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MEASURING THE SPATIAL EFFECT OF MULTIPLE SITES

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Abstract

Geographical relationships between a housing unit and the surrounding major sites, such as public transportation and crime scenes, are fundamental factors that determine the value of housing. In this paper, we propose an empirical model to estimate the spatial effect caused by surrounding multiple sites that addresses the following three assumptions: (A1) the closer a site, the greater the impact may be; (A2) the impact differs according to the characteristics of a site; and (A3) the higher the ranking of proximity to a site, the greater the impact may be. We demonstrate an empirical application by using rental housing data in Tokyo, Japan, to examine how the clustering of train and subway stations influences the surrounding housing rental prices. We find that at least the three nearest stations (and at most the five nearest stations) from each housing unit need to be considered in the hedonic model. The results also suggest that the assumption (A3) can be a crucial factor in evaluating the spatial effect of multiple sites, and ignoring it would lead to a serious estimation bias. The proposed methodology is worth testing with such various spatial topics as transportation, foreclosures and polycentric cities.

Keywords: spatial analysis, hedonic, accessibility measure, transportation

1. Introduction

Geographical relationships between a housing unit and the surrounding major sites, such as public transportation, commercial facilities, schools, and crime scenes, as well as their characteristics, are fundamental factors determining the value of housing. In this paper, we propose an empirical model to estimate the aggregate spatial effect of multiple sites that accounts for the following three general assumptions: (A1) the closer a site, the greater its impact may be; (A2) an impact may differ according to the characteristics of a site; and (A3) the higher the ranking of proximity to a site, the greater the impact may be.

In previous studies that use point-to-point data (accompanied by detailed addresses of housing and sites) to examine the spatial effect of multiple sites, three types of proximity variables have predominantly been used, namely, (i) the distance between a housing unit and its closest site,[1]

[1] Troy and Grove (2008), for example, compute the distance to the nearest park from each housing unit in Maryland and examine the impact of the crime rate at the park on neighboring housing values. Dorantes et al. (2011) and Gobbons and Machin (2005) both estimate the impact of the public transport infrastructure by comparing the coefficients of the distance to the closest stations before and after completion of the infrastructure. Ahlfeldt (2011) and Ahlfeldt and Wendland (2010) include minimum distances to various

(ii) the number of sites within a certain distance from a housing unit,[2] and (iii) an indicator of whether any site is located within a certain distance from a housing unit.[3] None of these proximity variables satisfies all the general assumptions above (Table 1). The use of each of these variables is justifiable under strict criteria, and failure to meet these criteria can lead to a biased estimate (Table 2). For instance, using only the first type of proximity variable (i.e., the distance to the closest site) in the hedonic estimation assumes that the second and third closest sites have no influence on the housing value, which is likely to result in overestimating the impact of the closest site.[4] One possible solution to address the effect of multiple sites is to regress a housing value on distances to the sites that are closest, second closest, third closest, and so forth. However, adding multiple distances in the hedonic model would lead to a serious multicollinearity problem, preventing us from drawing reliable and meaningful interpretations of the spatial effect.[5] Another possible remedy is to coordinate the second type of proximity variables with the first type,[6] or to use a distance-weighted sum of sites within a certain area.[7] The main concern with these practices is the choice of an adequate buffer, which researchers typically determine in an arbitrary manner. Some studies attempt to avoid problems associated with multiple sites and spatial heterogeneity by restricting housing samples to those located very close to sites rather than by implementing variables to account for multiple sites.[8]

<< insert Table 1 and 2, here >>

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locations, such as the station, main road, school, water space, green space, and industrial area, to estimate the land price.

[2] Many studies on the impact of foreclosures on neighborhoods use this type of variable (Gerardi et al., 2015; Harding et al., 2009; Immergluck and Smith, 2006; Leonardo and Murdoch, 2009; Lin et al., 2009; Rogers and Winter, 2009; Schwartz et al., 2006; Shuetz et al., 2008). Instead of simply counting the sites, Srour et al. (2002) estimate the impact of social recreation areas, shopping centers, and workplaces by counting the number of retail employments and total employments and by measuring the area of park spaces.

