THE EXTERNALITY OF STIGMATIZED PROPERTY: WHAT DOES HEDONIC REGRESSION TELL US UNDER INCOMPLETE INFORMATION?

Taisuke Sadayuki

REAL 13-T-01 January, 2013

The Externality of Stigmatized Property: What Does Hedonic Regression Tell Us Under Incomplete Information?

Taisuke Sadayuki

Department of Economics, and Regional Economics Applications Laboratory (REAL), University of Illinois at Urbana-Champaign

e-mail: tai_rachmaninov@msn.com, sadayuk2@illinois.edu

Abstract: A stigmatized property, or a psychologically impacted property, is a real estate property that suffers from an undesirable past event, such as a suicide or homicide, that affects the present property value. This paper provides the first empirical evidence of the existence of the negative externality of stigmatized property, based on data on rental housing and stigmatizing events recorded in Tokyo, Japan. Although the estimation result using the standard hedonic approach ensures the presence of the externality, it does not represent the degree of the implicit externality under complete information, in which prospective renters are fully informed. This is because property owners strategically assign offered rental prices by assuming that prospective renters face incomplete information about the surrounding stigmatized properties. Therefore, we examine the implications underlying the estimated hedonic functions by imposing several valid assumptions.

Keywords: stigmatized property, psychologically impacted property, externality, hedonic model, incomplete information

Introduction

A stigmatized property, or a psychologically impacted property, is a real estate property that suffers from an undesirable past event, such as a death by fire, a suicide, a homicide, or any other tragedy that affects the present value of the property. Although the definition of a stigmatized property is controversial and state laws vary in the United States,[1] the various definitions share the concept that a reduction in the value of a stigmatized property is associated with a psychological impact, not a material deficit (Brown and Thurlow, 1996; Sanchez-Behar, 2008; Edmiston, 2010). The general rule regarding a housing supplier's disclosure of a stigmatized property in the United States is caveat emptor, that is, "Let the buyer beware." No cause of action arises against suppliers of stigmatized properties for failing to disclose the fact that a stigmatizing event took place on the property. In contrast, Japanese property transaction law "prohibits suppliers from misrepresenting or intentionally failing to disclose a fact when

[1] The types of stigmatizing events listed in the statutes are mostly homicide, suicide, HIV, and AIDS, followed by "any other felony." The website Real Estate Webmasters (http://www.realestatewebmasters.com/) provides the following description of a stigmatized property: "[W]hile the exact legal definition varies by state and country, typically it is construed to be where something has taken place on a property (such as the death of one of the occupants in a traumatic or notorious fashion) such that it has affected the value of the property."

concluding a contract if the fact has a critical influence on the transactional partners' decision,"[2] which certainly includes a past incident on the property such as a suicide or murder.

However, it is important to note that in practice in both the United States and Japan, housing suppliers have no obligation to disclose stigmatized properties to their customers if the transactional property is not the one in which the stigmatizing event took place. Because prospective renters have only partial information about the existence of stigmatized properties, some individuals may buy or rent housing without being aware there are stigmatized properties in the neighborhood, or even in the same apartment building. When such information is asymmetrical, housing suppliers strategically assign offered prices that maximize their expected discounted future revenues, conditional on what prospective renters would learn about the surrounding stigmatized properties. Consequently, suppliers do not adjust their offered prices to as low a level as when people are fully informed. This means that under incomplete information, a hedonic approach does not reveal the implicit externality that is present under complete information, in which prospective renters are fully informed of the existence of stigmatized properties.

The first aim of this paper is to examine the existence of the externality of stigmatized properties. Although numerous empirical studies have been conducted on the externality of hazardous waste sites and environmental contamination,[3] to our knowledge, this paper is the first to examine the externality of stigmatized property.[4] Estimation results based on rental housing data listed in the housing market and on stigmatized properties recorded in Tokyo, Japan, verify the presence of a negative externality: the value of rental housing near stigmatized properties is low and increases as the properties are located farther from the sites. Furthermore, the strength of the externality is ameliorated as time passes after the stigmatizing event.

The second objective of this study is to investigate hidden factors behind coefficients of the hedonic model under incomplete information. Using the estimation results, we explore two main hidden factors in the latter part of this paper: 1) the externality under complete information,

---

2 Article 47, item 1, of the Building Lots and Buildings Transaction Business Act.

3 See Boyle and Kiel (2001) for a literature review. For recent studies, see McCluskey and Rausser (2003a, 2003b), Inlanfeldt and Taylor (2004), Messer et al. (2006), Deaton and Hoehn (2004), Kiel and Williams (2007), and Gamper-Rabindran and Timmins (2011). Most of these studies estimate hedonic housing price functions by using the distance to hazardous sites as an explanatory variable to evaluate the degree of effect of the externality. Simons and Saginor (2006) and Braden et al. (2011) conducted meta-analysis of previous studies to investigate factors involved in the externality.

4 Various articles and papers have reported how much stigmatized properties are devalued relative to nonstigmatized properties. For example, Larsen and Coleman (2004), who conducted a survey of real estate licensees in Ohio, found that the sale prices of stigmatized properties were, on average, approximately 3% less than those of nonstigmatized houses. Randall Bell, an appraiser in California, stated that well-recognized homicide events devalue property values by 15 to 35% after the incident (Umberger, 1999).

and 2) the information on stigmatized properties provided to prospective renters. As mentioned, although the estimates with hedonic models indicate that a negative externality is present for stigmatized property, they do not represent the degree of the externality under complete information.

To examine the relationship between incomplete information and the hedonic model, Kask and Maani (1992) studied the consequences on the hedonic price when consumers possessed incomplete information and believed in a biased subjective probability of a future event. The authors discussed the direction of biases in the hedonic price, depending on the information and the subjective probability that consumers possessed. Pope (2008a, 2008b), on the other hand, considered a situation in which consumers faced incomplete information. He empirically verified the existence of incomplete information among consumers by estimating differences in equilibrium prices before and after suppliers disclosed “bads” (disamenities) that were initially available to the public but not well recognized.

Our approach to examining the relationship between the hedonic model under incomplete information and hidden factors regarding the externality under complete information and consumers’ information on bads (in this case, stigmatized properties) differs significantly from those of Kask and Maani (1992) and Pope (2008a, 2008b) in the following two respects. First, although each study considered a single bad, our study assumes a variety of hidden factors, such as the degree of externality under complete information and the types of prospective renter information, which can differ by the type of stigmatizing event. This assumption makes the analysis more complex, but also more interesting. For example, we consider the possibility that prospective renters recognize the existence of some stigmatized properties but cannot identify the event types. Therefore, the rental price of housing around stigmatized properties is affected by such prospective renters, for whom all possible event types will have a psychological impact. Second, assuming that a variety of hidden factors exist, we propose using a unique approach to examine the relationship. As shown later, F-tests of coefficients in the hedonic function between two different event types play a significant role in this exploration of hidden factors.

The structure of the paper is as follows. We first explain the data used in this paper. Hedonic models and the associated estimation results are then demonstrated. On the basis of these results, we explore the implications of the hidden factors behind the estimated hedonic functions. Finally, some concluding remarks are made.

Data

Two types of data are used in this research. One is the stigmatized properties listed on the website Jikobukken.com,[5] which describes stigmatizing events and times, and the property locations. The other data source is rental housing listed by the real estate agency Door Chintai,[6] which describes rental prices offered and various housing characteristics.

Stigmatized properties

To our knowledge, no complete or official data are available on stigmatized properties in Japan or elsewhere. Although Japanese law requires housing suppliers to disclose stigmatizing events to prospective renters of these properties, the suppliers rarely provide such information at the beginning of negotiations with transactional partners or when they post descriptions of the properties on real estate agency websites. Rather, in most cases, the suppliers disclose stigmatizing events to prospective renters immediately before the renters sign a lease contract. One of the possible reasons for this practice is that property owners having had a stigmatizing event among their properties assets are concerned that potential customers might learn that a stigmatized property is located within the apartment building of interest, causing them to be reluctant to move into that building.

The data on stigmatized properties used in this paper were obtained from Jikobukken.com, a website that provides information on stigmatized properties in Japan, based on existing records and on information provided by the public. Consequently, the stigmatizing events reported on Jikobukken.com are not comprehensive and are recorded only if third parties have recognized the events. In this sense, well-known events or those that are easily revealed are more likely to be recorded on Jikobukken.com. Therefore, if an externality is present, we should be more likely to observe a large effect of the externality in this data set relative to other stigmatized properties that have been withheld from the public.

The data include descriptions of the stigmatizing events, dates of the events, and addresses where the events took place. Events are categorized into five groups: discovery of a body, death by fire, suicide, homicide, and others. Because the events categorized in the "others" group included many unknown types of events and ones that had occurred before the present buildings had been constructed, they were excluded from the following regression analyses. The largest number of events was recorded for death by fire, accounting for 308 cases, followed by murder (260 cases), suicide (193 cases), and the discovery of a body (189 cases). The years when the events took place ranged from 1954 to 2011, with more than 80% of the events happening after 2005. Only one event was observed in 2011, and the record ended by at least October 2012.

---

5 As of January 2013, the homepage of jikobukken.com (http://www.jikobukken.com) is removed and is merged to another website listing stigmatized property (http://www.oshimaland.co.jp) .

6 http://chintai.door.ac/

Figure 1 shows spatial scatter plots of stigmatized properties in Tokyo Prefecture as recorded on Jikobukken.com. Many of the recorded events were observed within the 23 wards of Tokyo, the area making up the core of Tokyo Prefecture. Moving to the west of Tokyo Prefecture, an area that is less densely populated, the number of data points becomes smaller. The second figure, which takes into account the number of housing units, illustrates the density of events by ward (number of events divided by 1,000 housing units). The figure illustrates the high propensity for stigmatized events in the 23 wards of Tokyo, even after controlling for the number of housing units.

<<insert figure 1 here>>

Figure 2 contains panels illustrating event densities by different types of events, namely, the discovery of a body, death by fire, suicide, and homicide, respectively. Although various kinds of events are more likely to be recorded within the 23 wards of Tokyo than elsewhere, different patterns were apparent. For instance, deaths by fire were observed frequently throughout the 23 wards of Tokyo, whereas finding a body and suicide were highly concentrated in the center of Tokyo's 23 wards, where the major train stations of Sinjuku, Shibuya, and Shinagawa are located. Generally, incidents of finding a body appeared to happen in empty spaces, such as a lake, river, or forest. However, these cases were excluded because Jikobukken.com considers only properties where people can interact as events that stigmatize a property. Finally, the panel indicating homicide is different from the others because of the high population density in the west of Tokyo. Thus, the westernmost ward in Tokyo Prefecture, Nishitamagun, had only one recorded event; however, the total number of housing units was only slightly more than 20,000, resulting in a high event density.

<<insert Figure 2 here>>

Rental housing

Samples of rental housing in Tokyo Prefecture were collected in 2011–2012 from the rental real estate agency Door Chintai. After removing outlying rental price observations above the 99th percentile and below the 1st percentile, there were 132,268 observations in total. The data included rental prices as well as housing characteristics, namely, address, floor area, number of bedrooms, floor level, number of stories in a building, years since building completion, time to the closest train station by walking, building type, and building structure.[7] Definitions of the

[7] Note that the rental prices observed for Door Chintai are available in the housing market; thus, they are not transactional prices, but are prices offered by property owners. One significant concern when conducting research using listed sale prices is that sale prices tend to be volatile across time and that some gaps generally exist between listed sale prices and transaction prices. However, housing rental prices change gradually over time compared with sale prices. This is because the rental price reflects the quality of housing services, the

variables are presented in table 1, and their basic statistics are shown in table 2.

<<insert tables 1 and 2 here>>

Using the addresses of properties listed on Door Chintai and Jikobukken.com, we computed distances between rental housing and stigmatized properties based on the Geocoding Information System (GIS) provided by the Center for Spatial Information Science (CSIS),[8] from which we obtained the distance to the closest stigmatized properties, Distance, and the number of stigmatized properties within a certain range from rental housing, #Events.

The geocoding of CSIS tracks the accuracy of the address up to the block level.[9] Consequently, distances between rental housing units and their closest stigmatized properties took values of zero if they were located in the same block, which accounted for 1,348 rental housing units. By matching the addresses of these two data sets with the building level, we obtained 198 rental housing units located within buildings having stigmatized properties. We did not find any rental housing units whose floor level matched the floor level of a stigmatized property in the same building, indicating that none of the rental housing samples was a stigmatized property recorded on Jikobukken.com.

