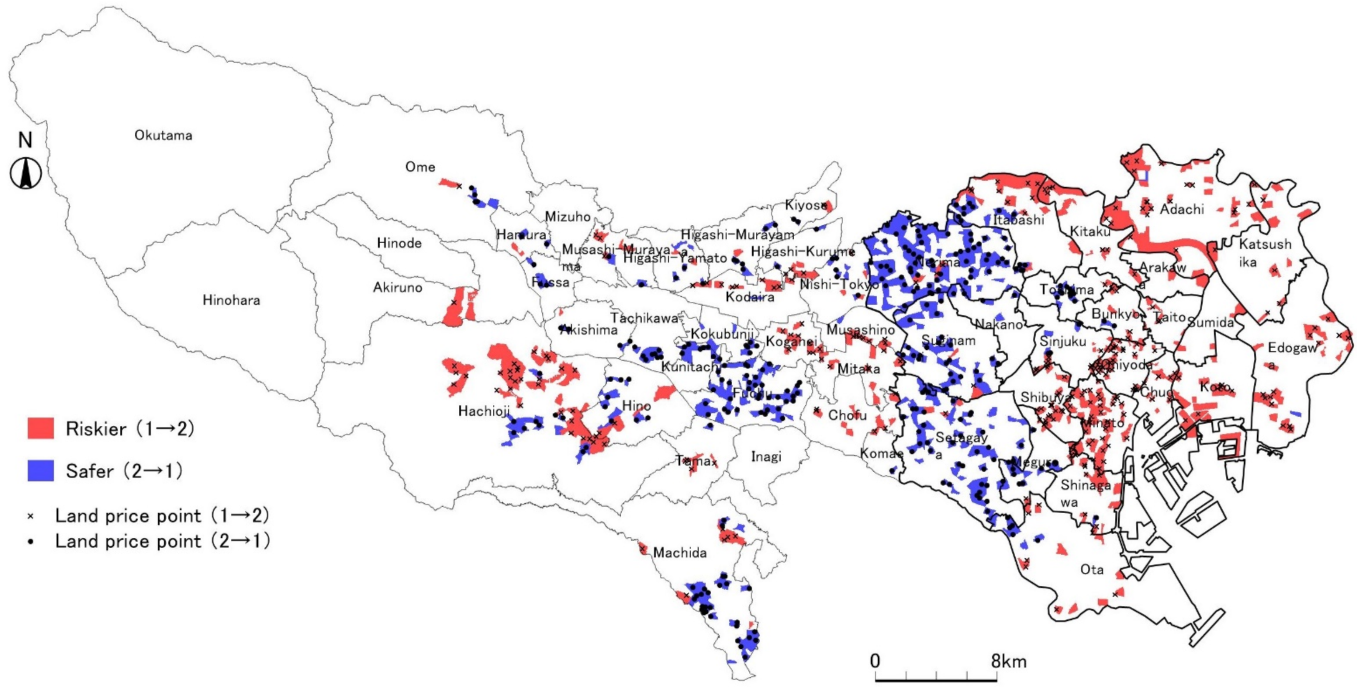

Figure 4-B: Numbered subdivisions and officially appraised points of location, where the risk rank changed between Rank 1 and Rank 2 in the period 2003–2008