[3] Linden and Rockoff (2008) use dummy variables indicating whether any sex offender is living within 0.1 miles or within 0.1 to 0.3 miles from a transactional housing unit to estimate its impact on the property value. Other papers using this type of variable include studies on the impacts of wind power projects (Ben, 2010) and of rail transit stations on housing values (Bowes and Ihlanfeldt, 2001; Forrest et al., 1995; Kahn, 2007) and on the effect of foreclosures on crime (Cui and Walsh, 2015).

[4] This is because distances to the second and third closest sites, which may influence the housing value, are usually positively correlated with the distance to the closest site. Omitting these variables will lead to the upward bias of the effect of the closest site. Table 2 describes functional restrictions and potential biases caused by each proximity variable.

[5] In Appendix 2, the results of our application show that variance inflation factors (VIFs) of distance variables exceed the value of ten when we include distances to the first three closest sites.

[6] Sadayuki (2013) examines the externality of stigmatized property on neighbor housing values by using the shortest distance to a stigmatized property for each housing unit in the estimation. As an explanatory variable, he includes a count of stigmatized properties within a certain range of each housing unit to control for the impact of the clustering of stigmatized properties.

[7] Campbell et al. (2011) study the impact of foreclosures along with two types of proximity variables as controls. One variable is a count of foreclosures within 0.25 miles from each transactional housing unit. The other variable is a distance-weighted sum of foreclosures within 0.01 mile. Nok et al. (2014) examine the determinants of land prices, in which a distance-weighted sum of job opportunities at each CBD is used as an explanatory variable to control for the accessibility to CBDs.

[8] Pope (2008) excludes housing units that have more than one sex offender living within 0.15 miles. McMillen and McDonald (2004) estimate the impact of the infrastructure of the Midway rapid transit line in Cook County, Illinois, by excluding housing units that are located farther than 1.5 miles from the Midway line or closer to other kinds of lines.

Our proposed proximity measure is based on another type of measure, namely, an "accessibility measure," which is characterized as a sum of gravity-base functions, each of which is decreasing in distance and increasing in the attractiveness of a destination. Among the numerous studies related to the accessibility measure, which has been developed in such fields of study as land use and transportation,[9] the number of studies that apply it to the hedonic approach has been increasing in the past two decades (Appendix 1). Most of the accessibility measures in these studies of hedonic analysis are based on zone-to-zone rather than point-to-point measures, i.e., the distances used in these measures are computed between zones (such as zip code areas, transportation analysis zones, and voting precincts) rather than between housing units and sites. This is done because the major purpose of these studies is to assess the accessibility from one city to employment opportunities in other cities by counting the number of employment or job opportunities in each area, thereby addressing the significance of a polycentric urban structure in determining the housing value.[10]

In comparison with these studies, our focus is more of a local examination in which the spatial effect of multiple sites, such as public transportation, parks, supermarkets, foreclosures, and crime scenes, is unlikely to affect anyone beyond the neighborhood. Although the accessibility measure is superior to the three types of proximity variables listed earlier in the sense that it provides flexibility in the functional form, it still fails to take into account the third assumption (A3), which would result in a biased estimate (Tables 1 and 2). In our proposed proximity measure, we make several modifications to the conventional accessibility measure to fit it within the context of a point-to-point spatial analysis and to account for the third assumption (A3). In addition, our estimation procedure allows us to provide insights into questions within the context of a point-to-point spatial analysis such as "How many neighbor sites affect the housing value?" and "To what extent does each site have an influence on the housing value?"

In the following section, we demonstrate two types of measures. The first type is the traditional accessibility measure with some minor modifications to the conventional accessibility measure used in previous studies, so that it fits within the context of point-to-point spatial analysis. The second type is a proposed proximity measure that also accounts for the third assumption (A3). In Section 3, we illustrate an application of the relationship between the housing rental value and the clustering of train and subway stations in Tokyo, Japan. In general, addressing a greater number of neighbor stations in an empirical model should be associated with a better estimation result if the model is correctly specified. However, we observe in the application that the traditional accessibility measure worsens the estimation result when the information of a greater number of stations is addressed in the model. This result is due to the incorrect functional specification of the spatial effect by failing to account for the third assumption (A3). The proposed measure solves this issue, and the estimation result improves with the number of stations considered in the model.