Empirical models and estimation results

Empirical models

The final versions of the hedonic models used are complex, with many interaction terms between variables. We begin with an explanation of the simple model:

$$\ln(Rent/ft2)_i = \boldsymbol{\alpha}_1 \mathbf{V}_i + \boldsymbol{\alpha}_2 \mathbf{X}_i + \varepsilon_i$$

$$\boldsymbol{\alpha}_1 = [\alpha_{Dis} \quad \alpha_{Bld} \quad \alpha_{Blk} \quad \alpha_{Age}], \quad \mathbf{V}_i = \begin{bmatrix} \ln(Distance + 1)_i \\ Building_i \\ Block_i \\ \ln(EventAge) \end{bmatrix}. \qquad (1)$$

location, and the environment, which require a longer period to adjust, whereas sale prices reflect not only the quality of the property, but also expectations of the future: the theoretical sale price is the expected discounted value of rental revenue in the future. In this sense, using rental housing enabled us to avoid problems associated with volatility and expectations of the future and to focus on the quality of housing services and the environment, although it would have been ideal to have explicit information about the transactional rental prices.

8 The CSIS is located at Tokyo University (http://www.csis.u-tokyo.ac.jp/japanese/index.html).

9 Unlike western addresses, Japanese addresses begin with the largest geographical entities. For instance, the address of the Tokyo Metropolitan Government Office Building is "Tokyo-to, Sinjyuku-ku, Nishi-Sinjyuku, 2-8-1," where "Tokyo-to" is the prefecture, "Sinjyuku-ku" is the city or ward, "Nishi-Sinjyuku, 2" is the city district, "8" is the block area, and "1" is the building number. If multiple housing units are in one building, room numbers are followed by the building number to express the address of the unit.

Here, $\ln(Rent/ft2)_i$ is the natural logarithmic value of a rental price per square foot of housing i, $\mathbf{V}_i$ is a column vector of variables measuring the effects of the externality, $\boldsymbol{\alpha}_1$ is a row vector of coefficients for these variables, $\mathbf{X}_i$ is a column vector of control variables of the characteristics of housing i, $\boldsymbol{\alpha}_2$ is a row vector of coefficients for the control variables, and ε_i is an error term. In the specification of model (1), $\mathbf{V}_i$ contains four variables that measure the externality of a stigmatized property: 1) $\ln(Distance + 1)_i$ is the natural logarithmic value of 1 plus the distance from housing i to its closest stigmatized property in feet. 2) $Building_i$ and 3) $Block_i$ are dummy variables indicating housing i located in the building and block, respectively, containing the stigmatized property. Because housing samples that take values of 1 for $Building_i$ also assign values of 1 for $Block_i$, the coefficient for $Building_i$, α_{Bld}, reflects the difference in rental prices between housing in buildings having stigmatized property and other housing in the same block. 4) $EventAge_i$ is the number of years that have passed since the occurrence of the stigmatizing event closest to housing i. If the stigma of events decreases over time, the coefficient for $EventAge_i$ is expected to be positive.

The control variables, $\mathbf{X}_i$, include the variables described in table 2, such as the time to the closest train station, floor level, floor space, number of bedrooms, total number of stories in the building, year of building completion, and dummy variables for building types and structures. We also include dummy variables for train stations, with 1 assigned if the station is the closest to housing i and zero otherwise. All continuous control variables are converted into natural logarithmic values and their squared values are also included in $\mathbf{X}_i$.

As can be seen in equation (1), the model is constructed to capture the externality on the housing rental price of the closest stigmatized property. However, it is possible that the rental prices are also influenced by other surrounding stigmatized properties. To control for the effect of having multiple stigmatizing sites close to housing i, the natural logarithmic value of $\#Events_i$, the number of stigmatized properties within a certain range from housing i, and its squared value are also included in $\mathbf{X}_i$.

The primary interest is in the coefficient for $Building_i$, α_{Bld}, which was expected to show the greatest externality among three variables, $\ln(Distance + 1)_i$, $Building_i$, and $Block_i$. If no externality exists within the building, it is unlikely that we would observe an externality outside the building. However, their coefficients may also reflect some indirect effects because of the existence of the stigmatized property. For instance, stigmatizing events may have a positive influence on neighboring housing values by inducing an improvement in facilities or security systems, characteristics that are omitted from the control variables, $\mathbf{X}_i$. In addition, because of the small number of observations for rental housing located in buildings containing stigmatized properties, the coefficient for $Building_i$, α_{Bld}, may not be significant, whereas a significant externality might be observed for other variables, $\ln(Distance+1)_i$ and $Block_i$.

Effects of the externality in terms of distance to the closest stigmatizing event are captured by the coefficient for $\ln(Distance+1)_i$. If a spatial externality exists because of a stigmatized property, the coefficient is expected to have a positive sign because the rental price should increase as housing is located farther from the site.

The coefficient for $Block_i$, α_{Blk}, in model (1) is not easy to interpret because, by including $\ln(Distance+1)_i$ as an explanatory variable, the coefficient indicates the difference in rental prices between housing in blocks with stigmatizing events and housing outside the areas that are assumed to be located at zero distance from the stigmatized property. The simplest remedy for this problem is to exclude $\ln(Distance+1)_i$ from model (1) so that differences in rental prices between inside and outside the block area can be estimated directly by looking at the coefficients for $Block_i$. This corresponds to the model in which vectors $\boldsymbol{\alpha}_1$ and $\mathbf{V}_i$ are specified as follows:

$$\boldsymbol{\alpha}_1 = [\beta_{Bld} \quad \beta_{Blk} \quad \beta_{Age}], \quad \mathbf{V}_i = \begin{bmatrix} Building_i \\ Block_i \\ \ln(EventAge)_i \end{bmatrix}. \tag{2}$$

In models (1) and (2), the externality captured by the coefficients for $\ln(Distance+1)_i$, $Building_i$, and $Block_i$ are assumed to be constant over time. In other words, these coefficients evaluate mean effects because of the existence of stigmatized properties, regardless of when the events occurred. The following models are extensions of models (1) and (2), which alleviate the externality by taking into consideration the possibility that prospective renters not only are aware of the presence of a stigmatized property, but also know the time of the event:

$$\begin{cases} \boldsymbol{\alpha}_1 = [\gamma_0 \quad \gamma_{Age} \quad \gamma_{Bld} \quad \gamma_{Bld \times Age} \quad \gamma_{Blk} \quad \gamma_{Blk \times Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \end{cases}, \tag{3}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\delta_0 \quad \delta_{Age} \quad \delta_{Dis} \quad \delta_{Dis \times Age} \quad \delta_{Bld} \quad \delta_{Bld \times Age} \quad \delta_{Blk} \quad \delta_{Blk \times Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ \ln(Distance+1)_i \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \end{cases}. \tag{4}$$

To gain a clear sense of these equations, let us take a derivative of the rental price function of model (3) with respect to $\ln(EventAge)_i$; that is,

$$\frac{\partial \ln(Rent/ft2)_i}{\partial \ln(EventAge)_i} = \gamma_{Age} + \gamma_{Bld\square Age} Building_i + \gamma_{Blk\square Age} Block_i. \quad (5)$$

The left side of equation (5) shows an elasticity of the rental price with respect to the number of years that have passed since the stigmatizing event. Consequently, $\gamma_{Blk\square Age}$ indicates the percentage increase in the rental price of housing located in a block with a stigmatized property as 1% more time passes after the event. If time alleviates the stigma of events within that block, then $\gamma_{Blk\square Age}$ should take a positive value. Furthermore, if property owners enhance their building security yearly after the occurrence of a stigmatizing event within the same block, the rental prices should increase after the security measures are implemented, which would also positively affect $\gamma_{Blk\square Age}$. Conversely, if security measures are implemented immediately after the event, this does not affect $\gamma_{Blk\square Age}$, but rather, makes γ_{Blk} positive. To clarify this point, let us take a derivative of the rental price function of model (3) with respect to $Block_i$:

$$\frac{\partial \ln(Rent/ft2)_i}{\partial Block_i} = \gamma_{Blk} + \gamma_{Blk\square Age} \ln(EventAge)_i. \quad (6)$$

When $EventAge_i$ is equal to 1, $\ln(EventAge)_i$ is zero, indicating that γ_{Blk} in equation (6) is the externality of a stigmatized property within that block 1 year after the event. If the improvement in housing quality in the first year after the stigmatizing event has a great enough benefit to prospective renters to compensate for the stigma, γ_{Blk} could be greater than zero.

We estimate rental price functions based on models (1) to (4), assuming that the extent of the externality could differ by the event type. To see these differences, $\ln(Distance + 1)_i$, $Building_i$, $Block_i$ and $\ln(EventAge)_i$ are multiplied by a dummy variable for each event type: $Discovery_i$ (discovery of a body), $Fire_i$ (death by fire), $Suicide_i$ (suicide), and $Homicide_i$ (homicide). Let D, F, S, and H refer to the discovery of a body, a death by fire, a suicide, and a homicide, respectively, and let a column vector be defined as $\mathbf{Type}_i \equiv [Discovery_i \quad Fire_i \quad Suicide_i \quad Homicide_i]'$. This then gives the final version of the empirical models, with the following specifications of vectors $\boldsymbol{\alpha}_1$ and $\mathbf{V}_i$, from (7) to (10), which correspond to the extensions of models (2), (1), (3), and (4), respectively:

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\alpha} \quad \boldsymbol{\alpha}_{Bld} \quad \boldsymbol{\alpha}_{Blk}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ Building_i \\ Block_i \end{bmatrix} \otimes [\mathbf{Type}_i]' \end{cases} \quad (7)$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\beta}_{Dis} \quad \boldsymbol{\beta}_{Bld} \quad \boldsymbol{\beta}_{Blk}] \\ \mathbf{V}_i = \begin{bmatrix} \ln(Distance+1)_i \\ Building_i \\ Block_i \end{bmatrix} \otimes [\mathbf{Type}_i] \end{cases}, \tag{8}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\gamma} \quad \boldsymbol{\gamma}_{Age} \quad \boldsymbol{\gamma}_{Bld} \quad \boldsymbol{\gamma}_{Bld\square Age} \quad \boldsymbol{\gamma}_{Blk} \quad \boldsymbol{\gamma}_{Blk\square Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \otimes [\mathbf{Type}_i] \end{cases}, \tag{9}$$

$$\begin{cases} \boldsymbol{\alpha}_1 = [\boldsymbol{\delta} \quad \boldsymbol{\delta}_{Age} \quad \boldsymbol{\delta}_{Dis} \quad \boldsymbol{\delta}_{Dis\square Age} \quad \boldsymbol{\delta}_{Bld} \quad \boldsymbol{\delta}_{Bld\square Age} \quad \boldsymbol{\delta}_{Blk} \quad \boldsymbol{\delta}_{Blk\square Age}] \\ \mathbf{V}_i = \begin{bmatrix} 1 \\ \ln(Distance+1)_i \\ Building_i \\ Block_i \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \ln(EventAge)_i \end{bmatrix} \otimes [\mathbf{Type}_i] \end{cases}. \tag{10}$$

Here, the boldfaced parameters in brackets are (1 × 4) vectors containing coefficients for four event types, namely, $\boldsymbol{\alpha}_{Bld} \equiv [\alpha_{Bld}^{D} \quad \alpha_{Bld}^{F} \quad \alpha_{Bld}^{S} \quad \alpha_{Bld}^{H}]$. Note that we impose restrictions on a vector of coefficients, $\boldsymbol{\delta}$, in model (10) such that $\delta^D = \delta^F = \delta^S = \delta^H$ because otherwise, the effects of $\ln(Distance+1)_i$, δ_{Dis}^{k}, where $k \in \{D, F, S, H\}$, would be subtracted by the effects captured in δ^k, which is the mean effect of each event type on the area outside the block with the stigmatized property. If we use different parameters in $\boldsymbol{\delta}$, the effect of the externality in δ_{Dis}^{k} will be underestimated for event type k, which has a high spatial externality, because a large mean externality effect, δ^k, absolves the effects on δ_{Dis}^{k}.

Using models (7) to (10), we estimate each rental price function with different sample sizes; estimations are restricted to rental housing units located within 0.2, 0.3, and 0.5 miles from the observed stigmatized properties, for which the number of stigmatized properties within 0.2, 0.3, and 0.5 miles from housing i are used as $\#Events_i$ in $\mathbf{X}_i$, respectively. Estimations are conducted with different restricted sizes of data sets mainly for two reasons. First, although it is preferable to use a larger sample size to have more degrees of freedom, the spatial externality, if this exists, might be captured only within a certain distance from the stigmatized properties. If we were to include many samples located too far from the stigmatized properties, we might not find significant effects of $\ln(Distance+1)_i$, even if the externality existed within a limited range from the sites.

Second, as shown in Figure 1, some stigmatized properties are highly clustered, whereas others are sparse. In a district with highly clustered stigmatized properties, the area having the closest stigmatized properties in common is small. In such districts, the average distance to the closest stigmatized property would be nearby. If a correlation exists between the average distance to the closest stigmatized property and a rental price that is not controlled by $\mathbf{X}_i$, then the estimated coefficients for $\ln(Distance + 1)_i$ would suffer from an endogeneity problem, inducing biased estimates. In this regard, although some variables in $\mathbf{X}_i$, such as #Events, Time, and station dummies, are expected to resolve the issue of endogeneity, estimations with a restricted number of samples may give more accurate estimates of the distance to the closest stigmatized property, whereas the degrees of freedom are smaller with a smaller sample size. Concerning these two sample selection problems, we declined to elaborate on the coefficients of $\ln(Distance + 1)_i$. Instead, we examine the signs, significance, and tendencies of magnitudes of the coefficients of $\ln(Distance + 1)_i$ across different sample sizes and check the robustness of other variables.

