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The effect of seismic hazard risk information on property prices: Evidence from a spatial regression discontinuity design

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ABSTRACT

In this paper, we utilize a spatial two-dimensional regression discontinuity (RD) design to study how Tokyo's property market evaluates information on seismic hazard risk. This approach is superior to the conventional one-dimensional RD design as it is able to account for spatially heterogeneous treatment effects and reduce small-sample biases. Our data consists of residential property transactions from the 23-ward area of Tokyo. Our results show that the unit prices of residential properties in low-risk zones were between 13,970–17,380 JPY higher than those in high-risk zones depending on the type of seismic hazard risk. In addition, we find that information on seismic hazard risk does not significantly affect the prices of newly constructed apartments, which are more resistant to earthquake damage than older residences.

1. Introduction

Many studies have evaluated the effects of environmental attributes on property prices. The most common means of accomplishing this analysis is to estimate a hedonic price function by regressing property prices on environmental data as well as other explanatory variables. When a simple linear regression is utilized, the estimated coefficient on the environmental variable represents the marginal economic value of that attribute. However, due to potential endogeneity problems, such a simple regression may not capture the causal relationship between environmental attributes and property prices. For instance, it is reasonable to assume that developers and urban planners would be leery of constructing luxury buildings in unsafe zones as the risks of fire and building collapse from seismic activity would endanger their investments. As such, the standard regression estimation of the benefit of reducing the risk level will be greater than the real, that is, causal value. One potential way to identify such causal effects would be to conduct an experiment with randomization; however, cost and ethical problems would make this an unrealistic approach for a study of the residential market. As such, "quasi"-experimental designs have become increasingly popular in studies seeking to evaluate causal effects in social and economic activities, including environmental valuation studies with hedonic property price analyses (Bin et al., 2009; Chay and Greenstone, 2005; Greenstone and Gallagher, 2008; Greenstone and Gayer, 2009; Hallstrom and Smith, 2005; Kuminoff et al., 2010; Parmetar and Pope, 2009).[1]

This study uses a quasi-experimental technique to investigate how the property market in Tokyo evaluates seismic hazard risk information. Nakagawa et al. (2007) and Naoi et al. (2009) conducted Japanese case studies that explored the effect of seismic hazard risk on property prices and showed that the probabilities of earthquakes and of earthquake-related hazards have significant negative impacts. An influential paper by Brookshire et al. (1985) explored how the publication of the government's locational assessment of earthquake risk affected

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[1] Using quasi-experimental approaches in hedonic property price analyses is not a new idea. For example, a repeat-sales hedonic model is regarded as a quasi-experimental design technique that can identify the causal relationship between property prices and time-varying explanatory variables by examining the difference between periods. However, there are several drawbacks to repeat-sales hedonic models, including data availability and the restrictive assumption that there are no substantial structural changes between the periods that would alter consumers' or suppliers' taste parameters.

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property prices in California; they concluded that the risk information was fully cross-sectionally capitalized into the property values after its release,[2] and that price variations could be viewed as the willingness-to-pay (WTP) for reductions in property losses. Beron et al. (1997) showed that the Loma Prieta earthquake decreased the hedonic price of earthquake risk in the San Francisco Bay Area; the authors argue that this decrease most likely stemmed from the residents' initial over-estimation of the earthquake hazard.[3] However, these studies did not rigorously examine whether or not their results represented causal relationships between property prices and earthquake risk.

Although there are several quasi-experimental design techniques from which to choose, this study employs a regression discontinuity (RD) design to identify the causal impacts of seismic damage risk levels on property prices. Under relatively weak conditions to those imposed by other quasi-experimental techniques, such as the instrumental variables method or the matching method, the causal implications from RD design can be deemed as credible as those from a randomized experiment (at the points of discontinuity) (Imbens and Lemieux, 2008; Lee, 2005; Lee and Lemieux, 2010).

In our empirical analysis, we apply the RD design to data on individual apartment transactions within Tokyo's 23 wards from 2008 to 2012. The treatment variable is binary and takes the value of one if the property is located within a high-risk zone and zero if it is not. Each location's seismic hazard risk level is obtained from data published by the Tokyo Metropolitan Government. In order to estimate the treatment effect, we utilize the two-dimensional spatial RD (2DRD) design technique developed by Imbens and Zajonc (2011). Although Grout et al. (2011) used the standard one-dimensional RD design with the distance from the property to the nearest boundary point to estimate the price effect, the 2DRD design has two main advantages over the one-dimensional design: first, it allows us to account for neighborhood heterogeneity by identifying location-specific treatment effects.[4] Second, by combining a nonparametric local regression with the 2DRD design, we can automatically control for both observable and unobservable location specific effects without introducing additional variables, which will reduce estimation biases.

Our work makes a number of major contributions to the literature on the economic valuation of natural hazard risk: first, we present empirical evidence that the impacts of seismic hazard risk information on residential property prices are locationally heterogeneous and that, on average, the unit prices of residential apartment properties in low-risk zones are between 13,970 and 17,380 JPY higher than those in high-risk zones depending on the type of seismic hazard risk. It should be noted that the “true” risk level is likely to be continuously, rather than discretely, distributed as it is determined by geographical and physical conditions, that is, the differences in the magnitude of the true risk levels should be zero on the boundary of high and low risk zones. In other words, if the residents cared only about the true risk level and not about the risk information reported by the government, we would not observe significant treatment effects. Our empirical results suggest that this is not the case, that is, the provision of (ordinal) risk information does, in fact, affect the market's behavior. Second, we observe that information on seismic hazard risk does not significantly affect the prices of newly constructed apartments, which is reasonable as these newer properties were built under more stringent building code regulations. Finally, by using the estimation results from the 2DRD analysis and applying the expected utility theory presented in Brookshire et al. (1985), we show that the residents of Tokyo's 23 wards act as though the probability of large earthquake is significantly higher than that which is officially reported. In addition, we show that the difference between the estimated prices of properties in safe and unsafe zones is conservative and reasonable if one views it as the WTP for risk reduction, as compared to those obtained by Sato et al. (2009) who utilized the contingent valuation method.

The rest of the paper is organized as follows: In Section 2, we describe the 2DRD design technique. Section 3 presents the data used in our empirical study. Section 4 details the results of the standard regression-based hedonic analysis. In Section 5, we present the results of the 2DRD analysis and numerically demonstrate that the 2DRD design is more appropriate than the standard one-dimensional RD design when there are significant location specific effects. Section 6 contains our concluding remarks.

2. Two-dimensional regression discontinuity design

Recently, the RD design has become increasingly popular in applied economics literature. Most of the applications are based on the one-dimensional RD design, where the dimension of the forcing variable that determines the treatment status is one. However, as the forcing variable in our study, location, is two-dimensional (i.e., longitude and latitude), we may not use this approach and instead turn to the relatively new practice of including multiple forcing variables (Imbens and Zajonc, 2011; Papay et al., 2011; Wong et al., 2012). Specifically, we utilize Imbens and Zajonc's (2011) 2DRD design as it allows us to account for neighborhood heterogeneity and locational specific effects.