Although all existing empirical studies on hedonic housing price analysis in Tokyo, to our knowledge, have taken only distance to the nearest station into account,[11] our result shows that

[9] To name a few, Hansen (1959), Song (1996), Ottensmann and Lindsey (2008), Iacono et al. (2010), and Salze et al. (2011).
[10] Appendix 1 provides a detailed discussion on the traditional accessibility measures versus the hedonic approach in the previous empirical studies.
[11] To name a few, Diewert and Shimizu (2016), Gao and Asami (2001), Nakagawa et al. (2007), Shimizu

at least the first three closest stations need to be addressed to obtain a better estimate of the housing value in Tokyo, whereas including more than the five closest stations in the model does not improve the prediction. More importantly, this study reveals that both distances to sites and the order of proximity to each site can be a vital factor of the spatial effect, and ignoring this factor could result in a significant estimation bias.

Some additional examinations with generalized proposed proximity measures are discussed in Appendix 2. Finally, Section 4 offers conclusions from the study.

2. Traditional accessibility measure and proposed proximity measure

Traditional accessibility measure

As discussed earlier, the intention of previous studies adopting an accessibility measure for the hedonic approach is to take into account the polycentric urban structure by constructing a measure of accessibility from one region to employment opportunities in other regions. Therefore, the first part of this section makes some minor modifications to the conventional accessibility measure used in previous studies to fit within the context of point-to-point spatial analysis. See Appendix 1 for further discussion on the conventional accessibility measure.

Let us use a subscript i to refer to the ith housing unit and $s_{i(j)}$ to indicate the jth closest site from housing i. Then, the traditional accessibility measure redefined for our study is specified as follows:

(3) $G\left(\left\{d_{i(j)}, q_{i(j)}, k_{i(j)}\right\}_{j=1}^{J}\right) = \sum_{j=1}^{J}\left(\sum_{k=1}^{K} D_{i(j)}^{k} f^{k}\left(d_{i(j)}, q_{i(j)}\right)\right) + c_{(j)}.$

On the left-hand side of the equation, a gravity-base function $G(.)$, representing a traditional accessibility measure, is a function of $d_{i(j)}$, $q_{i(j)}$ and $k_{i(j)}$ for $\mathrm{j} = \{1,2,\dots,J\}$, where $d_{i(j)}$ is the distance from housing i to $s_{i(j)}$, $q_{i(j)}$ is a value representing quantitative characteristics of $s_{i(j)}$, $k_{i(j)}$ is a type of qualitative characteristic of $s_{i(j)}$, and J is the number of the closest sites addressed in the measure.

Here, we explicitly describe two types of characteristics of sites in the model. One type is quantitative characteristics, represented by $q_{i(j)}$, and the other is qualitative characteristics, $k_{i(j)}$. The latter type is addressed on the right-hand side of the equation by introducing an indicator, $D_{i(j)}^{k}$, to differentiate parameters among different types of sites. $D_{(j)}^{k}$ takes a value of one if the qualitative characteristic of $s_{i(j)}$ is of type $k \in \{1, \dots K\}$ and takes a value of zero otherwise.[12] The right-hand side of equation (3) shows that a traditional accessibility measure is basically a sum of $f^{k}(.)$ and $c_{(j)}$ over $\mathrm{j} = \{1,2,\dots,J\}$. $f^{k}(.)$ specifies a functional form of the spatial effect of a type-k site, and $c_{(j)}$ is an intercept of the spatial effect of the jth closest

and Nishimura (2007), Shimizu et al. (2010) and Yamagata et al. (2016).