Estimation results

Table 3 describes the estimation results for models (7) and (8). Each column uses samples lying within a certain range (0.2, 0.3, or 0.5 miles) of the stigmatized properties. Based on the number of observations in table 3, the sample size decreases from 92,436 to 60,774 and then to 35,545 as the range is restricted from 0.5 to 0.3 and then to 0.2 miles.

<<insert table 3 here>>

Let us begin by looking at the coefficients for $Building_i$, $\boldsymbol{\alpha}_{Bld}$, and $Block_i$, $\boldsymbol{\alpha}_{Blk}$, in model (7). The estimation results are shown in columns [3-1] to [3-3]. Regarding $Building_i$, the coefficients are negative and significant for the event types death by fire and homicide; specifically, the rental price of a housing unit in a building where an individual died in a fire is 2.2 to 3.4% lower than the rental price of other housing in the same block, and the rental price decreases by 5.3 to 5.6% in the case of a homicide. In contrast, the coefficients of $Block_i$ for death by fire, α^F_{Blk}, and homicide, α^H_{Blk}, are positive and significant. The only event type showing a negative effect for $Block_i$ is suicide; the rental price of housing in a block containing a property stigmatized by suicide is 3.8 to 4.0% lower than the rental price of housing located outside that block.

In columns [3-4] to [3-6] of table 3, all coefficients for $\ln(Distance + 1)_i$ have a positive effect on the rental price, whereas these magnitudes and significances vary by event type as well as by sample size. The coefficients of death by fire, α^F_{Dis}, are positive and significant in all estimations across the different sample sizes. In contrast, the discovery of a body does not have a significant effect on the externality for either $\ln(Distance + 1)_i$ or $Building_i$ and $Block_i$.

Recall that stigmatizing events are recorded on Jikobukken.com only when third parties have observed these facts. These events are revealed through media reports and by members of the public. Among the four event types, death by fire and homicide are the most likely to be recognized by large numbers of people. For a death by fire, members of the neighborhood can easily recognize the incident by observing or hearing firefighters in the area. This may reflect the fact that the externality of death by fire reaches a wide range of people because information about such an event is easily accessible compared with information about other event types. In addition, a fire does not spread beyond the block because each block is surrounded by streets. When an individual dies in a fire, property owners and residents in that block may realize the risk and move to install fire prevention devices. This is one possible explanation for the positive signs observed for $Block_i$, α^F_{Blk}.

This scenario applies in the case of homicide as well. The event of a homicide is more likely to be widely reported by the media than is any other event type, and a large number of people will be aware of the event. Consequently, as shown in the results, the rental price of housing in a building where a homicide was committed declines sharply. In contrast, the rental price of housing in that block increases after a homicide, suggesting that managers of the surrounding buildings might facilitate the installation of security systems to improve the quality of housing enough to compensate for the potentially stigmatizing event.

Regarding $\ln(EventAge)_i$, the signs of the coefficients and their significance values are not consistent. Although the time since the event is expected to have a positive influence on the rental price, only the coefficients for suicide, α^F_{Dis}, consistently show positive signs. Using models (9) and (10), we examine the effects on the externality of interactions between $\ln(EventAge)_i$ and other variables, such as $Building_i$, $Block_i$, and $\ln(Distance + 1)_i$. The estimation results are shown in table 4.

<<*insert table 4 here*>>

According to the results of model (9) presented in columns [4-1] to [4-3], the only event type consistently having a significant result for γ^k_{Bld} and $\gamma^k_{Bld\square Age}$ is homicide. One year after a homicide incident in the same building, the housing rental price is lower by 19.1 to 21.0% compared with the rental price of housing in the same block, whereas the rental price recovers by 8.04 to 8.94% as the same amount of time passes after an event. In contrast, $Fire_i$ does not have a significant effect for γ^F_{Bld} and $\gamma^F_{Bld\square Age}$, whereas a negative externality of $Fire_i$ was observed in the previous estimations. The primary reason for this observation is the presence of multicollinearity. Another possibility is that prospective renters are unaware of when an individual might have died in a fire, in which case the true specification for the empirical model for death by fire is to exclude the interaction between $Fire_i$ and $\ln(EventAge)_i$.

Regarding $Block_i$, the discovery of a body and suicide are the only event types whose coefficients, γ^k_{Blk} and $\gamma^k_{Blk\square Age}$, are significant; the rental price decreases by 6.4 to 6.5% and 11.8 to 13.1% in the first year after the discovery of a body and a suicide, respectively, and it recovers by 4.28 to 4.56% and 3.68 to 4.21%, respectively, as the same amount of time passes after an event. For example, if the rental price 5 years after an event is $1,000.0, then it will become $1,008.0 to $1,008.9 10 years after the event (an increase of 0.80 to 0.89% as another 5 years pass). In contrast, the coefficients for γ_{Blk}^{H} show positive signs. In the preceding estimations, we suggest that security may be improved in housing in a block where a homicide was committed, thus increasing the rental value. Given that γ_{Blk}^{H} is positive but $\gamma_{Blk\times Age}^{H}$ is not statistically different from zero, the estimation results imply that security systems are typically installed within the first year after a homicide.

In columns [4-4] to [4-6] in table 4, the coefficients for $\ln(Distance+1)_i$, δ_{Dis}^{k}, are positive and significant for all event types, indicating that a spatial negative externality exists after the occurrence of an event of any type. The coefficients for $Fire_i$, δ_{Dis}^{F}, and $Homicide_i$, δ_{Dis}^{H}, and their significance levels in particular are greater than those for the other two event types. This is consistent with the intuition that these two event types are easily revealed and that their externalities are far reaching. Finally, the coefficient for $\ln(Distance+1)_i \times \ln(EventAge)_i$, $\delta_{Dis\times Age}^{k}$, has a negative sign for all event types, implying that the extent of the spatial externality diminishes over time.

Implications of the hedonic estimates under incomplete information

The previous estimations detected the presence of an externality of stigmatized property. If prospective renters were fully informed about the stigmatized properties recorded on Jikobukken.com, and if other factors influencing the housing rental price were well controlled in the estimation, the estimated coefficients indicating the influence of stigmatized property would represent the implicit influence of such property on prospective renters under complete information, where prospective renters are fully informed of stigmatized properties via Jikobukken.com. However, the information on Jikobukken.com is not common knowledge, and only a portion of prospective renters are likely to recognize each stigmatized property listed. When prospective renters encounter imperfect information, the hedonic model under complete information may underestimate the implicit externality.

Although a small number of studies have examined how the hedonic model is interpreted under incomplete information, Pope (2008b) has provided intuitive explanation, including graphical demonstrations, regarding the relationship between the hedonic model and asymmetric information, in which suppliers have complete information on bads but consumers may have less information. Figure 3, which is taken from Pope (2008b), shows the possible bundle of equilibrium prices along with the quantity (or quality) of bads in the shaded area. If consumers are fully informed about bads, the equilibrium price will coincide with the envelope of minimum offers by suppliers, which will cause a decrease in the quantity of bads. On the contrary, if consumers possess no information on bads, the equilibrium price will be the envelope of maximum bids by consumers, which will be constant regardless of the quantity of bads. Between these envelopes, the equilibrium price given some quantity of bads can vary according to the fraction of consumers having information on the bads and the expectations of suppliers for that fraction. Intuitively, the path of the equilibrium price shifts downward as consumers become more informed.[10]

<<insert figure 3 here>>

In this section, we investigate estimates of the hedonic rental price function under incomplete information to obtain possible interpretations of the hidden factors behind these estimates, such as on the externality under complete information and on the information about stigmatized properties that prospective renters possess. These hidden factors cannot be identified from a single coefficient, and few implications are obtained without imposing restrictions on these factors.

To see how few implications we could obtain, consider, for example, the coefficients for $Building_i$ for death by fire, α^F_{Bld}, in model (7), which range between -0.0342 and -0.0217. As discussed, even though all other factors were well controlled in the model, these estimates do not represent the externality under complete information. It is surprising that although these coefficients are significantly different from zero, we cannot exclude the possibility that no significant externality of death by fire exists under complete information. This could be true when prospective renters recognize the presence of stigmatized properties but cannot identify the event as a death by fire and suspect that something worse may have happened on the premises.

For another example, consider the coefficients for $Building_i$ for discovery of a body, α^D_{Bld}, in model (7), which range from -0.0267 to -0.0221. Even when they are not statistically significant, we cannot exclude the possibility that the discovery of a body would have a significant externality under complete information. This is because properties stigmatized by the discovery of a body could be difficult for prospective renters to recognize, which attenuates the effect of the presence of these properties.

To clarify these points, we discuss the relationship between incomplete information and coefficients of the hedonic model in the following subsections. First, we decompose the coefficients of the hedonic model under several assumptions, enabling us to examine the

[10] As Pope (2008b) mentions, the exact path of the equilibrium price has not been formally proved.

relationship between the estimated coefficients and their hidden factors. Then, we discuss three cases in which we impose reasonable restrictions on some hidden factors, and examine the interpretation of unrestricted factors. Finally, we apply the analytical frameworks of these cases to the estimation results provided in the previous section.

Decomposition of coefficients of the hedonic model

We consider four submarkets of rental housing located a fixed distance from the closest stigmatized properties. Each submarket deals with rental housing whose closest stigmatized properties are of the same event type, $k \in K \equiv \{D, F, S, H\}$. Let J^k be a set of rental properties whose closest stigmatized properties are of event type $k \in K$, with an element of J^k denoted by j^k; then let I^k be a set of prospective renters of housing J^k. In addition, let S^k be a set of stigmatized properties whose event type is k, and let s^k be an element of S^k.

A prospective renter, $i \in I^k$, has one of the following three kinds of information about each stigmatized property, $s^k \in S^k$: (A) prospective renter i recognizes the presence of the stigmatized property and also identifies its event type k, (B) prospective renter i recognizes the presence of the stigmatized property but does not know the event type k, or (C) prospective renter i does not recognize the presence of the stigmatized property.

If all prospective renters in I^k are expected to have information (A) on all $s^k \in S^k$ (i.e., all prospective renters in the housing submarket of J^k are expected to recognize all stigmatized properties in S^k and their event type k), then the decrease in the offered rental price of J^k resulting from the presence of stigmatized properties S^k is equal to the influence of event type k under complete information. On the contrary, if all prospective renters in I^k are expected to have information (C) on all $s^k \in S^k$ for all $k \in K$ (i.e., no prospective renter knows the presence of any stigmatized property), then the offered rental prices in the housing market of J^k for all $k \in K$ will not be affected by stigmatized properties and are thus the same.

Figures 4 and 5 demonstrate how the externality under complete information and the expected possibility of prospective renters in I^k having information (A), (B), and (C) affects the offered rental price of J^k.

<<insert figures 4 and 5 here>>

In figure 4, A, B, and C are the demand curves when all the prospective renters in I^k have information (A), (B), and (C) on all $s^k \in S^k$, respectively. The heavy line in figure 5 describes one possible demand curve that property owners of J^k expect to encounter, and R^k is the offered rental price at which the expected demand curve intersects the supply curve.[11] Figure 3,

[11] The supply curve is vertical because we are considering the short-term housing market, where the temporal

from Pope (2008b), shows the path of the equilibrium price along with the quantity of bads, whereas figures 4 and 5 demonstrate the demand and supply curves given a fixed quantity of bads (in this case, the distance to the closest stigmatized property).

Next, we decompose the coefficient of the hedonic model for the externality. Let τ_A^k be the absolute degree of externality of stigmatized property j^k under complete information, let τ_B^k be the absolute degree of externality when prospective renters recognize the existence of the stigmatized property but cannot identify its event type k, and let τ_C^k be the absolute degree of externality when prospective renters do not recognize the existence of the stigmatized property. Then, we consider the following decomposition of a hedonic estimate regarding the externality:

$$|\alpha^k| = \theta_A^k\tau_A^k + \theta_B^k\tau_B^k + \theta_C^k\tau_C^k. \tag{11}$$

where parameters θ_A^k, θ_B^k and θ_C^k are defined as weights of τ_A^k, τ_B^k and τ_C^k such that the sum of their products equals the absolute value of the estimated coefficient. Here, $\tau_C^k = 0$ because no externality exists if the stigmatized property j^k is not recognized. Furthermore, we assume that prospective renters suspect all event types equally when they have information (B) on the stigmatized properties, implying that $\tau_B^k = \tilde{\tau}$ for all $k \in K$, where $\tilde{\tau}$ is the mean externality of all event types. By denoting τ_A^k and τ_B^k by τ^k and $\tilde{\tau}$, respectively, we have the following formula for the decomposition of the hedonic estimate:

$$|\alpha^k| = \theta_A^k\tau^k + \theta_B^k\tilde{\tau}. \tag{12}$$

Greater θ_A^k and θ_B^k imply, respectively, more prospective renters in I^k having information (A) and (B), shifting the expected demand curve from C closer to A and B in figures 4 and 5. Therefore, we can refer to θ_A^k and θ_B^k as I^k contributing information (A) and (B), respectively, to the position of the expected demand curve. The increase in θ_A^k and θ_B^k reduces the offered rental price, as seen in figures 4 and 5, which corresponds to the downward shift in the equilibrium price in figure 3 as the incompleteness of information increases.