Let Y be an outcome variable, such as the residential property price; X be the set of exogenous variables that affect Y; and D be the binary risk variable that equals one if the property is located in a risky zone and zero if it is not. Conventionally, the impact of D on Y is estimated by regressing Y on (D, X) to construct a hedonic price function. If D is exogenous, then such regression approach can be used to estimate the average benefit of a reduction in the risk level. However, as stated in the introduction, the exogeneity of D often does not hold. Also, it is often difficult for the researcher to determine an appropriate functional form for the regression. The RD design allows us to overcome these obstacles.

Let $r \in \mathbf{R}^2$ be the location of the property, which we treat as the forcing variable that determines whether $D = 1$ or 0. Additionally, let us suppose that we have a sample of size n, $\{(Y_i, D_i, X_i, r_i)\}_{i=1}^{n}$. Based on the Rubin causal model, we define the causal effects as follows:

$$Y_i = \begin{cases} Y_i(0) & \text{if } D_i = 0 \\ Y_i(1) & \text{if } D_i = 1 \end{cases},$$

where $Y_i\,(0)$ is the potential outcome when $D_i = 0$, and $Y_i\,(1)$ is the potential outcome when $D_i = 1$. As such, we can interpret $Y_i\,(0) - Y_i\,(1)$ as the causal effect of reducing the risk level on property i's price. However, it should be noted that we cannot directly compute $Y_i\,(0) - Y_i\,(1)$ because when $D_i = 0$ $(D_i = 1)$, we cannot observe $Y_i\,(1)$ $(Y_i\,(0))$. The 2DRD approach circumvents this problem by conditioning r to a point on the boundary where the value of D changes.

Let $R \subset \mathbf{R}^2$ be the sampling region, which we partition into two sub-regions, R_0 and R_1, such that $\mathbf{R_0} \equiv \{r \in R : D(r) = 0\}$ and $\mathbf{R_1} \equiv \{r \in R : D(r) = 1\}$. The “assignment boundary” is defined as $\mathbf{R_{01}} \equiv \overline{R_0} \cap \overline{R_1}$, where the bar denotes the closure. Consequently, the average effect of reducing risk on Y at a given boundary point, $c \in R_{01}$, and that on the entire boundary may be defined as

$$\tau_c(c) \equiv \mathrm{E}[Y(0) - Y(1) | r = c] \quad \text{and} \quad \tau \equiv \mathrm{E}[Y(0) - Y(1) | r \in R_{01}],$$

respectively. We will not only calculate the average effect over X, but it is also of interest to explore whether the benefit of risk reduction varies among properties with different X values. In order to do so, we

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[2] Following Hidano (2002) and Kanemoto (1988), we use the term “cross-sectional capitalization” to indicate that the cross-sectional, inter-regional variations in the provision of a local public good is capitalized into the regions' property prices.

[3] Studies that investigate the property market's responses to risk information on large-scale natural disasters include Bin et al. (2008) and Bin and Landry (2013) on floods, and Bin and Polasky (2004) and Hallstrom and Smith (2005) on hurricanes.

[4] Grout et al. (2011) estimated regionally heterogeneous treatment effects by partitioning the sample region into several sub-regions with the standard one-dimensional RD approach. This approach is similar, in principle, to our 2DRD approach.

define the following two types of "conditional" average risk reduction effects:

$$\tau_{cx}(c,x) \equiv \mathrm{E}[Y(0)-Y(1)|r=c, X=x] \text{ and } \tau_x(x) \equiv \mathrm{E}[Y(0)-Y(1)|r \in R_{01}, X=x],$$

for given $c \in R_{01}$ and x.

We here discuss the identification and estimation of $\tau_{cx}(c, x)$. Let $B_h(c)$ be the h-open ball around a boundary point $c \in R_{01}$ based on the Euclidean distance d_E, that is, $B_h(c) = \{r \in R : d_E(c, r) < h\}$. Furthermore, define $B_{0h}(c) \equiv B_h(c) \cap R_0$ and $B_{1h}(c) \equiv B_h(c) \cap R_1$. As illustrated in Fig. 1, $[B_{0h}(c), B_{1h}(c)]$ is an unequally sized, non-overlapping partition of $B_h(c)$ for $h > 0$, and as h approaches zero, it degenerates to c.

In order to identify $\tau_{cx}(c, x)$ for any $c \in R_{01}$ and x, we make the following assumption:Continuity: *For all* x, *the conditional mean functions* $\mathrm{E}[Y(0)|r=c, X=x]$ *and* $\mathrm{E}[Y(1)|r=c, X=x]$ *are continuous at any* $c \in R_{01}$.

This assumption states that the conditional mean prices for properties just inside (outside) of the boundary can identify the counterfactual prices of those just outside (inside). Consequently, for any $c \in R_{01}$, $\tau_{cx}(c, x)$ can be identified as

$$\tau_{cx}(c,x) = \lim_{h \downarrow 0} \mathrm{E}[Y|r \in B_{0h}(c), X=x] - \lim_{h \downarrow 0} \mathrm{E}[Y|r \in B_{1h}(c), X=x] \quad (1)$$

for all x. The conditional mean function can be generally written as

$$\mathrm{E}[Y|r=c, X=x] = g(c,x) \quad (2)$$

where the form of the unknown function $g(\cdot,\cdot)$ is not parametrically prespecified. In line with previous studies, we estimate $g(\cdot,\cdot)$ with a local linear kernel regression. The local linear method is more appropriate for the RD analysis than the popular local constant method because it corrects for biases at the boundary (Fan and Gijbels, 1996). Let $\hat{a}_0$ and $\hat{a}_1$ be the estimators of $g(c, x)$ based on the observations in $B_{0h}(c)$ and $B_{1h}(c)$, respectively. As such, we obtain the estimator of $\tau_{cx}(c, x)$ simply by

$$\hat{\tau}_{cx}(c,x) = \hat{a}_0 - \hat{a}_1. \quad (3)$$

It will be easy to show that $\hat{\tau}_{cx}(c,x)$ converges to $\tau_{cx}(c, x)$ as n approaches to infinity and h approaches to zero. Using Eq. (3), the estimator of $\tau_c(c)$ may easily be obtained with

$$\hat{\tau}_c(c) = \frac{\sum_{i=1}^{n} \hat{\tau}_{cx}(c, X_i) f_X(X_i|c)}{\sum_{i=1}^{n} f_X(X_i|c)} \quad (4)$$

where $f_X(\cdot|c)$ is the density function of X conditional on $r = c$.

In order to estimate $\tau_x(x)$ and τ, we need to integrate $\tau_{cx}(c, x)$ and $\tau_c(c)$ with respect to c over the boundary R_{01}, respectively. We can approximate these integrals with a numerical integration technique for a sufficiently large number of points uniformly drawn from R_{01}.