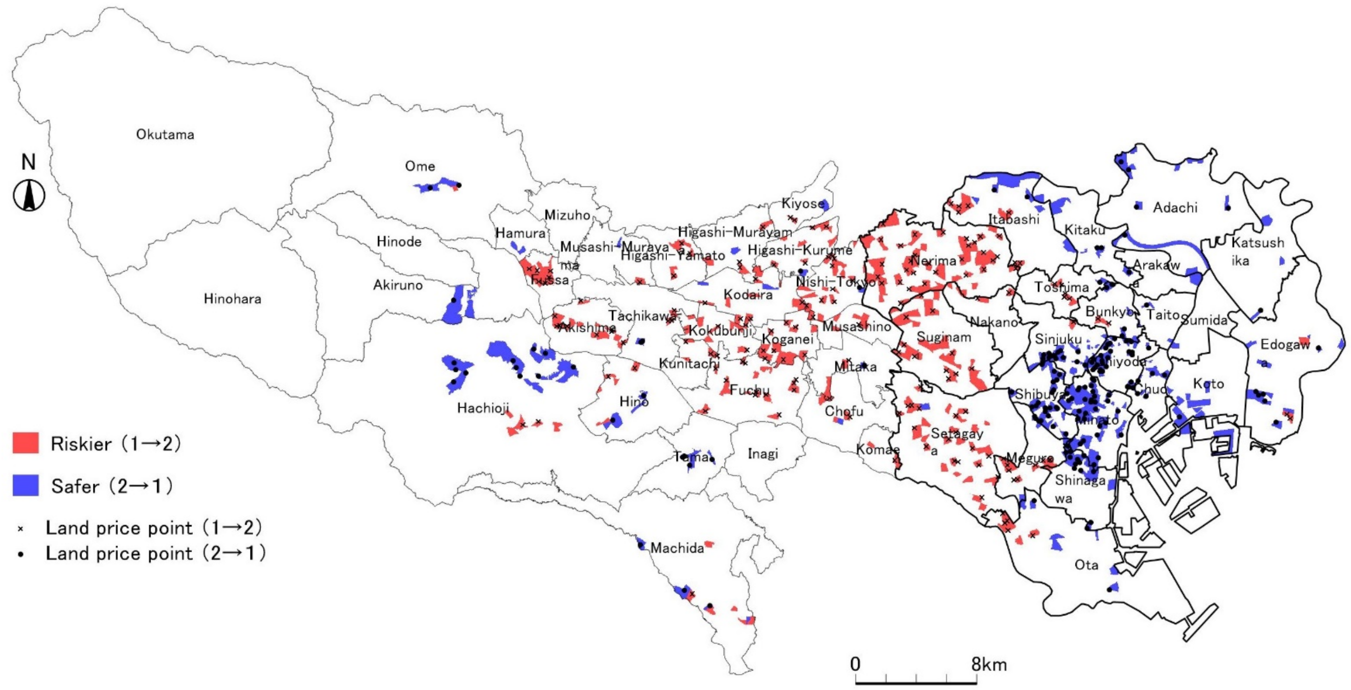

Figure 4-C: Numbered subdivisions and officially appraised points of location, where the risk rank changed between Rank 1 and Rank 2 in the period 2008–2013