[12] For instance, in the case of foreclosures (Xian, 2016), the quantitative characteristic can be the time that has passed since the evacuation of the previous owner, and the qualitative characteristic can be whether the foreclosing property receives the Neighborhood Stabilization Program (NSP) grant. In the case of crime scenes, the quantitative characteristic can be the time that has passed since the incident, and the qualitative characteristics can be the types of incidents, such as homicides, robberies, and assaults.

site. In regression, $c_{(j)}$ cannot be estimated, because it is absorbed into a constant term of the hedonic function.

Among various possible specifications for $f^k(.)$, the most commonly used exponential-type traditional accessibility measure can be written as:

(4) $f^k(.) = \tau^k q_{i(j)} e^{\alpha^k d_{i(j)}}$,

where τ^k and α^k are parameters to be estimated. If there is only a single type of qualitative characteristic, equation (3) reduces to $G(.) = \sum_{j=1}^{J} \tau q_{i(j)} e^{\alpha d_{i(j)}}$.[13] The positive spatial effect of the quantitative characteristic, $q_{i(j)}$, of a type-k site is associated with a positive τ^k, and vice versa. On the other hand, α^k is expected to be negative in most cases because the spatial effect usually weakens with distance. One drawback of this exponential-type specification is that when a group of sites of a certain type of qualitative characteristic has no spatial effect, its parameters cannot be estimated, due to the identification problem; in particular, the estimate of α^k cannot be obtained when τ^k is zero.[14] Accordingly, in addition to equation (4), we also examine an alternative specification for $f^k(.)$ as follows:

(5) $f^k(.) = \tau^k q_{i(j)} + \alpha^k d_{i(j)} + \omega^k$.

This linear-type specification assumes that the effect of distance and the effect of qualitative characteristics are determined independently. Here, a positive spatial effect of a type-k site is associated with a negative α^k, while a negative spatial effect is associated with a positive α^k. Equation (5) gives an estimate of α^k even when τ^k is zero, whereas equation (4) cannot.

Lastly, the traditional accessibility measure specified in equation (3) is a sum of $f^k(.)$ for the first J closest sites, instead of a sum for all destinations, as was typically done in previous studies (Appendix 1). Recall that the main objective of the previous studies is to examine the polycentric structure of labor markets, which requires a wide range in the study area to construct the accessibility measure, because individuals may commute far.[15] In contrast, the spatial influence of foreclosures, crime scenes, and access to public transportation is likely to be limited to a local area. In such point-to-point examinations, using all sites in the whole study area to construct a proximity measure does not seem rational. Rather, we estimate the traditional accessibility measure using a different number of J, and we observe how adding the

[13] This simplified specification is equivalent to a commonly used conventional accessibility measure described in equation (8) in Appendix 1.

[14] Based on equation (4), the spatial effect of the jth closest site converges to a constant, $c_{(j)}$, as the distance increases. One can also construct an alternative formula that allows a different limit for each type, such as $f^k(.) = \tau^k q_{i(j)} e^{\alpha^k d_{i(j)}} + \omega^k$. However, when the true specification of the spatial effect is close to linear with respect to distance, absolute values of α^k and τ^k as well as their standard errors in this formula become so large that the estimation fails to identify parameters. In our application, although the results are not shown in this paper, the author estimates hedonic models using several alternative specifications of the proximity measure, including the one above, and finds that sites with some qualitative characteristics have the linear relationship between the distance and the rent.

[15] According to the 2011 American Community Survey, among U.S. workers who did not work at home, 8.1 percent had commutes of 60 minutes or longer and 35.7% had commutes of 30 minutes or longer in 2011. Census Bureau. In Tokyo, Japan, 24.2% had commutes of 60 minutes or longer and 69.8% had commutes of 30 minutes or longer in 2013, according to the 2013 Housing and Land Survey conducted by the Ministry of Internal Affairs and Communications.

number of closest sites to the model alters the estimation result.