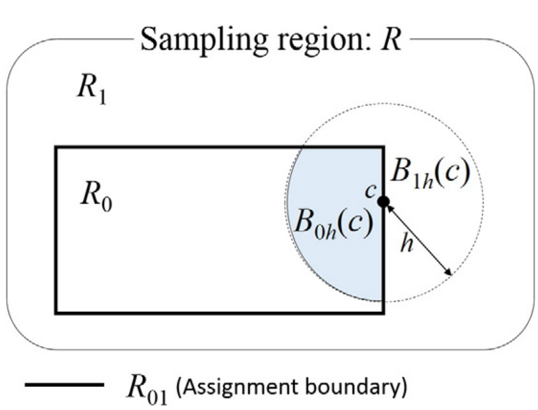

Fig. 1. Sampling region.

Here, the estimators of $\tau_x(x)$ and τ are given by

$$\hat{\tau}_x(x) = \frac{\sum_{j=1}^{J} \hat{\tau}_{cx}(c_j, x) f_r(c_j|x)}{\sum_{j=1}^{J} f_r(c_j|x)} \quad (5)$$

and

$$\hat{\tau} = \frac{\sum_{j=1}^{J} \hat{\tau}_c(c_j) f_r(c_j)}{\sum_{j=1}^{J} f_r(c_j)} \quad (6)$$

respectively, where J is the total number of points drawn from R_{01}, $f_r(\cdot|x)$ is the conditional density function of r on $X = x$, and $f_r(\cdot)$ is the marginal density function of r.

Remark 1. The continuity assumption given above is violated if the density of residential location is discontinuous at a point on the boundary. For example, this can occur if a boundary point, c, is exclusively covered by non-residential developments. Therefore, in the empirical analysis shown below, we statistically check the location variable's continuity using McCrary's (2008) density test and omit the evaluation points that may violate the assumption. It should be noted that if we were using a one-dimensional RD design, then a violation of the continuity assumption would prevent us from identifying any causal parameters; however, the 2DRD design still allows us to obtain some meaningful causal estimates by focusing on other parts of the boundary.

Remark 2. For the estimation of $\tau_c(c)$, we can use a simple nonparametric regression of Y on r without X. However, including additional covariates of X helps to eliminate small-sample biases, especially when X is strongly correlated with Y (Frölich, 2007; Imbens and Lemieux, 2008, 4.3). It should be noted, though, that when the dimension of X is large, direct nonparametric estimations suffer from dimensionality problems.[5] For the same reason, although one may use the distance-based RD (DBRD) design to estimate τ, it would entail finite-sample biases in the presence of significant location specific effects. We will confirm this point using a small set of numerical simulations in Section 5.

3. Data

In our analysis, we use data on individual residential apartment transactions in the 23 wards of Tokyo from 2008 to 2012, which was collected from a government survey managed by the Tokyo Association of Real Estate Appraisers.[6] The data includes information on not only transaction prices and the apartments' structural and locational characteristics, but also their specific addresses. We are then able to use this information to determine the properties' exact locations (longitude and latitude).

Accurate and comprehensive information on the risks of large-scale seismic hazards in Tokyo is published approximately every five years by the Tokyo Metropolitan Government's Bureau of Urban Development (URL: http://www.toshiseibi.metro.tokyo.jp/index.html). The 6th and 7th official reports were released in 2008 and 2013, respectively. As our study focuses on transactions that took place between June 2008 and the end of 2012, we rely primarily on the 6th report.

[5] Since our estimation method is localized at each c, any covariates whose values are determined by location are not included in X. This is another appealing property of the 2DRD design as it is often very difficult to list all of the neighborhood characteristics that could affect Y.

[6] We could also use land transactions data to estimate the effects of risk information on land prices. However, as there are considerably fewer residential land transactions than apartment transactions in Tokyo's central business district, we focus solely on apartment transactions. As one of the reviewers suggested, estimating the effects of risk information with particular focus on single-family housing prices would be an interesting topic for future research.

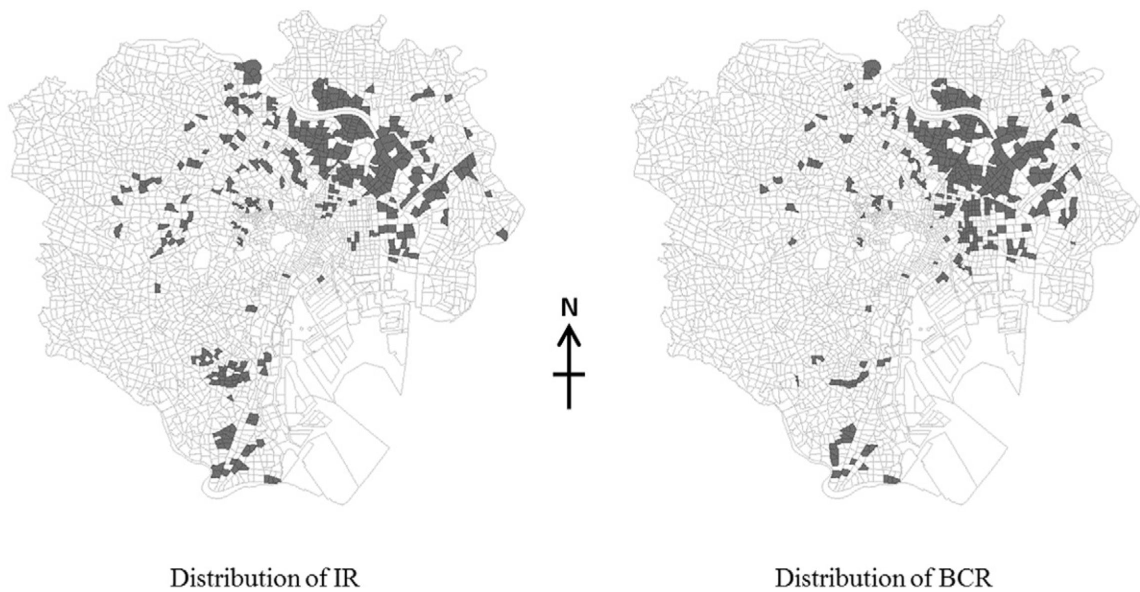

Fig. 2. Distribution of the risk variables in Tokyo's 23-ward area. (The gray zones have risk scores higher than 3).

The bureau measures the relative seismic hazard risk for each block (there are a total of 3130 blocks in the study area) based on a five-point scale: 1 = very low (about 23.5% of the blocks in Tokyo's 23 wards); 2 = low (40.4%); 3 = medium (24.4%); 4 = high (8.9%); 5 = very high (2.7%), where the score represents an integrated risk index of building collapse and fire hazard risks. The risk of building collapse is calculated based on the number of buildings in each block and their type (e.g., structure, age, and number of floors), as well as the characteristics of ground structures, including the risk of liquefaction. The risk of building-collapse is also evaluated in a five-point scale: 1 = very low (about 24.2% of the blocks in Tokyo's 23 wards); 2 = low (39.5%); 3 = medium (24.6%); 4 = high (9.0%); and 5 = very high (2.7%). In this study, we focus on the impacts of both the integrated seismic hazard risk (IR) and the risk of building collapse (BCR). The risk of fire hazard is calculated based on both the potential for an outbreak as well as the likelihood that a fire will spread, where the former is based on the number of places where fire is used (e.g., restaurants) and the latter takes into account the ratio of open spaces, the density of buildings, and a number of other factors. The estimation results for fire risks are omitted in order to save space (but available upon request).