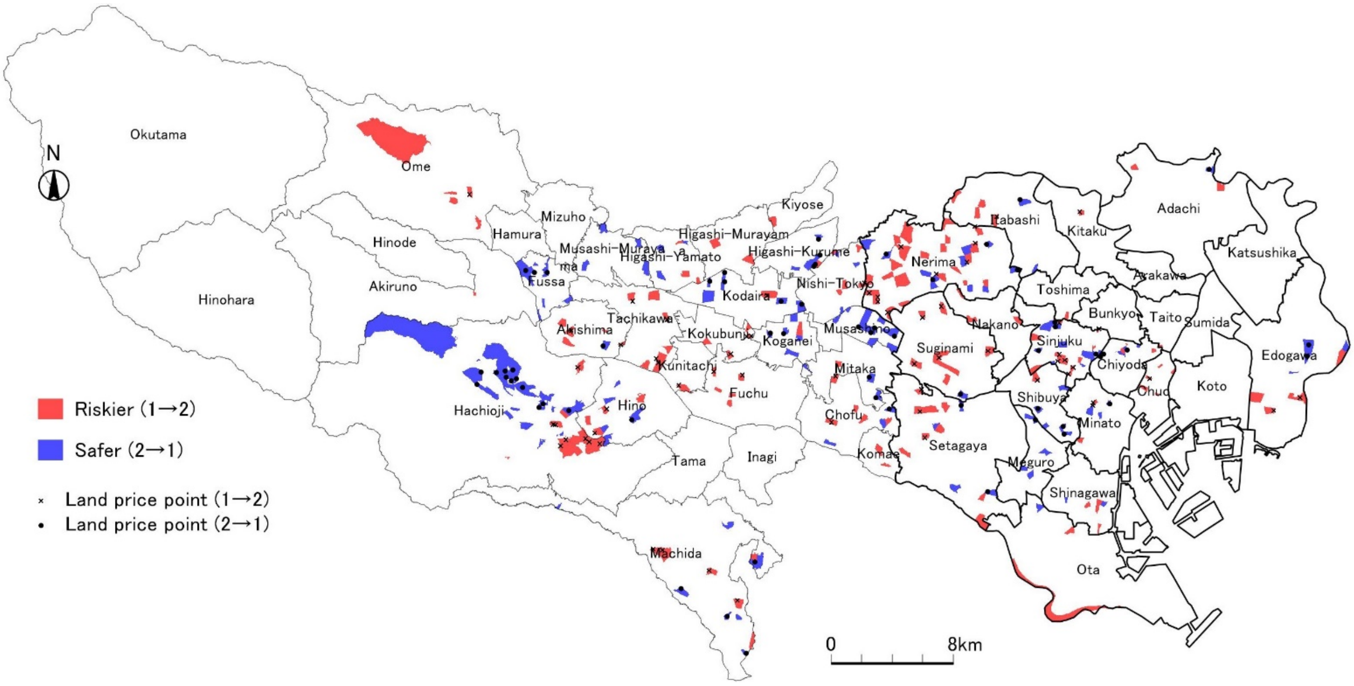

Figure 4-D: Numbered subdivisions and officially appraised points of location, where the risk rank changed between Rank 1 and Rank 2 in the period 2013–2018

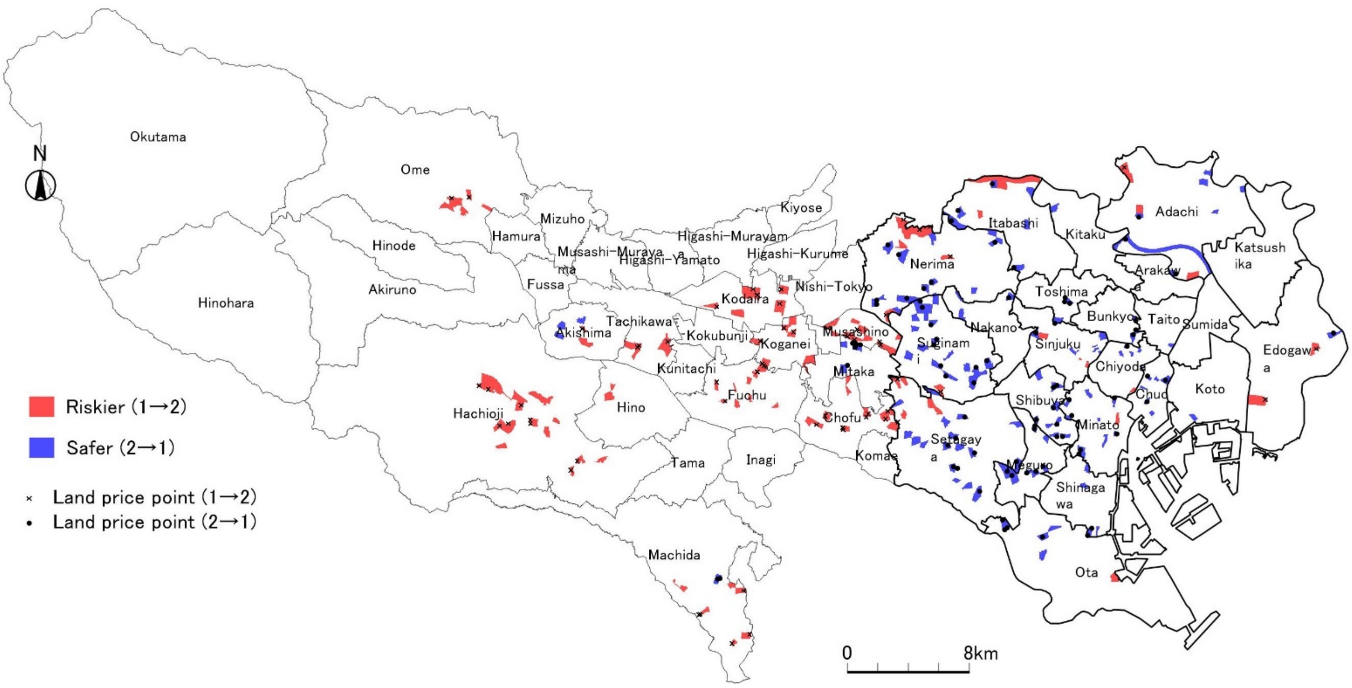

Figure 5: Numbered subdivisions and officially appraised points of location, where the risk rank changed between Rank 4 and Rank 5 or Rank 3 and Rank 4 in the period 1998–2003