Last, we note two points regarding the hidden parameters in equation (12). First, the fact that θ_A^k is zero does not necessarily mean that no prospective renters have information (A) on any $s^k \in S^k$; in other words, even if θ_A^k is zero, it is possible to have a number of prospective renters who identify event type k of some $s^k \in S^k$. This is because a demand curve in the housing market of J^k is determined endogenously in such a way that prospective renters intend to avoid renting housing nearby recognizable stigmatized properties whose event type might have a significant negative psychological impact on them. In this sense, in addition to the incomplete information, the estimated coefficient may underestimate the implicit influence of

housing stock is fixed.

stigmatized property because of the endogeneity such that prospective renters intend to avoid areas they recognize as stigmatized properties, whereas they may live around properties they do not recognize as being stigmatized.

Secondly, hedonic rental price functions in our estimations use natural logarithmic values for the independent variables. This means that the coefficient α^k indicates the percentage change in the rental price when a variable increases marginally; that is, $|\alpha^k| = \left(R_C^k - R^k\right)/R_C^k$. Accordingly, τ^k and $\tilde{\tau}$ are characterized as $\tau^k = \left(R_C^k - R_A^k\right)/R_C^k$ and $\tilde{\tau} = \left(R_C^k - R_B^k\right)/R_C^k$.

Implications of the three cases

In equation (12), we have four unknown parameters, whereas we are given only a single value, α^k, from the estimation. If either θ_A^k or τ^k is zero, we no longer know the sign of the other parameter, as for θ_B^k and $\tilde{\tau}$. Therefore, when α^k is not statistically different from zero, nothing can be concluded about these hidden parameters unless we impose some assumptions. Now, let us consider three cases with different restrictions on some parameters and examine their implications for unrestricted parameters. All proofs are provided in the Appendix.

Case (a): $\theta_B^k = 0$ for all k.

In case (a), it is assumed that prospective renters do not recognize a stigmatized event whose event type is unknown. In other words, prospective renters recognize properties as stigmatized only when they identify their event types. This is the case when people learn about stigmatized properties only through media reports that describe the events in detail. In this situation, the following relationship is derived between the parameters and the estimated coefficients:

$$\theta_A^k > 0,\ \tau^k > 0 \quad \text{if and only if} \quad |\alpha^k| > 0. \tag{13}$$

When the coefficient of event type k is strictly positive, it implies that property owners of J^k expect some prospective renters in I^k to identify event type k in their closest stigmatized properties; furthermore, event type k has a negative externality under complete information.

Case (b): $\tau^k = \tau^l$ for all k and l.

The second case assumes that all stigmatizing event types have the same effect. This assumption appears strict because the psychological impact of the stigmatizing event seems to differ according to the manner in which the event occurs. However, if prospective renters are concerned, especially about the fact that someone in the neighborhood has died, regardless of how the incident happened, then this assumption statistically represents the reality. In this circumstance, the following relationships are implied:

$$\theta_A^k + \theta_B^k > 0 \text{ and } \tau^k = \tau^l = \tilde{\tau} > 0 \text{ for all } l \quad \text{if and only if} \quad |\alpha^k| > 0. \tag{14}$$

If $\exists m$ s.t. $|\alpha^m| > 0$, then $\theta_A^k + \theta_B^k = 0$ if and only if $|\alpha^k| = 0$. (15)

If $\exists m$ s.t. $|\alpha^m| > 0$, then $\theta_A^k + \theta_B^k > \theta_A^l + \theta_B^l$ if and only if $|\alpha^k| > |\alpha^l|$. (16)

The sum of θ_A^k and θ_B^k represents the contribution of prospective renters in I^k, who recognize the existence of the closest properties stigmatized by event type k; thus, a positive $|\alpha^k|$ implies that a number of prospective renters in I^k are aware of stigmatized properties of event type k. Furthermore, if some event type $m \neq k$ exists such that $|\alpha^m| > 0$, then $|\alpha^k|$ being zero implies that prospective renters in I^k do not contribute to the change in the offered rental price, whereas the externality under complete information is significant. Finally, if some event type m exists such that $|\alpha^m| > 0$, then $|\alpha^k| > |\alpha^l|$ implies that prospective renters who recognize the closest stigmatized properties have a greater contribution to the change in the offered price in the housing market of J^k relative to the housing market of J^l.

Case (c): $\theta_A^k = \theta_A(\tau^k)$ and $\theta_B^k = \theta_B\left(\theta_A^k\right)$,

$$\text{where} \begin{cases} -1 < \frac{\partial ln\theta_A(\tau^k)}{\partial ln\tau^k} < 0 & \text{if} \quad \theta_A^k \in (0, \theta_A(0)] \\ \frac{\partial ln\theta_A(\tau^k)}{\partial ln\tau^k} = 0 & \text{if} \quad \theta_A^k = 0 \\ \frac{\partial ln\theta_B(\theta_A^k)}{\partial ln\theta_A^k} < 0 & \text{if} \quad \theta_B^k \in (0, \theta_B(0)] \\ \frac{\partial ln\theta_B(\theta_A^k)}{\partial ln\theta_A^k} = 0 & \text{if} \quad \theta_B^k = 0 \end{cases}$$

In case (c), we assume that θ_A^k is a function of τ^k and θ_B^k is a function of θ_A^k. Under these conditions, θ_A^k and θ_B^k are determined solely by τ^k. First, we assume that θ_A^k is a decreasing function of τ^k. This assumption recognizes the endogenous issue in which prospective renters intend to avoid neighbors renting stigmatized properties whose event type has a great psychological impact on them. Here, the elasticity of θ_A with respect to τ^k is assumed to be greater than -1, meaning that even if the extent of the externality under complete information were to double, θ_A^k would not decrease as low as half of its initial value. Secondly, θ_B^k is assumed to be a decreasing function of θ_A^k, meaning that prospective renters in I^k are more likely to have information (B) when fewer prospective renters in I^k have information (A). From these assumptions, the following conditions are derived:

$\tau^k > \tau^l$, $\theta_A^k < \theta_A^l$ and $\theta_B^k \geq \theta_B^l$ if $|\alpha^k| > |\alpha^l|$. (17)

$\tau^l = 0$ and $\theta_A^l = \theta_A(0)$ if $|\alpha^k| > |\alpha^l| = 0$. (18)

If $\exists m$ s.t. $|\alpha^k| = |\alpha^l| > |\alpha^m| = 0$, then $\tau^k = \tau^l > 0, \theta_A^k = \theta_A^l > 0$ and $\theta_B^k = \theta_B^l$. (19)

If $\exists m$ s.t. $|\alpha^m| > |\alpha^k| = |\alpha^l| = 0$, then $\tau^k = \tau^l = 0, \theta_A^k = \theta_A^l = \theta_A(0)$ and $\theta_B^k = \theta_B^l$.

(20)

$$\text{If } \nexists m \text{ s.t. } |\alpha^m| > |\alpha^k| = |\alpha^l| > 0, \text{ then } \tau^k = \tau^l > 0, \theta_A^k = \theta_A^l \text{ and } \theta_B^k = \theta_B^l. \quad (21)$$

Unlike in cases (a) and (b), the implications are obtained only by using the F-test to examine the difference in coefficients between two event types in case (c). If $|\alpha^k| > |\alpha^l|$, this ensures that the externality of event type k, τ^k, is greater than that of event type l, τ^l. In addition, under this condition, if $|\alpha^l|$ is zero, then no externality exists for event type l under complete information. On the other hand, if $|\alpha^l|$ is greater than zero, and if some event type exists whose coefficient is zero, then both θ_A^l and τ^l are greater than zero. Finally, consider $|\alpha^k| = |\alpha^l|$. If these values are greater than zero and some event type exists whose coefficient is zero, then all parameters between k and l are the same, whereas the degree of their externality under complete information is zero. On the other hand, if these values are zero and no event type exists whose coefficient has an absolute value greater than those of event types k and l, then the degree of the externality of event types k and l is greater than zero.

Application to the estimated results

Finally, we examine implications of the hidden parameters in equation (12) based on the three cases described in the previous subsection by using the estimation results from columns [4-1] and [4-4] in table 4. To do this, we first conduct F-tests on the coefficients to determine the externality of a stigmatized property 1, 5, and 10 years after the event. The coefficients for the externality of the stigmatized property 1, 5, and 10 years after the event are computed by $\gamma_{Bld}^k + \gamma_{Bld\square Age}^k \ln(\#years)$ and $\gamma_{Blk}^k + \gamma_{Blk\square Age}^k \ln(\#years)$ from estimates for model (9) for Building and Block, respectively, and $\delta_{Dis}^k + \delta_{Dis\square Age}^k \ln(\#years)$ from model (10) for ln(Distance + 1). For each of these three variables, F-tests are then conducted on the coefficients for every combination of two event types, whose null hypothesis is that coefficients of the two event types are equal.

Table 5 shows P-values of the F-tests and t-tests for the coefficients for Building, Block, and ln(Distance + 1) 1, 5, and 10 years after the event for each event type. We reject the null hypotheses on F-tests and t-tests by using two-sided tests and a 5% significance level. Here, we adjusted these tests for coefficients showing unexpected signs, indicating the positive externality of stigmatized property. First, absolute values of the coefficients with unexpected signs are set to zero, meaning that we assume no externality where the coefficient shows a positive externality. Secondly, the F-test between two coefficients, one with an unexpected sign and the other with an expected sign, is discarded and the difference between these coefficients is evaluated based on the t-test for the one having the expected sign. The difference between two coefficients whose signs are both unexpected is set at zero. According to these criteria, coefficients showing a significant externality and combinations of two coefficients showing significant differences are re-marked with plus signs (+) in table 5.

Finally, the implications of hidden parameters among four event types for the three cases, (a), (b), and (c), are shown in table 6. The shaded text in the table indicates the assumptions made in each case. Now, let us look at the results for each case.

Case (a): It is assumed that θ_B^k is zero for all event types. In this case, under complete information, homicide has a significant negative externality within the building 1 and 5 years after the incident, and prospective renters in I^H, having information (A), contribute to reducing the offered rental price. Nothing can be concluded about θ_A^k and τ^k for the other event types because $|\alpha^k|$ being zero means that either θ_A^k or τ^k is zero; however, we do not know which parameter takes the value of zero. Ten years after an event, nothing can be said about θ_A^k and τ^k for any event type. This is because the impact of homicide fades over time and prospective renters are not expected to remember, or are no longer concerned about, stigmatizing events that happened 10 years ago.

Regarding Block, suicide has a significant externality even 10 years after the event. This implies that some prospective renters are still expected to identify the event type that stigmatized the property if a suicide occurred within the last 10 years in the block where their prospective rental housing is located, and they are reluctant to live in the neighborhood. For ln(Distance + 1), all event types have a significant spatial externality under complete information in the first year after an event. However, in 5 years, the evidence of a significant impact remains only for the discovery of a body and a homicide, and no event type leaves evidence of an externality 10 years after an event.

Here, we observe some counterintuitive results. For example, although the results suggest evidence of a spatial externality under complete information for all event types, we do not obtain such strong evidence within the block and the building, where the degree of externality is expected to be greater. Furthermore, we observed a strong and long-lasting externality of suicide within the block; however, its negative externality is not observed within the building. One possible reason for these results is the small sample size for rental housing located within buildings and blocks that contain stigmatized properties; for instance, we had only 198 rental units in buildings containing stigmatized properties. When using dummy variables for event types and the interaction terms between these dummy variables and the number of years since an event, the estimation suffers from fewer degrees of freedom as well as multicollinearity. Another possibility is the endogeneity attributable to omitted variables, as discussed in the previous section, whereby stigmatizing events may induce an indirect positive externality on the quality of housing in the neighborhood as security systems and facilities are implemented.

Case (b): This case assumes that all event types have the same degree of externality under complete information. One and 5 years after an event, property owners of J^H expect that some prospective renters in I^H will recognize the presence of the closest stigmatized properties; thus, they reduce their offered price. On the contrary, other event types do not have an influence on the offered rental price within the building, implying that in cases of the discovery of a body, death by fire, and suicide, property owners do not expect many prospective renters to know about the closest stigmatized properties. Ten years after an event, no event type k is recognizable by prospective renters in I^k.