In the report, areas that scored either 4 or 5 were formally designated as "high-risk". As such, we define our binary risk such that it equals one if the property is located in such an area and zero otherwise. The geographical distributions of our risk variables, IR and BCR, are presented in Fig. 2, with the IR distribution being shown on the left and the BCR on the right. The figure shows that the high-risk zones are not distributed randomly, but rather exhibit high spatial correlations. In particular, we note that there are high concentrations of risky zones in the northeast.

4. Hedonic regression analysis

Before conducting the RD design analysis, we shall first explore the impacts of risk information on property prices using the conventional hedonic regression approach.

One of the primary concerns expressed by the recent literature on hedonic property price regression is that the parameter estimates will be biased if the spatial correlation effects are incorrectly accounted. In our dataset, it is reasonable to assume that there will be spatial autocorrelation among the property prices (i.e., a spatial endogenous effect) as well as a spatial spillover effect in the seismic hazard risk across neighboring blocks (i.e., a spatial external effect).[7] Then we may check for the presence of spatial effects and estimate the effects of D on Y by estimating the following model:

$$Y_i = \rho \sum_{j \neq i}^{n} w_{i,j} Y_j + \alpha D_i + \lambda \sum_{j \neq i}^{n} w_{i,j} D_j + X_i' \beta + \varepsilon_i \quad \text{for } i = 1, \ldots, n, \tag{7}$$

where $(\rho, \alpha, \lambda, \beta)$ are the parameters to be estimated, and $w_{i,\,j}$ is the (i, j)-th element of the spatial weight matrix. ρ, λ, and α represent the degree of spatial autocorrelation among the property prices, the spatial external effect of the risk variable, and the direct (first-order) effect of the risk variable on the property price, respectively. It should be noted that since $\sum_{j \neq i}^{n} w_{i,j} Y_j$ is correlated with the error term by construction, the ordinary least squares (OLS) estimator will not be consistent. Thus, we estimate the model in Eq. (7) using the two-stage least squares (2SLS) method (Kelejian and Prucha, 1998). For the choice of spatial weight matrix, we use the following row-normalized distance-based spatial weight matrix:

$$w_{i,j} = \frac{\omega_{i,j}}{\sum_{j \neq i}^{n} \omega_{i,j}}, \quad \omega_{i,j} = \begin{cases} 0 & \text{if } i = j \text{ or } d_{\mathrm{E}}(r_i, r_j) \geq \bar{d} \\ 1/d_{\mathrm{E}}(r_i, r_j) & \text{if } i \neq j \text{ and } d_{\mathrm{E}}(r_i, r_j) < \bar{d} \end{cases}$$

where $\bar{d}$ is a predetermined threshold value, which we set at 0.2 km.[8]

Table **1** presents the variables used in the regression analysis and their definitions. From our sample of property transactions, we exclude observations with missing data. Additionally, in order to lower the risk of misreporting biases, we exclude observations in which the unit price was more than 5,000,000 JPY and less than 1000 JPY. Consequently, our final sample consisted of 36,489 observations (75.8% of the total observations). Table **2** summarizes the descriptive statistics.

[7] In the RD analysis presented below, we do not consider the presence of both of these factors. The literature on treatment evaluations has discussed means by which to account for the cross-sectional interactions between outcomes (Lazzati, 2015; Manski, 2013). Ferracci et al. (2014) have developed a treatment evaluation method with matching techniques for when there are treatment spillovers within the market.

[8] We checked the robustness of the estimation results by changing this threshold value. We found that the results were quite similar to those obtained when 0.2 km was used.

Table 1
Variables and their definitions.

Variable	Definition
(Dependent variable)	
Unit price	Unit price of the property (10,000 JPY/m^2).
(Risk variables)	
IR/BCR	Dummy variable: 1 when the property lays in a high-risk zone with an IR/BCR score greater than 3; 0 otherwise.
(Explanatory variables)	
Log Area	Natural log of the property's area (m^2).
Log Age	Natural log of (age (years) + 1).
1981[a]	Dummy variable: 1 when the property was built before 1981; 0 otherwise.
Log Floor	Natural log of the floor level.
Log WidthRd	Natural log of (width (m) + 1) of the road in front of the property.
Log DistSt	Natural log of the distance (km) to the nearest railway station.
North	Dummy variable: 1 for north-facing properties; 0 otherwise.
Log TotFloor	Natural log of the total number of floors in the building.
RC	Dummy variable: 1 for Reinforced Concrete (RC) framed buildings; 0 otherwise.
Renovation	Dummy variable: 1 when the property has a history of renovations; 0 otherwise.
AN Dwellings	Average number of dwellings per floor.
Detach[b]	Proportion of households living in detached houses.
Owner[b]	Proportion of owner-occupied houses.
Elderly[b]	Proportion of households headed by the elderly (over 65 years old).
Log Retail[b]	Natural log of (area (m^2) per capita + 1) of retail stores.
BL Ratio	Maximum building-to-land ratio regulated by the Building Standard Law.
FA Ratio	Maximum floor-area ratio regulated by the Building Standard Law.
LU Com[c]	Dummy variable: 1 when the property is located in a commercially zoned area; 0 otherwise.
LU Ind[c]	Dummy variable: 1 when the property is located in an industrially zoned area; 0 otherwise.
2008	Dummy variable: 1 when the property was sold in 2008; 0 otherwise.
2009	Dummy variable: 1 when the property was sold in 2009; 0 otherwise.
2010	Dummy variable: 1 when the property was sold in 2010; 0 otherwise.
2011	Dummy variable: 1 when the property was sold in 2011; 0 otherwise.

[a] The Japanese Building Standard Law was substantially amended in 1981, and a new, more stringent earthquake-resistance standard was enacted. We are grateful to a referee for pointing out this fact.
[b] Block-level variables.
[c] We set residential zoning as the benchmark.

In Table 3, we report the results of the hedonic regression analysis both for when the variable interest is IR and for when it is BCR.[9] As a benchmark, we also present an OLS-estimated model in which the spatial terms are excluded. In the table, we use $\overline{Y}$ and $\overline{D}$ to denote the terms corresponding to $\overline{Y}_i = \sum_{j\neq i}^{n} w_{i,j} Y_j$ and $\overline{D}_i = \sum_{j\neq i}^{n} w_{i,j} D_j$, respectively.