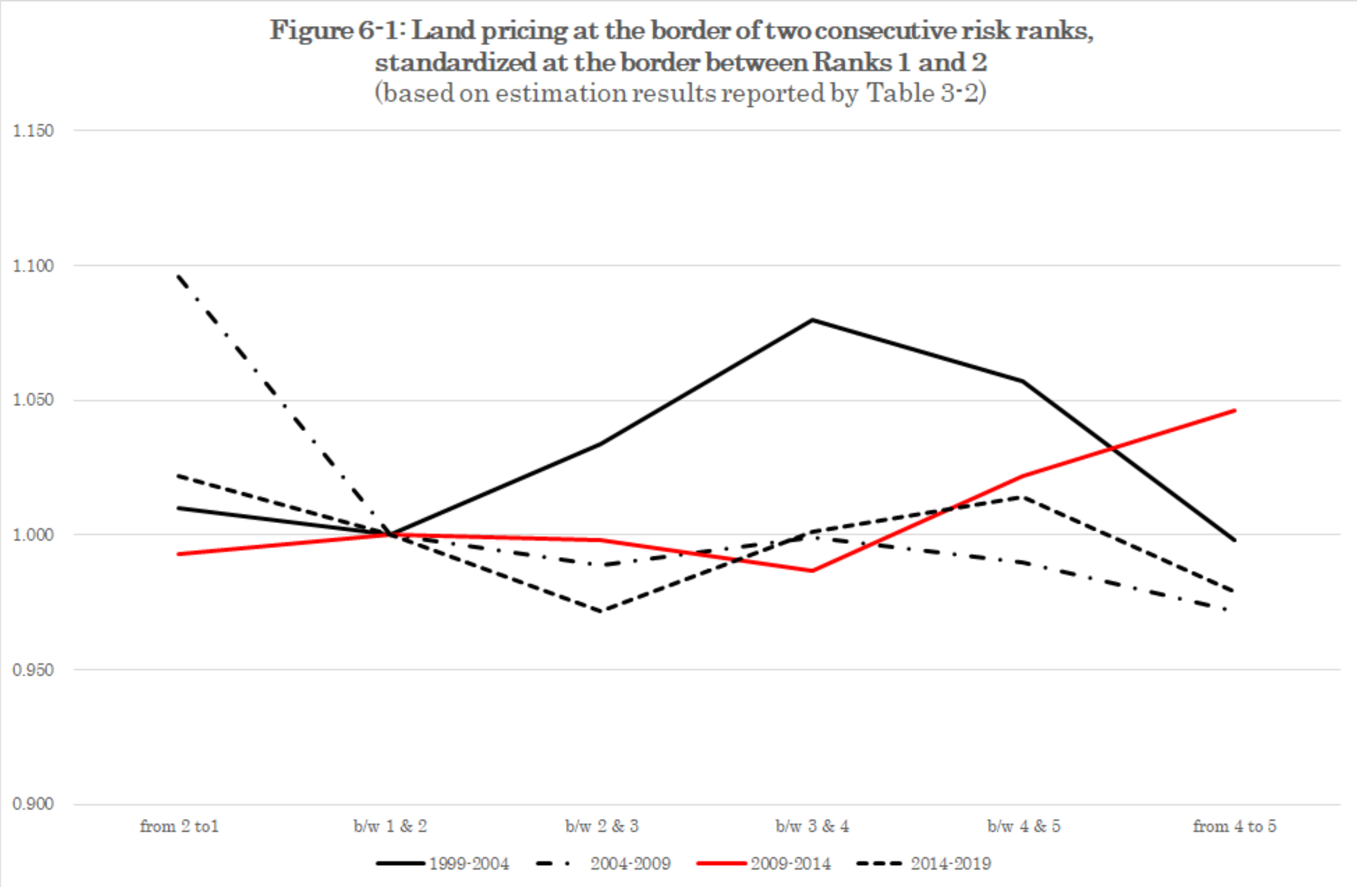

Figure 6-1: Land pricing at the border of two consecutive risk ranks, standardized at the border between Ranks 1 and 2
(based on estimation results reported by Table 3-2)
1.150
1.100
1.050
1.000
0.950
0.900
from 2 to1
b/w 1 & 2
b/w 2 & 3
b/w 3 & 4
b/w 4 & 5
from 4 to 5
1999-2004
2004-2009
2009-2014
2014-2019