Within one block of a stigmatized property, numerous prospective renters are expected to recognize suicide for more than 10 years, whereas there is no evidence of prospective renters recognizing the presence of other event types. Regarding the spatial externality, ln(Distance + 1), all event types are expected to be easily recognizable 1 year after the event. An F-test shows that homicide, death by fire, and suicide have the same externality effect under complete information, and these event types are greater than the effect of the discovery of a body. Five years after an event, however, the significance of the effect remains only for homicide and for the discovery of a body, and it disappears for all event types after 10 years. These results indicate that prospective renters recognize fewer stigmatizing events as time passes.

Case (c): The last case assumes, first, that prospective renters intend to avoid living near stigmatizing events that have a greater psychological impact. Secondly, the elasticity of the externality of θ_B^k is greater than minus one. Finally, the greater the possibility of prospective renters identifying the event type, the smaller the possibility that they will recognize but not be able to identify the event type.

For the first 5 years after an incident within a building, only homicide has a negative externality under complete information, whereas other event types have no significant externality. By assumption, the fraction of prospective renters in I^k having information (A) is strictly smaller than the fraction having information about other event types. Within that block, on the other hand, suicide is the only event type showing a negative externality under complete information, and the effect persists even 10 years after an incident. Regarding the spatial externality, the discovery of a body has the smallest externality under complete information. It is interesting that we are not sure whether the spatial externality of the discovery of a body is significant, unlike in cases (a) and (b). Furthermore, we cannot interpret anything 5 years after the incident because no combination of coefficients between two event types is significantly different.

Conclusion

Housing suppliers are not obligated to disclose the presence of stigmatized properties as long as no incident has taken place on the transactional properties. However, if a prospective renter is aware of a stigmatized property nearby rental housing in which he or she is interested, the renter may not want to rent that unit unless the rental price is low enough to compensate for his or her discomfort with the event. Consequently, housing suppliers determine the offered rental price based not only on the effect of nearby stigmatizing events, but also on the information that their prospective renters may have about these stigmatized properties.

When data on rental housing and stigmatized properties recorded in Tokyo, Japan, were used, the hedonic approach revealed the presence of a negative externality of stigmatized properties. The estimation results showed that the rental price decreases by 5.3 to 5.6% relative to the rental price of other housing in the same block if the building has had a homicide and by 2.2 to 3.5% in the case of a death by fire. In contrast, there are no significant effects on properties stigmatized by the other two event types. It is surprising that one year after a homicide, the rental price of housing within the same building is 19.1 to 21.0% lower than the rental price of other housing in the same block, although it recovers gradually over time.

Regarding the spatial externality, we found significant positive relationships between the offered rental price and the distance from the closest stigmatized property, implying that the offered rental price decreases the closer the housing is to a stigmatized property. The spatial externalities become weaker as time passes after an incident. Among the four event types, properties stigmatized by death, fire and homicide have greater spatial externalities than the other two types.

Because the stigmatized properties in our data set are not common knowledge, these estimates using the hedonic model do not represent the implicit externality under complete information, when prospective renters are fully informed of an event. We discussed the possibility that under complete information, the externality may not exist even when the hedonic estimates are significant. This problem was addressed by Kask and Maani (1992) and Pope (2008a, 2008b); when assessing policy implications, one should use caution in interpreting results of a hedonic model that is estimated under incomplete information.

To explore hidden factors behind the hedonic estimates, such as the externality under complete information and the possibility that prospective renters are aware of each stigmatized property, we considered three cases with different assumptions. Under each assumption, we derived the relationships between estimates and the hidden factors, and possible implications were examined by using the estimated coefficients. Although the implications of hidden factors could vary among these cases, they all ensured that a negative externality existed within the building and block for incidents of homicide and suicide, respectively. Furthermore, a spatial externality outside the one-block area was observed for homicide, suicide, and death by fire 1 year after the incident, whereas that evidence became weaker as more time passed after the incident.

References

Boyle, Melissa A., Kiel, Katherine A. (2001) "A survey of house price hedonic studies of the impact of environmental externalities," *Journal of Real Estate Literature*, 9, 117–144.

Braden John, B., Xia Feng, DooHwan Won. (2011) "Waste sites and property values: A Meta-Analysis," *Environmental and Resource Economics*, 50, 175-201.

Brown, Ronald B., Thurlow, Thomas H. (1996) "Buyers beware: Statutes shield real estate brokers and sellers who do not disclose that properties are psychologically tainted," *Oklahoma Law Review*, 49, 625–628.

Deaton, B. James, Hoehn, John P. (2004) "Hedonic analysis of hazardous waste sites in the presence of other urban disamenities," *Environmental Science and Policy*, 7, 499–508.

Edmiston, Stuart C. (2010) "Secrets worth keeping: Toward a principled basis for stigmatized property disclosure statutes," *UCLA Law Review*, 58, 281–320.

Gamper-Robindran, Shanti., Timmins, Christopher. (2011) "Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data," *American Economics Review*, 101, 620-624.

Inlanfeldt Keith R., Taylor, Laura O. (2004) "Externality effects of small-scale hazardous waste sites: Evidence from urban commercial property markets," *Journal of Environmental Economics and Management*, 47, 117–139.

Kask, S.B., Maani, S.A. (1992) "Uncertainty, information, and hedonic pricing," *Land Economics*, 68, 170–184.

Kiel, Katherine A., Williams, Michael. (2007) "The impact of superfund sites on local property values: Are all sites the same?" *Journal of Urban Economics*, 61, 170–192.

Larsen, James E., Coleman, Joseph W. (2004) "Psychologically impacted houses: Broker disclosure behavior and perceived market effects in an unregulated environment," *Journal of Real Estate Practice and Education*, 4, 1–16.

McCluskey, Jill J., Rausser, Gordon C. (2003a) "Hazardous waste sites and housing appreciation rates," *Journal of Environmental Economics and Management*, 45, 166–176.

McCluskey, Jill J., Rausser, Gordon C. (2003b) "Stigmatized asset value: Is it temporary or long-term?" *The Review of Economics and Statistics*, 85, 276–285.

Messer, Kent D., Schulze, William D., Hackett, Katherine F., Cameron, Trudy A., McClelland, Gary H. (2006) "Can stigma explain large property value losses? The psychology and economics of superfund," *Environmental and Resource Economics*, 33, 299–324.

Pope, J.C. (2008a) "Buyer information and the hedonic: The impact of a seller disclosure on the implicit price for airport noise," *Journal of Urban Economics*, 63, 498–516.

Pope, J.C. (2008b) "Do seller disclosures affect property values? Buyer information and the hedonic model," *Land Economics*, 84, 551–572.

Sanchez-Behar, Daniel. Disclosing stigmatized properties—A real estate agent's quandary. The Professional Line, 8, 2008, available at:
http://www.hinshawlaw.com/files/Publication/04e7c220-3d36-4fe3-a5f6-005defcc6d1c/Presentation/PublicationAttachment/d1f674aa-b485-4f9d-87e3-0465a0810b1b/0108TheProfLine.pdf.

Simons, Robert A., Saginor, Jesse D. (2006) "A meta-analysis of the effect of environmental contamination and positive amenities on residential real estate values," *Journal of Real Estate Research*, 28, 71–104.

Umberger, M. (1999) "When bad things happen in good houses," *San Francisco Examiner*, October 29.

Table 1

Definitions of variables

Variable	Definition
Stigmatized property	
Discovery	1 = body found; 0 = otherwise
Fire	1 = death by fire; 0 = otherwise
Suicide	1 = suicide; 0 = otherwise
Homicide	1 = homicide; 0 = otherwise
EventYear	Year when a stigmatizing event happened
Rental housing unit	
Rent	Rental price per month (yen/month)
Distance	Distance from the closest stigmatized property (mile)
Building	1 = stigmatized property located in the same building; 0 = otherwise
Block	1 = stigmatized property located in the same block; 0 = otherwise
#Events (*0.2miles*)	Number of stigmatized properties within 0.2 miles
#Events (*0.3miles*)	Number of stigmatized properties within 0.3 miles
#Events (*0.5miles*)	Number of stigmatized properties within 0.5 miles
WalkTime	Time to the closest train station on foot (minute)
FloorLevel	Floor level
Stories	Total number of floor levels in a building
ft2	Floor space (square foot)
#Bedrooms	Number of bedrooms
BuiltYear	Year when an apartment building was completed
Building type	
Apartment1	1 = standard apartment; 0 = otherwise
Townhouse	1 = townhouse; 0 = otherwise
Terraced	1 = terraced house; 0 = otherwise
Apartment2	1 = luxury apartment; 0 = otherwise
House	1 = family home; 0 = otherwise
Dorm	1 = dormitory; 0 = otherwise
Building structure	
PC	1 = prestressed concrete; 0 = otherwise
RC	1 = reinforced concrete; 0 = otherwise
SRC	1 = steel-reinforced concrete; 0 = otherwise
Steel	1 = steel; 0 = otherwise
Wooden	1 = wooden; 0 = otherwise
Other	1 = none of the above; 0 = any one of the above

Table 2

Basic statistics

Variable	Minimum	Median	Maximum	Mean	S.D.	Sum
Stigmatized property						
Discovery	0	0	1	0.199	0.399	189
Fire	0	0	1	0.324	0.468	308
Suicide	0	0	1	0.203	0.403	193
Homicide	0	0	1	0.274	0.446	260
EventYear	1954	2008	2011	2005	8.92	—
Rental housing unit						
Rent	1.5	7.5	190	8.273	3.801	—
Distance	0	0.309	5.725	0.409	0.365	—
Building	0	0	1	0.001	0.038	198
Block	0	0	1	0.010	0.098	1,348
#Events (*0.2miles*)	0	0	13	0.391	0.759	—
#Events (*0.3miles*)	0	0	16	0.883	1.295	—
#Events (*0.5miles*)	0	2	33	2.381	2.810	—
WalkTime	0	7	125	8.308	5.359	—
FloorLevel	-8	2	58	2.678	2.303	—
Stories	1	3	101	4.296	3.591	—
ft2	33.368	268.667	5,334.804	329.258	168.322	—
#Bedrooms	1	1	8	1.323	0.602	—
BuiltYear	1950	1997	2012	1996.380	10.940	—
Building type						
Apartment1	0	0	1	0.428	0.495	58,785
Townhouse	0	0	1	0.000	0.010	13
Terraced	0	0	1	0.004	0.064	571
Apartment2	0	1	1	0.564	0.496	77,362
House	0	0	1	0.004	0.062	536
Dorm	0	0	1	0.000	0.003	1
Building structure						
PC	0	0	1	0.004	0.061	516
RC	0	0	1	0.367	0.482	50,331
SRC	0	0	1	0.056	0.230	7,713
Steel	0	0	1	0.013	0.112	1,738
Wooden	0	0	1	0.296	0.457	40,679
Other	0	0	1	0.264	0.441	36,291

Table 3

Estimation results of equations (7) and (8)