First, when the spatial correlations are ignored, the estimated coefficients on the risk variables are -1.214 for $D = IR$ and -0.711 for $D = BCR$ as well as significant, implying that the buyers recognized and acted on the risk information. These results are consistent with previous studies, including Nakagawa et al. (2007) and Naoi et al. (2009). In the last row of the table, we report the robust Lagrange multiplier (LM) test statistic for the null hypothesis that there is no spatial autocorrelation in the dependent variable. The values of the robust LM test imply that there is significant spatial autocorrelation in both *IR* and *BCR*. In the spatial models, the magnitudes of the coefficients on D decrease to -1.095 and -0.554 when $D = IR$ and $D = BCR$, respectively. Furthermore, as suggested by the robust LM test, we observe that the unit price variable is significantly spatially autocorrelated and also that there is a significant spatial external effect with respect to both *IR* and *BCR*.

The coefficient on the 1981 dummy is negative and significant. Since we control for the effects of aging with *Log Age*, this result implies that the amendment of the Building Standard Law had a significant impact on the housing market. *Log WidthRd* is negatively and significantly related to the price variable. Recalling that our sample is comprised of residential apartments, this finding is understandable as residents would place greater value on a quiet environment than on accessibility to wider roads. For the directional dummy variable, *North*, the coefficient is positive and significant. Because north-facing rooms receive less sunlight, families often regard them as inferior; as such, north-facing rooms tend to be built on a smaller scale, which would mean that they are relatively more expensive than rooms facing other directions when measured in terms of unit price. It should also be noted that the variable *Owner* positively affects the price. This suggests that apartments in areas with high home-ownership rates tend to be more expensive. The land-use variables, *LU Com* and *LU Ind*, are both negative and significant, implying that residents prefer apartments in residential areas to

Table 2
Descriptive statistics (sample size = 36,489).

Variable	Mean	Median	Std. dev.	Min	Max
Unit Price	65.602	60.047	30.221	0.192	471.230
IR	0.100	0	0.300	0	1
BCR	0.098	0	0.298	0	1
Log Area	3.724	3.922	0.574	2.306	6.590
Log Age	1.814	2.079	1.298	0	4.477
1981	0.111	0	0.314	0	1
Log Floor	1.537	1.609	0.789	0	4.143
Log WidthRd	2.173	2.303	1.099	0	6.066
Log DistSt	−0.941	−0.866	0.654	−5.839	1.071
North	0.202	0	0.402	0	1
Log TotFloor	2.254	2.303	0.592	0.000	4.382
RC	0.660	1	0.474	0	1
Renovation	0.254	0	0.435	0	1
AN Dwellings	9.566	7	9.919	0.157	758
Detach	0.186	0.168	0.121	0	0.758
Owner	0.456	0.447	0.135	0.027	0.926
Elderly	0.150	0.148	0.044	0.017	0.440
Log Retail	0.477	0.323	0.532	0	7.229
BL Ratio	69.057	60	18.068	0	800
FA Ratio	357.077	300	147.315	0	900
LU Com	0.309	0	0.462	0	1
LU Ind	0.225	0	0.418	0	1
2008	0.092	0	0.289	0	1
2009	0.279	0	0.448	0	1
2010	0.226	0	0.418	0	1
2011	0.205	0	0.404	0	1

[9] In computing the variance–covariance (VC) matrix for each model, we assumed the error terms to be i.i.d. However, the i.i.d. assumption is often inappropriate in spatial contexts. See Conley (1999) and Kelejian and Prucha (2007) for more information on estimating VC matrices that are robust to a general form of spatial dependence.

Table 3
Regression results.

Model	Benchmark model (OLS)				Spatial model (2SLS)			
	$D = IR$		$D = BCR$		$D = IR$		$D = BCR$	
Variable	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value
Intercept	83.769	60.405	83.716	60.366	75.566	52.797	75.090	52.450
D	−1.214	−2.953	−0.711	−1.913	−1.095	−2.696	−0.554	−1.748
Log Area	−7.728	30.309	−7.723	−30.288	−7.089	−28.081	−7.058	−27.932
Log Age	−13.827	−84.395	−13.826	−84.385	−13.733	−85.965	−13.710	−85.768
1981	−4.585	−9.770	−4.586	−9.772	−3.308	−7.043	−3.329	−7.082
Log Floor	2.841	13.714	2.844	13.726	2.808	13.728	2.804	13.695
Log WidthRd	−1.238	−10.295	−1.240	−10.311	−1.101	−9.274	−1.098	−9.238
Log DistSt	−3.389	−16.070	−3.391	−16.077	−2.394	−11.335	−2.384	−11.269
North	2.122	6.799	2.124	6.803	1.912	6.207	1.917	6.214
Log TotFloor	5.285	14.991	5.282	14.980	5.159	14.821	5.201	14.925
RC	6.930	21.869	6.930	21.866	6.078	19.344	6.065	19.285
Renovation	0.596	2.038	0.590	2.018	0.851	2.946	0.821	2.838
AN Dwellings	−0.023	−1.732	−0.023	−1.726	−0.001	−0.100	−0.001	−0.071
Detach	−36.413	−27.330	−36.443	−27.348	−32.345	−24.423	−32.360	−24.410
Owner	5.020	4.620	5.028	4.626	4.008	3.735	4.123	3.835
Elderly	−18.037	−5.858	−18.100	−5.877	−15.601	−5.128	−16.060	−5.273
Log Retail	2.072	8.294	2.079	8.323	1.871	7.587	1.926	7.803
BL Ratio	−0.035	−4.559	−0.035	−4.568	−0.039	−5.084	−0.039	−5.129
FA Ratio	0.003	2.063	0.003	2.086	−0.002	−1.107	−0.002	−0.970
LU Com	−2.283	−4.808	−2.291	−4.826	−2.030	−4.330	−2.046	−4.361
LU Ind	−10.737	−32.307	−10.744	−32.297	−10.141	−30.728	−10.070	−30.354
2008	24.863	45.246	24.847	45.214	30.774	53.965	30.640	53.700
2009	23.311	52.948	23.304	52.925	29.492	62.503	29.450	62.357
2010	26.523	57.556	26.514	57.533	32.705	66.349	32.640	66.166
2011	25.701	53.939	25.693	53.918	31.977	62.645	31.880	62.406
$\overline{Y}$					0.157	23.334	0.156	23.121
$\overline{D}$					−11.004	−12.945	−8.535	−10.275
Adj. R-squared	0.396		0.396		0.412		0.411	
Robust LM	626.140		621.472					

those in industrial and commercial areas. On the other hand, the variable *Log Retail* is positively related to the price; indicating that although residents do not prefer to live in commercial areas (relative to residential areas), they still desire easy access to retail stores. The coefficient on *RC* is positive and significant; this is reasonable as developers recently are reluctant to use SRC (Steel-Reinforced Concrete), which is more durable but expensive, on the upper levels of high-rise apartments while still using SRC on the lower levels.