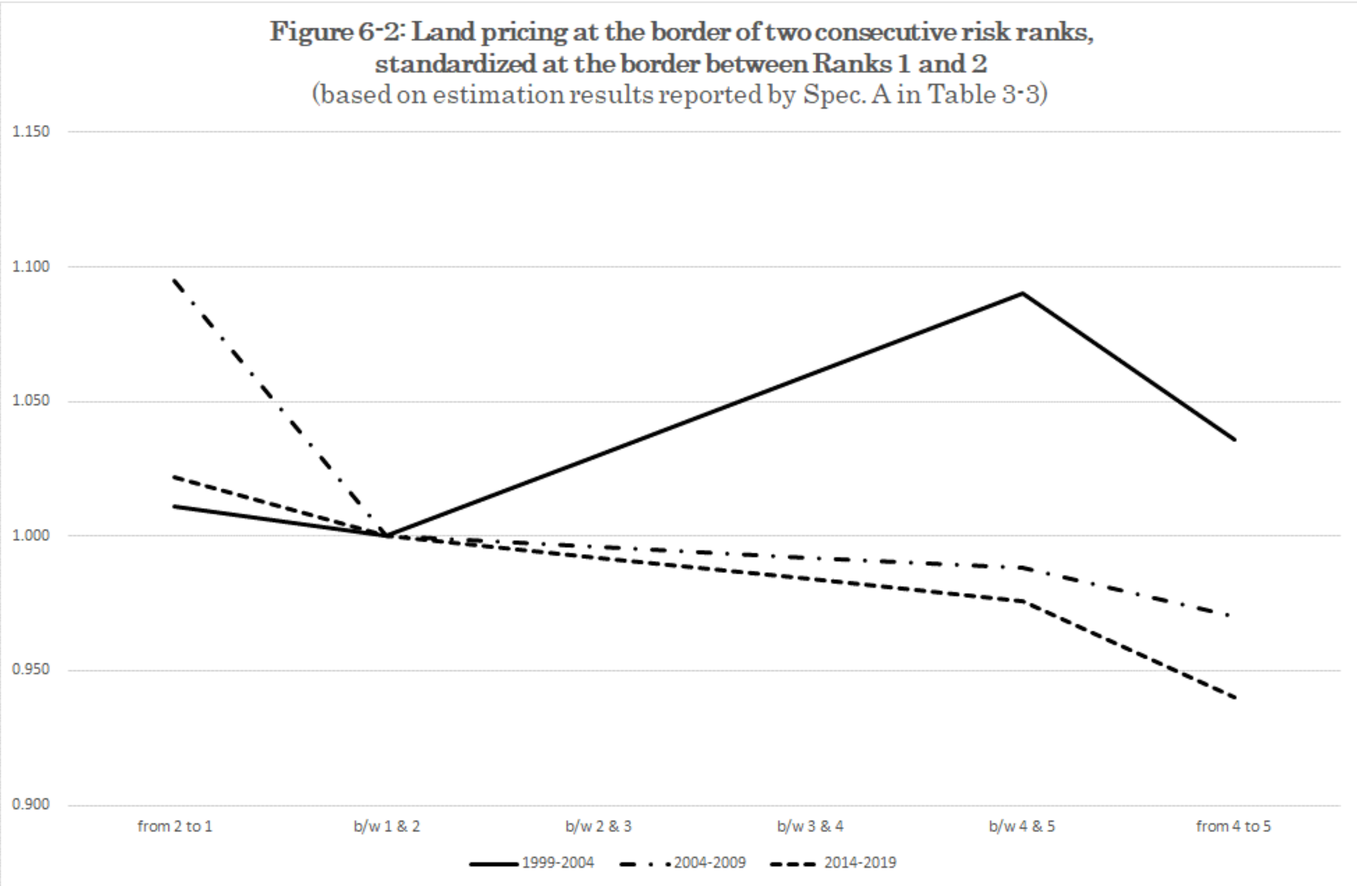

Figure 6-2: Land pricing at the border of two consecutive risk ranks, standardized at the border between Ranks 1 and 2
(based on estimation results reported by Spec. A in Table 3-3)
1.150
1.100
1.050
1.000
0.950
0.900
from 2 to 1
b/w 1 & 2
b/w 2 & 3
b/w 3 & 4
b/w 4 & 5
from 4 to 5
1999-2004
2004-2009
2014-2019