	[3-1]	[3-2]	[3-3]	[3-4]	[3-5]	[3-6]
		Equation (7)			Equation (8)	
Variable	0.2 miles	0.3 miles	0.5 miles	0.2 miles	0.3 miles	0.5 miles
ln(*Distance* + 1) ×						
Discovery				0.0004	0.0018	0.0011
				(0.0016)	(0.0012)	(0.0009)
Fire				0.0029**	0.0031***	0.0016**
				(0.0014)	(0.0010)	(0.0008)
Suicide				0.0034**	0.0008	-0.0013
				(0.0016)	(0.0011)	(0.0008)
Homicide				0.0042***	0.0019*	0.0011
				(0.0015)	(0.0011)	(0.0008)
Building ×						
Discovery	-0.0245	-0.0221	-0.0267	-0.0237	-0.0217	-0.0260
	(0.0289)	(0.0278)	(0.0301)	(0.0288)	(0.0278)	(0.0300)
Fire	-0.0217	-0.0288**	-0.0342**	-0.0218	-0.0286**	-0.0342**
	(0.0147)	(0.0144)	(0.0142)	(0.0147)	(0.0144)	(0.0142)
Suicide	-0.0133	-0.0114	-0.0015	-0.0130	-0.0111	-0.0014
	(0.0273)	(0.0263)	(0.0256)	(0.0273)	(0.0263)	(0.0256)
Homicide	-0.0536***	-0.0562***	-0.0532***	-0.0538***	-0.0561***	-0.0532***
	(0.0142)	(0.0139)	(0.0141)	(0.0142)	(0.0139)	(0.0141)
Block ×						
Discovery	0.0046	0.0043	0.0006	0.0069	0.0160	0.0077
	(0.0090)	(0.0092)	(0.0089)	(0.0136)	(0.0119)	(0.0108)
Fire	0.0114**	0.0086*	0.0098*	0.0300***	0.0291***	0.0211***
	(0.0052)	(0.0051)	(0.0051)	(0.0105)	(0.0085)	(0.0073)
Suicide	-0.0398***	-0.0375***	-0.0389***	-0.0183	-0.0321***	-0.0480***
	(0.0090)	(0.0098)	(0.0097)	(0.0135)	(0.0120)	(0.0112)
Homicide	0.0152**	0.0169**	0.0156**	0.0421***	0.0293***	0.0228***
	(0.0068)	(0.0068)	(0.0068)	(0.0119)	(0.0099)	(0.0088)
ln(*EventAge*) ×						
Discovery	0.0138***	0.0003	0.0005	0.0115***	-0.0007	-0.0020
	(0.0037)	(0.0028)	(0.0023)	(0.0036)	(0.0027)	(0.0022)
Fire	-0.0027	-0.0061***	-0.0070***	-0.0013	-0.0067***	-0.0068***
	(0.0030)	(0.0022)	(0.0018)	(0.0029)	(0.0021)	(0.0017)
Suicide	0.0004	0.0022	0.0041***	0.0005	0.0029**	0.0047***
	(0.0022)	(0.0014)	(0.0011)	(0.0021)	(0.0014)	(0.0011)
Homicide	-0.0047*	-0.0013	-0.0043***	-0.0048*	-0.0013	-0.0039**
	(0.0026)	(0.0020)	(0.0016)	(0.0025)	(0.0019)	(0.0015)
ln(#*Events*)	0.0235***	-0.0148	-0.0144*	-0.0127	-0.0127	0.0241***
	(0.0049)	(0.0166)	(0.0079)	(0.0166)	(0.0079)	(0.0049)
ln(#*Events*)^2	-0.0040**	0.0116	0.0099***	0.0114	0.0097***	-0.0040**
	(0.0017)	(0.0077)	(0.0033)	(0.0077)	(0.0033)	(0.0017)
ln(*WalkTime*)	0.0537***	0.0282***	0.0439***	0.0276***	0.0434***	0.0535***
	(0.0037)	(0.0067)	(0.0048)	(0.0067)	(0.0048)	(0.0037)
ln(*WalkTime*)^2	-0.0187***	-0.0127***	-0.0167***	-0.0125***	-0.0166***	-0.0186***
	(0.0010)	(0.0018)	(0.0012)	(0.0018)	(0.0012)	(0.0010)
ln(*ft2*)	-0.4004***	-0.4724***	-0.4183***	-0.4719***	-0.4182***	-0.4003***
	(0.0227)	(0.0345)	(0.0289)	(0.0345)	(0.0289)	(0.0227)
ln(*ft2*)^2	0.1492***	0.1622***	0.1533***	0.1621***	0.1533***	0.1492***
	(0.0034)	(0.0051)	(0.0043)	(0.0051)	(0.0043)	(0.0034)
ln(*Age*)	0.1469***	0.1414***	0.1493***	0.1414***	0.1493***	0.1470***
	(0.0021)	(0.0034)	(0.0026)	(0.0034)	(0.0026)	(0.0021)
ln(*Age*)^2	-0.0555***	-0.0539**	-0.0556***	-0.0539***	-0.0556***	-0.0556***

		*				
	(0.0005)	(0.0008)	(0.0006)	(0.0008)	(0.0006)	(0.0005)
ln(*FloorLevel*)	0.0240***	0.0249***	0.0256***	0.0249***	0.0256***	0.0240***
	(0.0017)	(0.0027)	(0.0020)	(0.0027)	(0.0020)	(0.0017)
ln(*FloorLevel*)^2	0.0052***	0.0052***	0.0045***	0.0052***	0.0045***	0.0052***
	(0.0008)	(0.0012)	(0.0010)	(0.0012)	(0.0010)	(0.0008)
ln(*Stories*)	0.0159***	-0.0219***	0.0036	-0.0215***	0.0036	0.0160***
	(0.0048)	(0.0072)	(0.0057)	(0.0072)	(0.0057)	(0.0048)
ln(*Stories*)^2	0.0043***	0.0156***	0.0078***	0.0155***	0.0078***	0.0043***
	(0.0014)	(0.0020)	(0.0016)	(0.0020)	(0.0016)	(0.0014)
ln(#*Bedrooms*)	0.0251***	0.0337***	0.0304***	0.0335***	0.0303***	0.0250***
	(0.0067)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0067)
ln(#*Bedrooms*)^2	-0.0367***	-0.0553***	-0.0471***	-0.0551***	-0.0470***	-0.0366***
	(0.0084)	(0.0101)	(0.0122)	(0.0101)	(0.0122)	(0.0084)
Observations	35,545	60,774	92,436	35,545	60,774	92,436
R-squared	0.909	0.904	0.902	0.909	0.904	0.903

Dependent variable is ln(Rent/ft2)i. ***, **, * indicate statistical significance at the 1, 5 and 10% levels using two-sided tests. Figures in parentheses are White's robust standard deviations. Coefficients of a constant and of dummy variables for building types, building structures, train stations and event types are not shown in the table. Age is the number of years passed since the building was completed (i.e. Age = Year of data – BuiltYear).

Table 4

Estimation results for equations (9) and (10)

Variable	[4-1]	[4-2]	[4-3]	[4-4]	[4-5]	[4-6]
	Equation (9)			Equation (10)		
	0.2 miles	0.3 miles	0.5 miles	0.2 miles	0.3 miles	0.5 miles
ln(*Distance* + 1) ×						
Discovery				0.0111**	0.0086**	0.0066***
				(0.0051)	(0.0035)	(0.0025)
Discovery × ln(*EventAge*)				-0.0027	-0.0040*	-0.0010
				(0.0035)	(0.0024)	(0.0017)
Fire				0.0142***	0.0096***	0.0076***
				(0.0051)	(0.0035)	(0.0025)
Fire × ln(*EventAge*)				-0.0084***	-0.0038*	-0.0043***
				(0.0033)	(0.0022)	(0.0016)
Suicide				0.0149***	0.0079**	0.0047*
				(0.0052)	(0.0034)	(0.0024)
Suicide × ln(*EventAge*)				-0.0075***	-0.0057***	-0.0031***
				(0.0027)	(0.0017)	(0.0011)
Homicide				0.0151***	0.0084**	0.0070***
				(0.0051)	(0.0035)	(0.0025)
Homicide × ln(*EventAge*)				-0.0055*	-0.0031	-0.0040***
				(0.0031)	(0.0020)	(0.0014)
Building ×						
Discovery	0.0687	0.0569	0.0829	0.0699	0.0569	0.0812
	(0.0798)	(0.0774)	(0.0832)	(0.0805)	(0.0775)	(0.0833)
Discovery × ln(*EventAge*)	-0.0563	-0.0505	-0.0671	-0.0568	-0.0506	-0.0663
	(0.0472)	(0.0461)	(0.0503)	(0.0475)	(0.0461)	(0.0503)
Fire	0.0370	0.0025	-0.0142	0.0383	0.0034	-0.0137
	(0.0753)	(0.0721)	(0.0710)	(0.0754)	(0.0720)	(0.0710)
Fire × ln(*EventAge*)	-0.0374	-0.0200	-0.0129	-0.0380	-0.0204	-0.0132
	(0.0444)	(0.0430)	(0.0427)	(0.0445)	(0.0430)	(0.0426)
Suicide	0.0556	0.0627	0.0784	0.0542	0.0607	0.0765
	(0.0534)	(0.0522)	(0.0499)	(0.0533)	(0.0520)	(0.0498)
Suicide × ln(*EventAge*)	-0.0305	-0.0332	-0.0370*	-0.0295	-0.0320	-0.0362*
	(0.0225)	(0.0216)	(0.0210)	(0.0224)	(0.0214)	(0.0208)
Homicide	-0.2037***	-0.2097***	-0.1910**	-0.2028***	-0.2097***	-0.1917**
	(0.0735)	(0.0737)	(0.0763)	(0.0737)	(0.0737)	(0.0761)
Homicide × ln(*EventAge*)	0.0874**	0.0894**	0.0804*	0.0869**	0.0895**	0.0809*
	(0.0406)	(0.0410)	(0.0427)	(0.0407)	(0.0410)	(0.0426)
Block ×						
Discovery	-0.0645*	-0.0652*	-0.0644*	0.0266	-0.0076	-0.0199
	(0.0353)	(0.0358)	(0.0336)	(0.0478)	(0.0426)	(0.0376)
Discovery × ln(*EventAge*)	0.0448**	0.0456**	0.0428**	0.0151	0.0189	0.0371
	(0.0211)	(0.0215)	(0.0195)	(0.0304)	(0.0267)	(0.0229)
Fire	0.0023	0.0059	0.0071	0.0918**	0.0650*	0.0535*
	(0.0247)	(0.0243)	(0.0241)	(0.0406)	(0.0335)	(0.0295)
Fire × *ln*(*EventAge*)	0.0059	0.0019	0.0021	-0.0472*	-0.0201	-0.0238
	(0.0155)	(0.0152)	(0.0151)	(0.0260)	(0.0213)	(0.0188)
Suicide	-0.1182***	-0.1275***	-0.1309***	-0.0260	-0.0711**	-0.0883***
	(0.0253)	(0.0272)	(0.0268)	(0.0413)	(0.0354)	(0.0316)
Suicide × ln(*EventAge*)	0.0368***	0.0418***	0.0421***	-0.0099	0.0020	0.0169
	(0.0096)	(0.0102)	(0.0101)	(0.0194)	(0.0152)	(0.0129)
Homicide	0.0560**	0.0580**	0.0436	0.1482***	0.1155***	0.0888***
	(0.0264)	(0.0270)	(0.0270)	(0.0419)	(0.0357)	(0.0320)
Homicide × ln(*EventAge*)	-0.0231	-0.0235	-0.0159	-0.0562**	-0.0453**	-0.0419**
	(0.0144)	(0.0149)	(0.0149)	(0.0241)	(0.0201)	(0.0179)
ln(*EventAge*) ×						
Discovery	0.0008	-0.0014	0.0003	0.0304	0.0258	0.0062
	(0.0019)	(0.0013)	(0.0011)	(0.0222)	(0.0161)	(0.0121)
Fire	-0.0022	-0.0019	-0.0020*	0.0520**	0.0193	0.0228**
	(0.0018)	(0.0013)	(0.0010)	(0.0209)	(0.0150)	(0.0114)
Suicide	0.0010	-0.0002	-0.0002	0.0475***	0.0406***	0.0262***

	(0.0013)	(0.0009)	(0.0007)	(0.0170)	(0.0115)	(0.0082)
Homicide	-0.0011	-0.0016	-0.0018**	0.0315	0.0205	0.0239**
	(0.0016)	(0.0011)	(0.0009)	(0.0195)	(0.0136)	(0.0100)
ln(*#Events*)	-0.0144	-0.0133*	0.0237***	-0.0135	-0.0114	0.0241***
	(0.0166)	(0.0079)	(0.0049)	(0.0166)	(0.0079)	(0.0049)
ln(*#Events*)^2	0.0114	0.0094***	-0.0040**	0.0119	0.0091***	-0.0040**
	(0.0077)	(0.0033)	(0.0017)	(0.0077)	(0.0033)	(0.0017)
ln(*WalkTime*)	0.0284***	0.0439***	0.0537***	0.0282***	0.0435***	0.0535***
	(0.0067)	(0.0048)	(0.0037)	(0.0067)	(0.0048)	(0.0037)
ln(*WalkTime*)^2	-0.0127***	-0.0167***	-0.0187***	-0.0127***	-0.0166***	-0.0187***
	(0.0018)	(0.0012)	(0.0010)	(0.0018)	(0.0012)	(0.0010)
ln(*ft2*)	-0.4731***	-0.4186***	-0.4007***	-0.4732***	-0.4184***	-0.4004***
	(0.0345)	(0.0289)	(0.0227)	(0.0345)	(0.0289)	(0.0227)
ln(*ft2*)^2	0.1623***	0.1534***	0.1492***	0.1623***	0.1533***	0.1492***
	(0.0051)	(0.0043)	(0.0034)	(0.0051)	(0.0043)	(0.0034)
ln(*Age*)	0.1415***	0.1494***	0.1469***	0.1417***	0.1494***	0.1470***
	(0.0034)	(0.0026)	(0.0021)	(0.0034)	(0.0026)	(0.0021)
ln(*Age*)^2	-0.0539***	-0.0556***	-0.0556***	-0.0539***	-0.0556***	-0.0556***
	(0.0008)	(0.0006)	(0.0005)	(0.0008)	(0.0006)	(0.0005)
ln(*FloorLevel*)	0.0248***	0.0255***	0.0240***	0.0248***	0.0255***	0.0239***
	(0.0027)	(0.0020)	(0.0017)	(0.0027)	(0.0020)	(0.0017)
ln(*FloorLevel*)^2	0.0052***	0.0045***	0.0052***	0.0052***	0.0045***	0.0052***
	(0.0012)	(0.0010)	(0.0008)	(0.0012)	(0.0010)	(0.0008)
ln(*Stories*)	-0.0221***	0.0034	0.0158***	-0.0216***	0.0036	0.0157***
	(0.0072)	(0.0057)	(0.0048)	(0.0072)	(0.0057)	(0.0048)
ln(*Stories*)^2	0.0157***	0.0079***	0.0044***	0.0156***	0.0078***	0.0044***
	(0.0020)	(0.0016)	(0.0014)	(0.0020)	(0.0016)	(0.0014)
ln(*#Bedrooms*)	0.0342***	0.0306***	0.0252***	0.0342***	0.0304***	0.0251***
	(0.0092)	(0.0092)	(0.0067)	(0.0092)	(0.0092)	(0.0067)
ln(*#Bedrooms*)^2	-0.0558***	-0.0473***	-0.0368***	-0.0556***	-0.0469***	-0.0366***
	(0.0101)	(0.0122)	(0.0084)	(0.0101)	(0.0122)	(0.0084)
Observations	35,545	60,774	92,436	35,545	60,774	92,436
R-squared	0.909	0.904	0.902	0.909	0.904	0.903

Dependent variable is ln(Rent/ft2)i. ***, **, * indicate statistical significance at the 1, 5 and 10% levels using two-sided tests. Figures in parentheses are White's robust standard deviations. Coefficients of a constant and of dummy variables for building types, building structures, train stations and event types are not shown in the table. Age is the number of years passed since the building was completed (i.e. Age = Year of data – BuiltYear).