5. RD analysis

5.1. Testing the continuity of residential density

In order to conduct the 2DRD analysis, we first uniformly and randomly select 1000 boundary points (cs) from the assignment boundary. Then, as mentioned in Remark 1, we check the continuity of residential density at each c. Following the same principle of the test proposed by McCrary (2008), we define our test statistic as follows:

$$\begin{aligned}\theta(c) &\equiv \ln f_{0,r}(c) - \ln f_{1,r}(c) \\ &= \ln \lim_{h\downarrow 0} f_r(r|r\in B_{0h}(c)) - \ln \lim_{h\downarrow 0} f_r(r|r\in B_{1h}(c))' \end{aligned} \tag{8}$$

where $f_r(r|r\in B_{0h}(c))$ ($f_r(r|r\in B_{1h}(c))$) is the marginal density of r for $r\in B_{0h}(c)$ ($r\in B_{1h}(c)$), which can be calculated with the local linear density estimator using the subsample of $D = 0$ ($D = 1$). Due to space restrictions, we omit the details of the implementation procedure (see Cheng (1997) and McCrary (2008) for more information on this topic). After $\theta(c)$ is estimated, we compute its bootstrap confidence interval (CI) with 300 repetitions. As the results, in the case of $D = IR$, we failed to reject the hypothesis that $\theta(c) = 0$ at the 95% significance level for 877 of the 1000 boundary points; for $D = BCR$, we failed to reject 764 of the evaluation points. Consequently, in the following analyses, we shall limit our sample to only those observations that we failed to reject.

In what follows, we compare the results of the 2DRD and the DBRD analysis. For the DBRD analysis, we approximate the distance from the property to the nearest boundary point where the continuity condition holds by using instead the distance to the nearest evaluation point in the sample obtained as above.

5.2. Simulation experiments: DBRD vs. 2DRD

Before presenting the results of the RD analyses, we shall briefly demonstrate how the DBRD approach could produce biased treatment effect estimates in the presence of significant location specific effects.With the dataset used in our empirical analysis, we may generate a hypothetical dependent variable, Y_i^* for $i = 1, \ldots, n$, by the following data generating process (DGP):

$$Y_i^* = 60 + \alpha IR_i + \delta\left(\sin\left(\overline{lon}_i\right) + \cos\left(\overline{lat}_i\right)\right) + \varepsilon_i$$

where $\alpha = -1.5$, δ represents the magnitude of the location specific effects; $\overline{lon}_i$ and $\overline{lat}_i$ are the standardized longitude and latitude of the i-th observation, respectively; and ε_i is the normally distributed error term with mean zero and standard deviation 7.5. For δ, we try three values: $\delta \in \{0, 0.4, 2\}$. $\delta = 0$ corresponds to the case where there are no location specific effects (DGP 1); $\delta = 0.4$ would indicate that there are small location specific effects (DGP 2); and $\delta = 2$ would indicate that there are strong location effects (DGP 3). We estimate α using both the DBRD and the 2DRD approaches. For the DBRD estimation, we use a local linear kernel regression as in Hahn et al. (2001), specifically the Epanechnikov kernel function, whose bandwidth length is either 0.1 km, 0.2 km, or 0.4 km for both subsamples with $IR = 0$ and $IR = 1$. In the 2DRD, we estimate the conditional mean function in Eq. (2) (without conditioning x) with the product Epanechnikov kernel function. The bandwidth parameters for each subsample's product

Table 4
Simulation results.

	DGP 1 ($\delta = 0$)		DGP 2 ($\delta = 0.4$)		DGP 3 ($\delta = 2$)	
	RMSE	Bias	RMSE	Bias	RMSE	Bias
DBRD (Bandwidth = 0.1 km)	1.9375	0.0166	1.9381	−0.0930	2.0251	−0.5917
DBRD (Bandwidth = 0.2 km)	1.0066	0.0140	1.0105	0.0919	1.0700	0.3634
DBRD (Bandwidth = 0.4 km)	0.5498	0.0071	0.5521	0.0511	0.5933	0.2232
2DRD	0.1546	0.0052	0.1545	0.0009	0.1553	−0.0016

kernel are chosen by the leave-one-out cross validation method. We evaluate the performance of each approach with the root mean squared error (RMSE) statistic and the bias based on 500 Monte Carlo replications.

A summary of the simulations' results is presented in Table 4. We can clearly see that the 2DRD approach outperforms the DBRD approach for all of the DGPs in terms of both the RMSE and level of bias. In the DBRD analysis, when there are no location specific effects (DGP 1), the bias values are almost zero; however, when there are strong location effects (DGP 3), the estimates are certainly biased. We also observe that the RMSE value for the DBRD estimate tends to decrease at a remarkable rate as the bandwidth widens, due to the reduction in variance. Conversely, the accuracy of the 2DRD estimation seems almost independent of the magnitude of location effects.

5.3. Estimation results from the RD analysis

As is conventional in the literature on RD design analysis, we first provide visual evidence of the boundary discontinuity. In our 2DRD design, the discontinuity could be visualized using three-dimensional (i.e., unit price, longitude, and latitude) or contour plots; however, such figures may not effectively convey the presence of discontinuity. As such, we present two-dimensional scatterplots with the distance to the nearest boundary point on the x-axis and the unit price on the y-axis for both $D = IR$ and BCR (see Fig. 3). In these plots, the points with negative (positive) distances represent observations in low-risk (resp. high-risk) zones. The figure clearly shows that the unit prices are distributed differently in the safe and unsafe zones; specifically, we observe that luxury apartments are more commonly found in low-risk zones than in high-risk zones.

As mentioned in Section 2, although including additional covariates of X in the estimation would reduce the small-sample bias, it also leads to the "curse of dimensionality" if the dimension of the conditioning variables is not small. In order to address this issue, we modify the conditional mean function in Eq. (2) so as to obtain the following "partially linear" model: $E[Y|r = c, X = x] = g(c, x_1) + \vartheta' x_2$, where $x = (x_1', x_2')'$, $x_1 = Log\ Age$, and x_2 are the explanatory variables listed in Table 1 (excluding the neighborhood characteristics and the 1981 dummy) and ϑ is the corresponding parameter vector. The results reported below are based on this specification rather than the fully nonparametric model.

Fig. 4 provides the histograms for the results for $\hat{\tau}_c(c)$ with the cs being the evaluation points described in Section 5.1. For both IR and BCR, the risk reduction effects are positive at most of the evaluation points; the few instances where there are large negative values for $D = BCR$ might be due to a sampling bias. These results indicate that the effects of seismic hazard risk information on property prices are spatially heterogeneously distributed.