Proposed proximity measure

On the basis of the above traditional accessibility measure, we propose a proximity measure that addresses the assumption (A3). This is done by adding a new term $g^k(j)$ to equation (4) such that $f^k(.)$ can be weighted differently depending on the proximity order and qualitative characteristics of a site:

(6) $G\left(\left\{j, d_{i(j)}, q_{i(j)}, k_{i(j)}\right\}_{j=1}^{J}\right) = \sum_{j=1}^{J}\left(\sum_{k=1}^{K} D_{i(j)}^{k} g^k(j) f^k\left(d_{i(j)}, q_{i(j)}\right)\right) + c_{(j)}.$

One rational specification for the weighting function is $g^k(j) = j^{\theta^k}$. The parameter θ^k takes a negative value if a type-k site with a higher order proximity is more important than the type-k site with a lower order proximity. If all sites are equally important regardless of proximity orders, θ^k takes a value of zero, and equation (4) reduces to equation (3). On the other hand, when there exists such a discounting factor of the spatial effect with respect to the proximity order, the traditional accessibility measure (which does not take into account the third assumption) is likely to overestimate the impact of the higher-order-proximity sites and underestimate the impact of the lower-order-proximity sites (Table 2).

The more general specification of the weighting function is given by $g^k(j) = \theta_{(j)}^{k}$, where a parameter can differ by the proximity order and qualitative characteristics. There are two concerns when using this type of generalized parameter. One is the multicollinearity problem caused by the fact that $f^k(.)$'s are likely to be highly correlated among different js, and thus, $\theta_{(j)}^{k}$ may not give reliable interpretations. The other is the identification issue when $\theta_{(j)}^{k}$ and the parameters in $f(.)$ are all supposed to be zero.

In the following application about the relationship between housing rent and access to clustering stations, we compare the estimation results between hedonic functions using the traditional accessibility measures and the proposed proximity measures. Note that although we discuss in the following section the results using the weighting function specified as $g^k(j) = j^{\theta^k}$, additional examinations with the generalized specification, $g^k(j) = \theta_{(j)}^{k}$, are reported in Appendix 2 in detail.

3. Application

In this section, using cross-sectional data of Tokyo's 23 wards, we examine the relationship between the housing rent and the surrounding train and subway stations. We first describe the data and the empirical models and then provide our estimation results.

Data

Data on rental housing in Tokyo's 23 wards were collected from November 2011 to July 2012 from the website of a rental real estate agency, Door Chintai.[16] We have 14,404 housing sample

[16] http://chintai.door.ac/.

units located in 8,955 rental apartment buildings after removing samples with missing values as well as outlying observations of rental prices above the 99th percentile and below the first percentile. The data include rental prices and housing characteristics such as address, floor area, number of bedrooms, floor levels, number of stories in a building, age of the building, amenities (gas, stove, and security systems), number of retail stores within 1 mile, and building type and structure.[17] Definitions of and basic statistics for the variables are described in Tables 3 and 4, respectively. The average rent in Tokyo's 23 wards in the samples is approximately 89,600 yen per month, which is $896 per month based on an exchange rate of $1 = 100 yen. Most of the samples are apartment units, and a few are family houses. The average floor level is 2.96, and 26% of the samples are located on the first floor. The average floor area is 30.73 square meters (330.77 square feet), and the average age of a building is 16.74 years.

<<insert Tables 3 and 4, here>>

We obtained geocodes for the existing train and subway stations as of October 2012 from the website EkiData.jp.[18] Figure 1 shows the train and subway stations around Tokyo's 23 wards. The data also include the names of the train and subway lines leading to each station. The number of lines leading to each station is used as a measure of the quantitative characteristics, $q_{i(j)}$. There are 490 stations in Tokyo's 23 wards, and we include an additional 137 stations surrounding Tokyo's 23 wards in our analysis. Of the total 627 stations, 457 have one line, 105 have two lines, 41 have three lines, and 27 have four or more lines.