Table 5

Coefficients and F-tests across event-types

Building

	1 year			5 years			10 years		
F-test (Ha)	P-value		Criteria	P-value		Criteria	P-value		Criteria
{D,F}	0.759			0.961			0.815		
{D,S}	0.874			0.480			0.364		
{D,H}	0.013	**	+	0.177			0.243		
{F,S}	0.841			0.365			0.424		
{F,H}	0.024	**	+	0.058	*		0.263		
{S,H}	0.005	***	+	0.035	**	+	0.755		
t-test	Coefficient		Criteria	Coefficient		Criteria	Coefficient		Criteria
D	0.071			-0.021			-0.061		
F	0.037			-0.023			-0.049		
S	0.056			0.006			-0.015		
H	-0.202	***	+	-0.063	***	+	-0.003		

Block

	1 year			5 years			10 years		
F-test (Ha)	P-value		Criteria	P-value		Criteria	P-value		Criteria
{D,F}	0.282			0.675			0.503		
{D,S}	0.079	*		0.000	***	+	0.001	***	+
{D,H}	0.031	**		0.354			0.181		
{F,S}	0.001	***	+	0.000	***	+	0.001	***	+
{F,H}	0.177			0.485			0.451		
{S,H}	0.000	***	+	0.000	***	+	0.004	***	+
t-test	Coefficient		Criteria	Coefficient		Criteria	Coefficient		Criteria
D	-0.045			0.008			0.030	*	
F	0.001			0.012	**		0.016		
S	-0.122	***	+	-0.061	***	+	-0.034	***	+
H	0.051	*		0.018	**		0.004		

ln(*Distance*+1)

	1 year			5 years			10 years		
F-test (Ha)	P-value		Criteria	P-value		Criteria	P-value		Criteria
{D,F}	0.010	***	+	0.081	*		0.046	**	
{D,S}	0.002	***	+	0.363			0.237		
{D,H}	0.001	***	+	0.887			0.645		
{F,S}	0.493			0.540			0.581		
{F,H}	0.366			0.072	*		0.089	*	
{S,H}	0.871			0.373			0.380		
t-test	Coefficient		Criteria	Coefficient		Criteria	Coefficient		Criteria
D	0.0111	**	+	0.0067	**	+	0.0048		
F	0.0142	***	+	0.0007			-0.0051		
S	0.0149	***	+	0.0029			-0.0023		
H	0.0151	***	+	0.0062	**	+	0.0024		

Table 6

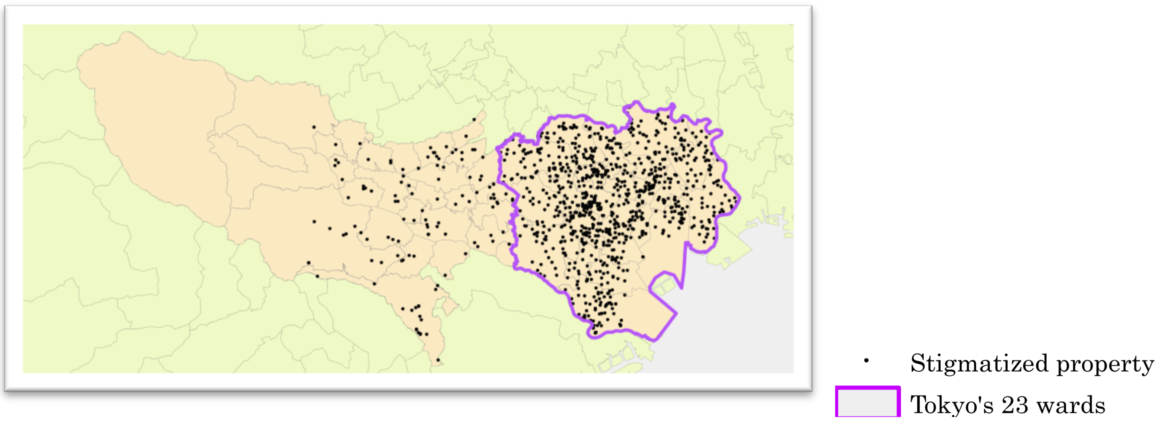
Implications of estimation results under three cases

Case 1		1 year	5 years	10 years
Building	$\theta_A^k,\ \tau^k$	H>0	H>0	-
	θ_B^k	D=F=S=H=0	D=F=S=H=0	D=F=S=H=0
Block	$\theta_A^k,\ \tau^k$	S>0	S>0	S>0
	θ_B^k	D=F=S=H=0	D=F=S=H=0	D=F=S=H=0
ln(*Distance*+1)	$\theta_A^k,\ \tau^k$	(D,F,S,H)>0	(D,H)>0	-
	θ_B^k	D=F=S=H=0	D=F=S=H=0	D=F=S=H=0

Case 2		1 year	5 years	10 years
Building	$\theta_A^k + \theta_B^k$	H>D=F=S=0	H>S=0, D=F=0	-
	τ^k	D=F=S=H>0	D=F=S=H>0	D=F=S=H
Block	$\theta_A^k + \theta_B^k$	S>F=H=0, D=0	S>D=F=H=0	S>D=F=H=0
	τ^k	D=F=S=H>0	D=F=S=H>0	D=F=S=H>0
ln(*Distance*+1)	$\theta_A^k + \theta_B^k$	F=S=H>D>0	D=H>0, F=S=0	-
	τ^k	D=F=S=H>0	D=F=S=H>0	D=F=S=H

Case 3		1 year	5 years	10 years
Building	τ^k	H>D=F=S=0	H>D=F=S>0	-
	θ_A^k	D=F=S>H	D=F=S>H	-
	θ_B^k	H≧D=F=S	H≧D=F=S=0	-
Block	τ^k	S>D=F=S=0	S>D=F=H=0	S>D=F=H=0
	θ_A^k	D=F=H>S	D=F=H>S	D=F=H>S
	θ_B^k	S≧D=F=H	S≧D=F=H	S≧D=F=H
ln(*Distance*+1)	τ^k	F=S=H>D	-	-
	θ_A^k	D>F=S=H	-	-
	θ_B^k	F=S=H≧D	-	-

Figure 1. Number of stigmatizing events recorded on Jikobukken.com.



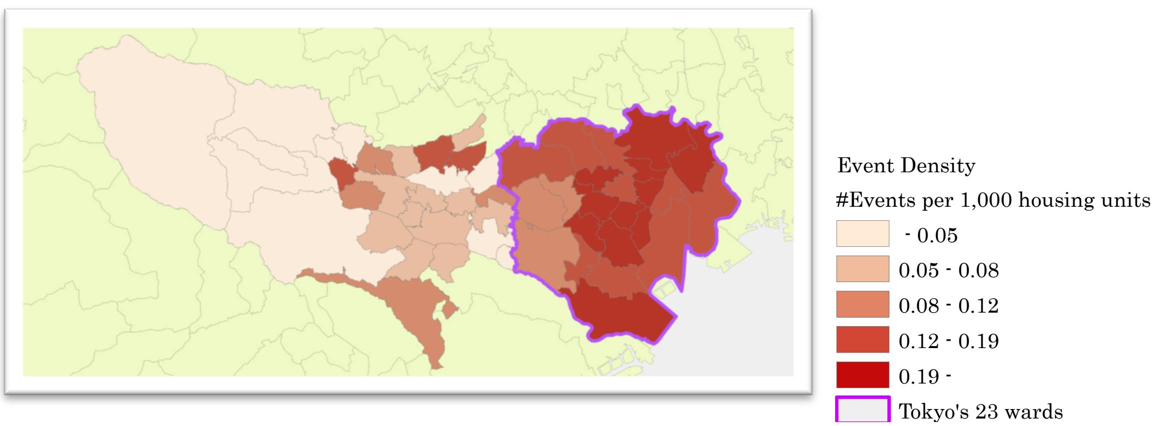
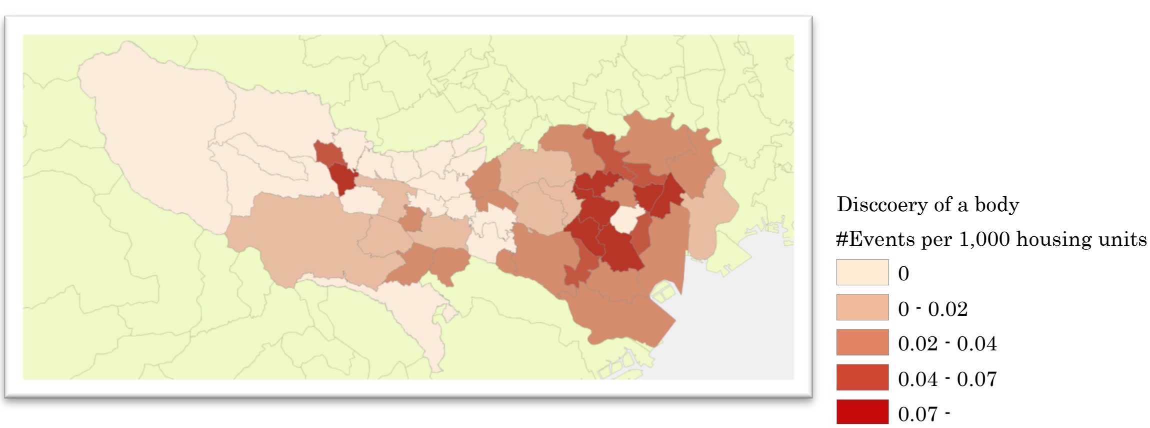
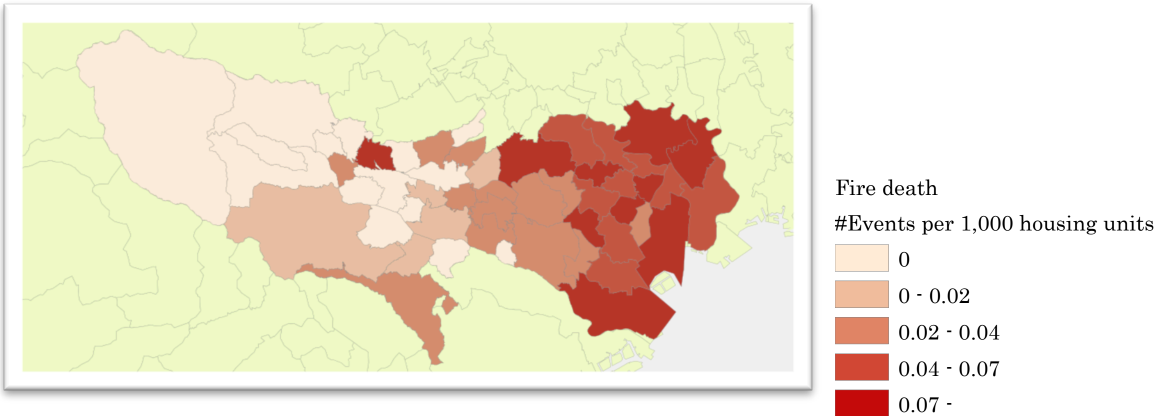
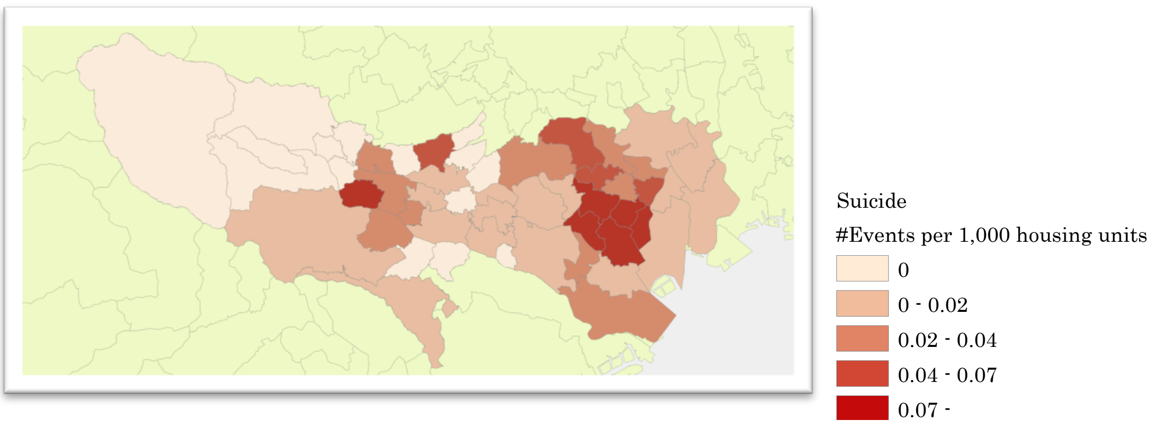


Figure 2. Event density by the type of event.