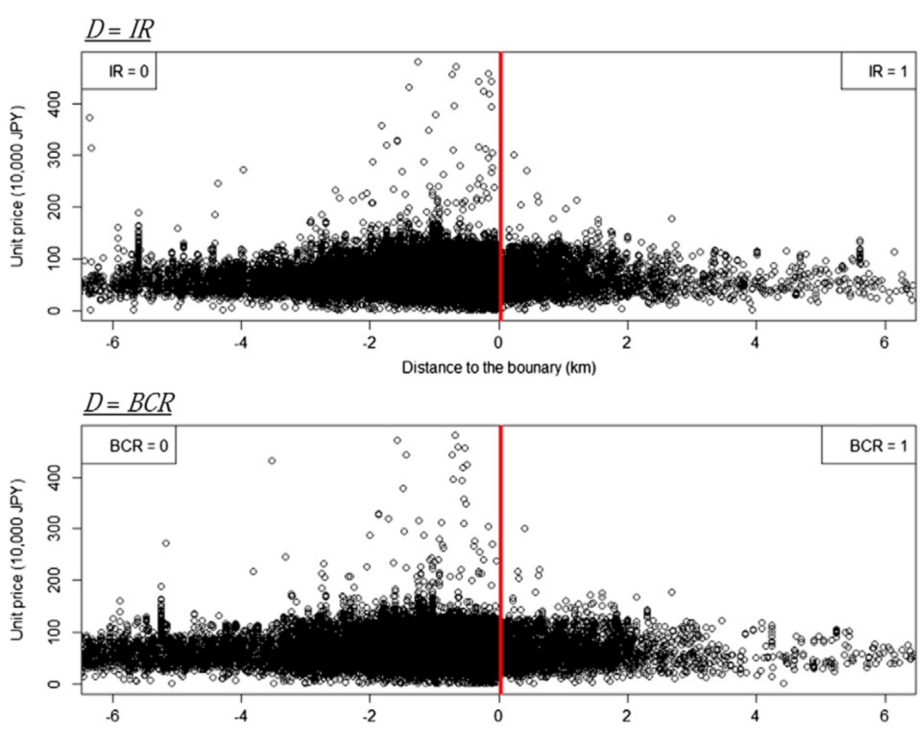

Fig. 3. Scatter plot of the distance to the boundary vs. the unit price.

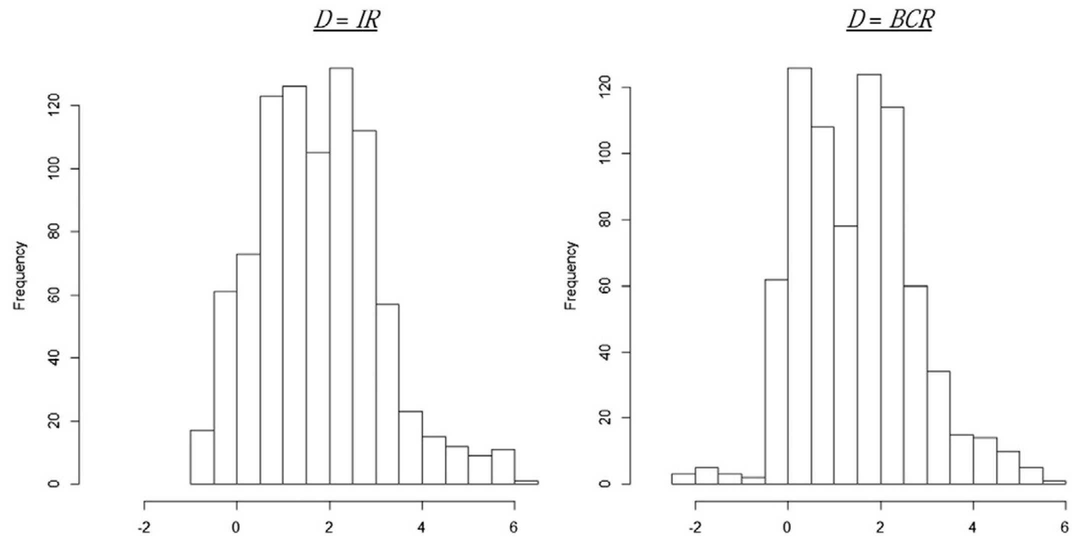

Fig. 4. Histogram of $\hat{\tau}_c(c)$.

We next investigate the relationship between the properties' age and the effects of seismic hazards' risk information on their prices. In order to do so, we estimate the conditional treatment effects of *Log Age* (we used the logarithm of age rather than age itself in order to avoid long-tails in the distribution). The conditional treatment effect is expected to increase with the age of building because older buildings are naturally vulnerable to seismic hazards, and in 1981, 1999, and 2000, the Japanese government made several amendments to the building code in an effort to lower the risk of building collapse.[10] We report the estimation results of τ_x(Log Age) in Fig. 5. The plot on the left reports the *IR* results and that on the right reports those for *BCR*. We also provide the 95% bootstrap CI for each case with 300 bootstrap replications. As expected, we observe that the benefit of reducing the risk score tends to increase as the building's age increases. In particular, for properties that were built less than 5 years ago, we cannot distinguish the impact of the risk score from zero at the 95% confidence level. On the other hand, the effects are mostly significant and positive for older properties. Consequently, we may conclude that residents have confidence in newly-built, regulation-compliant, buildings to withstand earthquake damage even in risky zones.

Table 5 summarizes the estimation of the average risk reduction effect, $\hat{\tau}$, as well as the results of the DBRD design estimation. According to the 2DRD design's results, $\hat{\tau}$ was 1.738 with the 95% CI being [1.150, 2.344] for $D = IR$, and it was 1.397 with the 95% CI being [0.884, 1.877] for $D = BCR$. In both cases, the average risk reduction effect was positive and significantly different from zero. The estimated benefits of risk reduction are larger than those in the regression analysis. On the other hand, when we estimated τ using DBRD design, we obtained much larger estimates than those from 2DRD. However, if there are locational specific factors that significantly affect property prices, the estimates from the DBRD method will not be precise (which we numerically confirmed in Section 5.2).

5.4. An application of expected utility theory

The financial risks of building collapse and fire can be mitigated with earthquake insurance. In Japan, the maximum insurable amount is 500 thousand USD (about 50 million JPY). The insurance fee is uniform across all of Tokyo's 23 wards, regardless of whether the property is located in a high- or low-risk zone. Thus, a likely explanation for the price difference between high- and low-risk zones is "self-insurance" (Ehrlich and Becker, 1972; Brookshire et al., 1985). The results of the RD analysis indicate that around 2.65% of a property's unit price may be explained by the differences in the integrated seismic hazard risk.

Following Brookshire et al. (1985), we suppose that consumers maximize their expected utility.[11] Then, by using Δ to denote the total difference in value between safe and unsafe properties in terms of IR, we obtain

$$\Delta\gamma \approx \frac{-pU'_e}{pU'_e + (1-p)U'}\Delta s \tag{9}$$

where γ is the unit price of a flat, s is the unit damage of a large earthquake, p is the annual probability of having a large earthquake, and the subscript e denotes the evaluation in the state of an earthquake. In the above equation, we estimate that, on average, $\Delta\gamma = 1.738$ (10,000 JPY) at the boundary of high- and low-risk zones. It should be noted that there are two unknown parameters on the right-hand side, p and Δs. If consumers are risk-neutral, by solving Eq. (8), we find that p is approximately 0.0602.[12] Alternatively, if consumers have a constant relative risk aversion measure of two, and the ratio of the housing value to total wealth is 0.2868 (as in Brookshire et al. (1985)),[13] then p is approximately 0.0411. These predicted "subjective" probabilities, 0.0602

[10] 1981: Building Standard Law; 1999: Housing Quality Assurance Act; 2000: Act on Advancement of Proper Condominium Management.