<<insert Figure 1, here>>

Using these data sets, we compute the Euclidian distances between all combinations of housing and stations. We identify, based on the computed distances, the first nine closest stations from each housing sample i, i.e., $s_{i(1)}, \ldots, s_{i(9)}$. For the qualitative characteristics, k, we categorize the first nine closest stations from each housing sample into two groups, $k \in \{0,1\}$. One is $k =$ 1, a set of stations that have at least one line that do(es) not lead to any other stations closer to housing i. In other words, these stations are the closest stations to reach certain line(s) from housing i. For the sake of convenience, we call this kind of line(s) "new line(s)" at each station for housing i, indicating that the station is the closest from housing i to take the(se) line(s). We construct an indicator, $D^1_{i(j)}$, named "new-line dummy," that takes a value of one for such a station with a new line(s) and takes a value of zero otherwise. Figure 2 is a visual illustration of how the values of the quantitative characteristics, $q_{i(j)}$, and the qualitative characteristics, $k_{i(j)}$, are assigned. By construction, a new-line dummy for the closest station, $D^1_{i(1)}$, always takes a value of one. When a new-line dummy takes a value of zero, that indicates that all lines leading to this particular station also lead to at least one closer station from housing i. Therefore, this type of station may be redundant for a person living in housing i in the sense that he/she can go to a closer station(s) to take any lines leading to this station.

Basic statistics on distances, numbers of lines, and new-line dummies are shown in Table 5. The average distance to the closest station is 0.56 miles, and the average distances increase to 0.93 and 1.20 miles for the second and third closest stations, respectively. The average number

[17] The geocoding system and the data on retail stores were provided by the Center for Spatial Information Science, The University of Tokyo.
[18] http://www.ekidata.jp/.

of lines leading to each station ranges from 1.38 to 1.49. Finally, approximately half of the second closest stations have a new line that does not lead to the closest station, whereas the proportion of stations with a new line decreases as the proximity order becomes lower.

<<insert Figure 2 and Table 5, here>>

Estimation models

We estimate the hedonic rental price function as follows:

(7) $Rent_i = G\left(\left\{j, d_{i(j)}, q_{i(j)}, D^1_{i(j)}, D^0_{i(j)}\right\}_{j=1}^{J}\right) + \mathbf{X}_i \boldsymbol{\beta} + e_i$,

where $Rent_i$ is the monthly rent of housing i; $G(.)$ is a proximity measure; $d_{i(j)}$ is the distance from housing i to the jth closest station, $s_{i(j)}$; $q_{i(j)}$ is the number of lines leading to $s_{i(j)}$; J is the number of closest stations in the proximity measure; $\mathbf{X}_i$ is a row vector of variables about neighborhood and housing characteristics; $\boldsymbol{\beta}$ is a column vector of parameters associated with $\mathbf{X}_i$; and e_i is an error term. $D^1_{(j)}$ = 1 if $s_{i(j)}$ has a line that does not lead to any of the closer stations, and $D^1_{(j)}$ = 0 otherwise. $D^0_{i(j)}$ = 1 if and only if $D^1_{(j)}$ = 0. We examine four types of measures.

Model A0 is an exponential-type traditional accessibility measure:

$$G_i = \sum_{j=1}^{J} D^1_{i(j)} \tau^1 q_{i(j)} e^{\alpha^1 d_{i(j)}} + D^0_{i(j)} \tau^0 q_{i(j)} e^{\alpha^0 d_{i(j)}} + c_{(j)}.$$

Model B0 is a linear-type traditional accessibility measure:

$$G_i = \sum_{j=1}^{J} D^1_{i(j)} \left(\tau^1 q_{i(j)} + \alpha^1 d_{i(j)}\right) + D^0_{i(j)} \left(\tau^0 q_{i(j)} + \alpha^0 d_{i(j)}\right) + D^0_{i(j)} \omega^0 + c_{(j)}$$

$$= \tau^1 \sum_j D^1_{i(j)} q_{i(j)} + \alpha^1 \sum_j D^1_{i(j)} d_{i(j)} + \tau^0 \sum_j D^0_{i(j)} q_{i(j)} + \alpha^0 \sum_j D^0_{i(j)} d_{i(j)} + \omega^0 \sum_j D^0_{i(j)} + c_{(j)}.$$