Fire death
#Events per 1,000 housing units
0
0 - 0.02
0.02 - 0.04
0.04 - 0.07
0.07 -


Suicide
#Events per 1,000 housing units
0
0 - 0.02
0.02 - 0.04
0.04 - 0.07
0.07 -

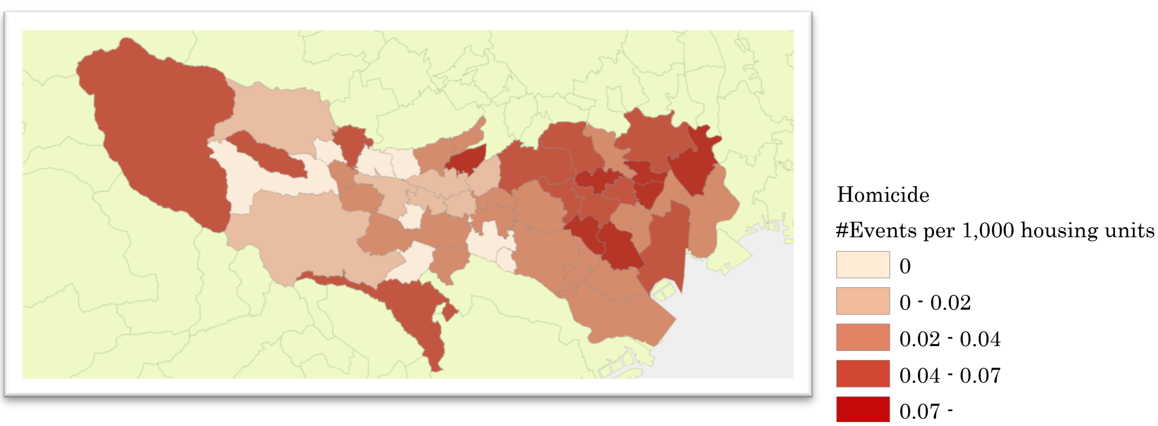

Homicide
#Events per 1,000 housing units
0
0 - 0.02
0.02 - 0.04
0.04 - 0.07
0.07 -

Figure 3. Hedonic price under incomplete information (from Pope; 2008b)

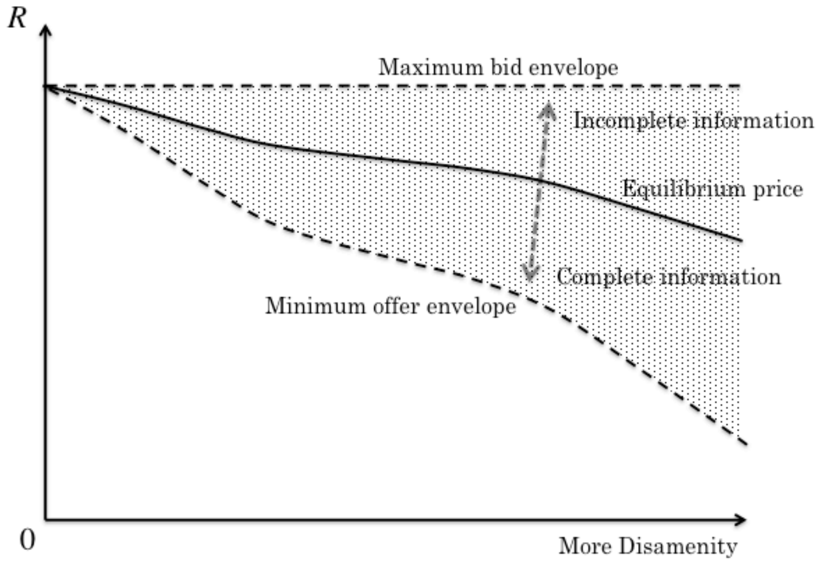


Figure 4

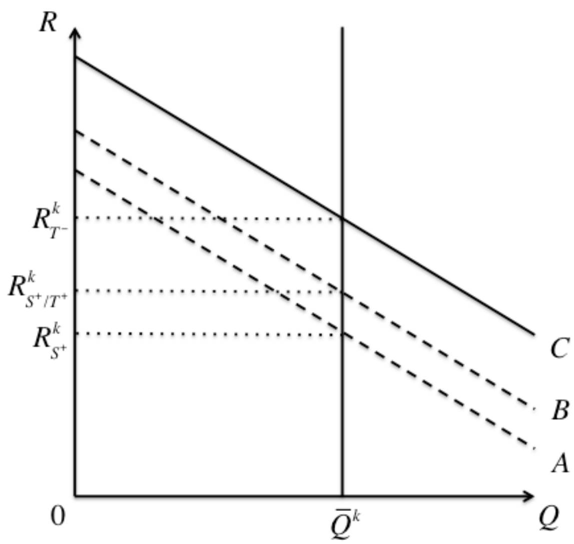
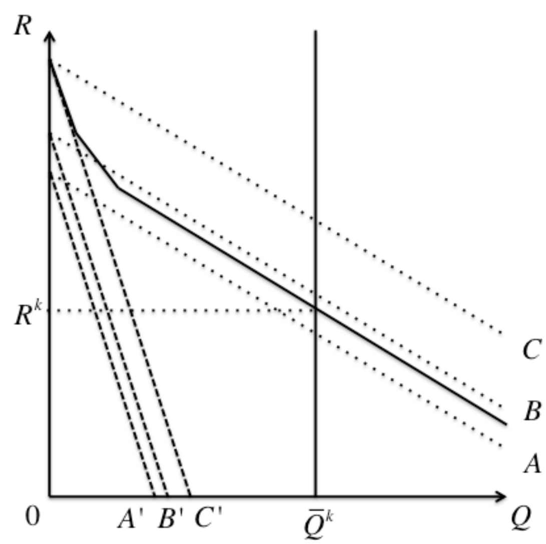


Figure 5



Appendix.

Case (a)

Proof of (13). By inserting $\theta_B^k = 0$ into equation (12), we obtain $|\alpha^k| = \theta_A^k \tau^k$. Therefore, $|\alpha^k| > 0$ if and only if $\theta_A^k \tau^k > 0$. Because all hidden parameters are nonnegative, $|\alpha^k| > 0$ if and only if $\theta_A^k > 0$ and $\tau^k > 0$ for all k. ■

Case (b)

Proof of (14) to (16). $\tau^k = \tau^l$ for all k and l implies that $\tau^k = \tilde{\tau}$ for all k, where $\tilde{\tau}$ is the mean effect of all event types under complete information. Inserting $\tau^k = \tilde{\tau}$ into equation (11) yields $|\alpha^k| = (\theta_A^k + \theta_B^k)\tilde{\tau}$. Because all hidden parameters are nonnegative, $|\alpha^k| > 0$ implies $(\theta_A^k + \theta_B^k) > 0$ and $\tau^k = \tau^l = \tilde{\tau} > 0$ for all l. Suppose some m exists such that $|\alpha^m| > 0$; then $\tilde{\tau} > 0$. Given that $\tilde{\tau} > 0$, $|\alpha^k| > 0$ if and only if $(\theta_A^k + \theta_B^k) > 0$. By comparing the coefficients of the two event types, we have $|\alpha^k| - |\alpha^l| = (\theta_A^k + \theta_B^k - \theta_A^l - \theta_B^l)\tilde{\tau}$. When some m exists such that $|\alpha^m| > 0$, because $\tilde{\tau} > 0$, $|\alpha^k| > |\alpha^l|$ if and only if $\theta_A^k + \theta_B^k > \theta_A^l + \theta_B^l$. ■

Case (c)

Proof of (17). By taking a derivative of equation (12) with respect to τ^k, we have $\frac{\partial|\alpha^k|}{\partial\tau^k} = \left(1 + \frac{\partial ln\theta_A(\tau^k)}{\partial ln\tau^k}\right) + \frac{\partial\theta_B(\theta_A^k)}{\partial\theta_A^k}\frac{\partial\theta_A(\tau^k)}{\partial\tau^k}\tilde{\tau} + \theta_B^k\frac{\tilde{\tau}}{\partial\tau^k}$, which is strictly larger than zero, based on the assumptions. Therefore, $|\alpha^k| > |\alpha^l|$ implies $\tau^k > \tau^l$. When $\tau^k > \tau^l$, we have the following four possibilities: 1) $\theta_A^l > 0$ and $\theta_B^k > 0$, 2) $\theta_A^l > 0$ and $\theta_B^k = 0$, 3) $\theta_A^l = 0$ and $\theta_B^k > 0$, and 4) $\theta_A^l = 0$ and $\theta_B^k = 0$. From these assumptions, the first case (1) implies $\theta_A^k < \theta_A^l$ and $\theta_B^k > \theta_B^l$, and the second case (2) implies $\theta_A^k < \theta_A^l$ and $\theta_B^k = \theta_B^l = 0$. However, the third (3) and fourth (4) cases yield $|\alpha^k| = |\alpha^l| = 0$, which contradicts the initial assumption, $|\alpha^k| > |\alpha^l|$. Thus, $\tau^k > \tau^l$ implies $\theta_A^k < \theta_A^l$ and $\theta_B^k \geq \theta_B^l$. ■ Proof of (18). $|\alpha^l| = 0$ requires $\theta_A^l = 0$ or $\tau^l = 0$. Because $|\alpha^k| > |\alpha^l|$, $0 \leq \theta_A^k < \theta_A^l$; thus, $\theta_A^l \neq 0$ and $\tau^l = 0$. ■ Proof of (19). Suppose some m exists such that $|\alpha^m| = 0$. Because $\tau^k = \tau^l > 0$ implies $\theta_A^k = \theta_A^l > 0$ and $\theta_B^k = \theta_B^l$, it is sufficient to show that $|\alpha^k| = |\alpha^l| > 0$ implies $\tau^k = \tau^l > 0$. First, suppose that $\tau^k \neq \tau^l$; then because $|\alpha^k|$ is strictly increasing in τ^k, $|\alpha^k| \neq |\alpha^l|$, which contradicts $|\alpha^k| = |\alpha^l|$. Second, suppose that $\tau^k = \tau^l = 0$; then $\theta_B^k \tilde{\tau} = \theta_B^l \tilde{\tau} > 0$, implying that $\theta_B^k = \theta_B^l > 0$ and $\tilde{\tau} > 0$. Because θ_B^k is not decreasing in τ^k, $\theta_B^m > 0$ for all m; thus, $|\alpha^m| > 0$ for all m. This contradicts $|\alpha^m| = 0$ for some m.■ Proof of (20). By equation (18), $|\alpha^m| > |\alpha^k| = 0$ implies that $\tau^k = 0$, $\theta_A^k = \theta_A(0)$. Because $|\alpha^k|$ is strictly increasing in τ^k, $|\alpha^k| = |\alpha^l|$ implies $\tau^k = \tau^l = 0$; thus, $\theta_A^k = \theta_A^l = \theta_A(0)$ and $\theta_B^k = \theta_B^l$.■ Proof of (21). Because $\tau^k = \tau^l$ implies $\theta_A^k = \theta_A^l$ and $\theta_B^k = \theta_B^l$, it is sufficient to show that $\nexists m$ such that $|\alpha^m| > |\alpha^k| = |\alpha^l| > 0$ implies $\tau^k = \tau^l > 0$. First, suppose that $\tau^k \neq \tau^l$; then because $|\alpha^k|$ is strictly increasing in τ^k, $|\alpha^k| \neq |\alpha^l|$, which contradicts $|\alpha^k| = |\alpha^l|$. Second, suppose that $\tau^k = \tau^l = 0$. Because $|\alpha^k| = |\alpha^l| > 0$, then $\tilde{\tau} > 0$ and $\theta_B^k = \theta_B^l > 0$; thus, it requires some m such that $\tau^m > 0$ to have $\tilde{\tau} > 0$. Because $|\alpha^m|$ is strictly increasing in τ^m, it contradicts that $\nexists m$ such that $|\alpha^m| > |\alpha^k| = |\alpha^l|$.■