[11] We define the utility function as follows: $V = pU(w(a, l) - \gamma(a, s)l - sl) + (1 - p)U(w(a, l) - \gamma(a, s)l)$, where p is the annual probability of having a large earthquake, w is the wealth of a household, a is a vector of housing attributes, l is the area of an apartment, γ is the unit price of an apartment, and s is the unit damage of a large earthquake. We assume that apartments on the boundaries of the safe and unsafe zones have the same area. Under the assumption that U is differentiable, the first order condition for the maximization problem may be taken with respect to s.

[12] Suppose that 44% of the property price stems from the value of the building, while 56% is based on the land value (which is typical of residential building transaction in Tokyo; this ratio is the average land value over total stock of major residential real estate investment trusts (REITs) throughout the country), and that properties in low-risk zones do not incur any losses under present building codes, such that the unit damage cost, Δs, equals the average building construction cost, with $\Delta s = 0.44 \times 65.602 = 28.864$ (10,000 JPY).

[13] We calculate the total wealth, including human capital, using the method proposed by Friend and Bluem (1975). As such, we use data from the National Survey of Family Income and Expenditure 2009 (*Zenkoku Shohi Jittai Chosa*, in Japanese) and divide the population into 6 cohorts based on the head of household's age.

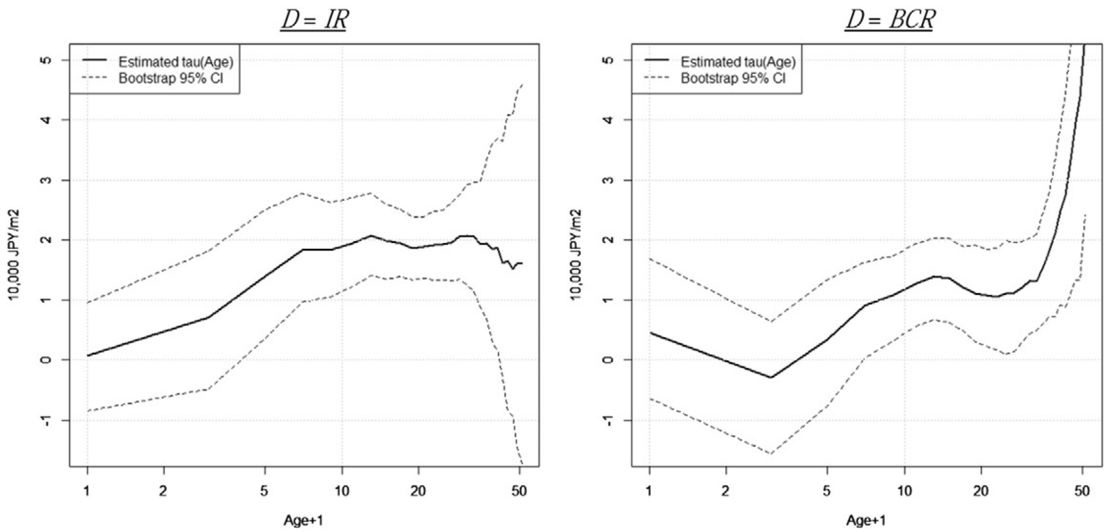

Fig. 5. Estimated τ_x(Log Age).

Table 5
Average risk reduction effect τ.

	2DRD		DBRD	
Risk variable *D*	*IR*	*BCR*	*IR*	*BCR*
Estimate	1.738	1.397	3.390	5.227
Bootstrap 95% CI	[1.150, 2.344]	[0.884, 1.877]	[0.550, 10.540]	[2.674, 8.552]

and 0.0411, are much higher than the officially announced probability of a large earthquake, which is only 0.0088.[14,15]

When we regard $\Delta\gamma$ as an approximation of a unit WTP, the average total WTP may be approximated by $17,380 \times 41.430 = 720,050$ JPY (similarly for BCR, we estimate it to be 578,877 JPY). Using a contingent valuation method (CVM), Sato et al. (2009, in Japanese only) reported that the WTP for anti-seismic reinforcement in the Tokyo metropolitan area is around 915,000 JPY for households that have yet to reinforce their residences. Due to the experimenter's demand effect and hypothetical biases, it is known that the CVM tends to overestimate WTP, and as such, our estimate of 720,050 JPY appears to be reasonable.

6. Concluding remarks

In this study, we used the 2DRD design, which has several advantages over the standard hedonic regression approach and the conventional one-dimensional RD approach, to determine how the property market in Tokyo's 23 wards evaluates seismic hazard risk information. We showed that, on average at the boundary, the unit prices of residential properties in low-risk zones were about 13,970–17,380 JPY higher than those in high-risk zones, depending on the type of seismic hazard risk. In addition, we found that the impact of risk information was significant for older apartments, but not for new ones. Thus, introducing policies aimed at replacing old apartments in high-risk zones with new buildings would substantially improve consumers' satisfaction. By applying the expected utility theory as in Brookshire et al. (1985), we showed that the residents in Tokyo's 23 wards subjectively believe that the probability of a large earthquake is much greater than the officially reported probability. Furthermore, we also showed that the estimated difference in property prices in safe and unsafe zones is conservative and reasonable if it is interpreted as the WTP for risk reduction.

However, we must be careful in interpreting our results. As stated above, the true risk level, which is determined by geographic and physical conditions, should be continuous rather than ordinal in most districts. The true difference in risk at the boundary should be less prominent than the one shown by the risk score that we used in our analysis. Therefore, the RD analysis cannot be used to estimate the value of changes in the true risk level. Instead, this study focuses on how the property market perceives and reacts to the reported risk level, although the degree to which residents actually take into account the government's risk information is unclear.[16] In addition, we controlled for the presence of spatial correlation effects in the hedonic regression analysis but not in our RD analysis. As mentioned in footnote 7, accounting for such cross-sectional interactions in a quasi-experimental framework is challenging and an interesting topic for future research.

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[14] The officially announced probability of an earthquake occurring in Tokyo's 23 wards that rates six or higher on the Richter scale within 30 years from 2012, is 23.2%. If we assume that the probability is uniform over time, the annual probability of an earthquake is roughly 0.0088.

[15] In general, it is impossible to know a person's subjective risk assessment without directly asking him/her. As such, Naoi et al. (2009) assume that the subjective risk probability can be represented as a function of an objective risk probability and use a measurement error model to thereby infer subjective risk.

[16] Pope (2008a, 2008b) empirically showed that simply placing environmental information in the public domain does not guarantee that economic agents will utilize it.

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