Figure 6-3: Land pricing at the border of two consecutive risk ranks, standardized at the border between Ranks 1 and 2
(based on estimation results reported by Spec. B in Table 3-3)

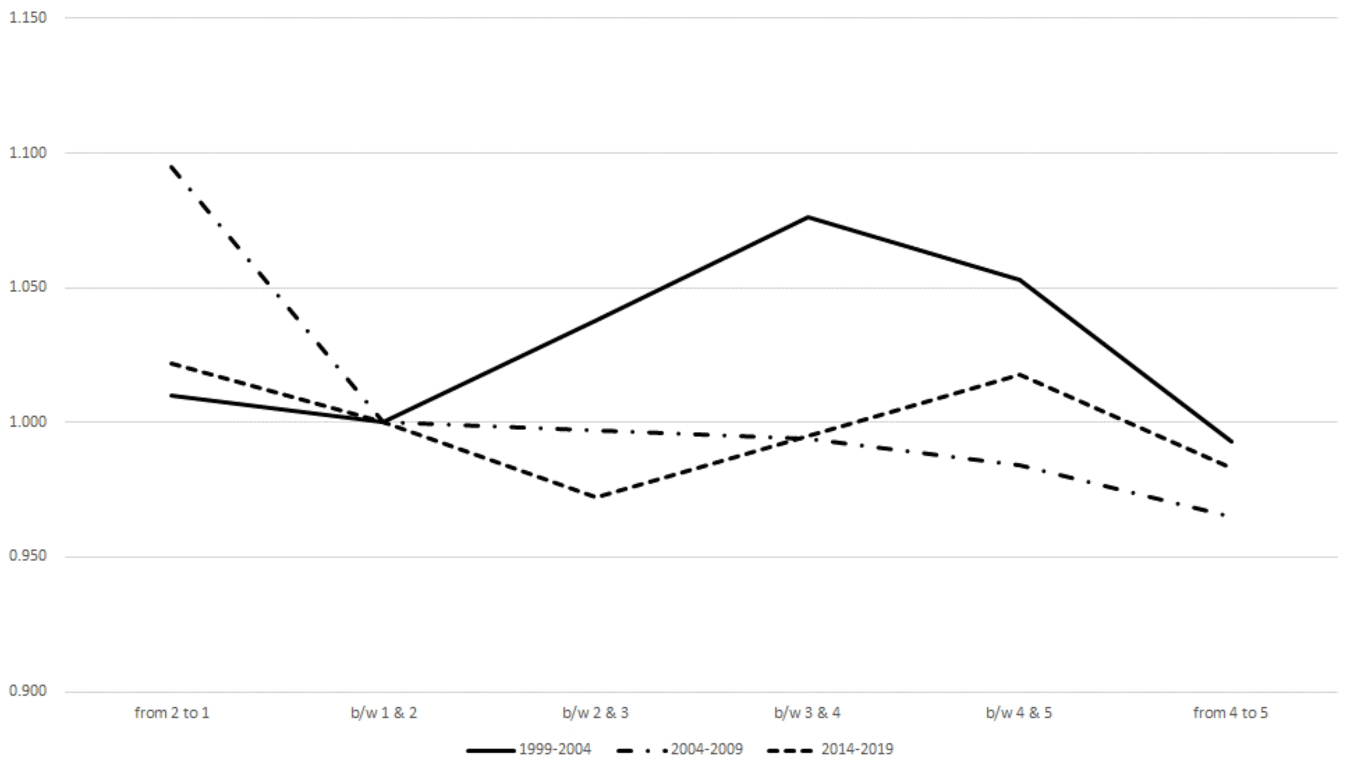

Figure 6-4: A comparison between with and without population density of land pricing at the border of two consecutive risk ranks, standardized at the border between Ranks 1 and 2