Model A1 is a proposed proximity measure with weighting terms added to Model A0:

$$G_i = \sum_{j=1}^{J} D^1_{i(j)} j^{\theta^1} \tau^1 q_{i(j)} e^{\alpha^1 d_{i(j)}} + D^0_{i(j)} (j-1)^{\theta^0} \tau^0 q_{i(j)} e^{\alpha^0 d_{i(j)}} + c_{(j)}.$$

And Model B1 is a proposed proximity measure with weighting terms added to Model B0:

$$G_i = \sum_{j=1}^{J} D^1_{i(j)} j^{\theta^1} \left(\tau^1 q_{i(j)} + \alpha^1 d_{i(j)}\right) + D^0_{i(j)} (j-1)^{\theta^0} \left(\tau^0 q_{i(j)} + \alpha^0 d_{i(j)}\right) + D^0_{i(j)} (j-1)^{\theta^2} \omega^0 + c_{(j)}$$

Model A0 is the traditional accessibility measure based on equation (4). Parameters differ between stations with and without a new line, namely, $D^1_{i(j)}$ = 1 and $D^0_{i(j)}$ = 1. Model B0 is a linearized version of Model A0, with the intent to estimate the effects of quantitative characteristics and distance separately. Model A0 has four parameters to be estimated, τ^1, α^1, τ^0, and α^0, and Model B0 has five parameters, τ^1, α^1, τ^0, α^0, and ω^0. When J = 1, there are only two parameters, τ^1 and α^1, to be estimated in both models, because the new-line dummy at the closest stations, $D^1_{i(1)}$, is always one for all i. Because Model B0 can be expressed as a linear function, we employ OLS to estimate the hedonic function, whereas we employ the maximum likelihood method for the hedonic functions using the other three measures.

Model A1 adds the weighting terms j^{θ^1} and $(j-1)^{\theta^0}$ to Model A0. If the spatial effect of a station diminishes with the proximity order ranking, these weighting parameters, θ^1 and θ^0, will be negative. To gain a better understanding of the role of weighting parameters, consider a case in which the closest station is located one mile away from housing *i*. Suppose that a new station on a different line will be constructed just half a mile away from housing *i* such that this new station will become the closest one and the former closest station will be the second closest. Will the impact of the former closest station on housing *i* stay the same even after the new station is constructed? If the answer is yes, it implies that $\theta^1 = 0$, because the proximity order does not matter, only the distance does. If the impact of the former station is reduced because of the presence of the new station, then $\theta^1 < 0$. The traditional accessibility measure can be regarded as a special case of Model A1, in which $\theta^1 = 0$ and $\theta^0 = 0$.

In Model A1, when $J = 1$, there are only two parameters to be estimated, τ^1 and α^1, and the result will be the same as the result in Model A0. Because the new-line dummy always takes a value of one, the second term on the right-hand side of the equation appears for $j \geq 2$. This is why we construct $(j-1)$ as the base of $g^k(j, k=0)$, so that τ^0 and α^0 can be interpreted as the effects of the second closest station without a new line.[19] On the other hand, τ^1 and α^1 are the effects of the closest station because we have j as the base of $g^k(j, k=1)$.

Model B1 is an extension of Model B0 with weighting parameters θ^1, θ^0, and θ^2. Here, ω^0 is a rental difference between two hypothetical housing units (that are located at the second closest stations with and without a new line, which are evaluated at $d_{i(2)} = 0$ and $q_{i(2)} = 0$). Because no such housing units exist, we will evaluate the rental difference at the mean value of $d_{i(2)}$ and at $q_{i(2)} = 1$ in the application. There are two parameters in the proximity measure to be estimated in the model with $J = 1$, six parameters with $J = 2$, and eight parameters with $J = 3$ and above.

Estimation results

Model A0: Table 6 shows maximum likelihood estimates of hedonic functions with the traditional exponential-type accessibility measure, Model A0. Each column shows the results using a different number of stations in the accessibility measure (i.e., $J = 1, 2, 3, 5$, and 9). The table shows the results of estimated parameters in the accessibility measures as well as coefficients of some control variables in **X**. Numbers in parentheses are cluster-robust standard errors, assuming that residuals can be correlated within the same apartment buildings and are independent across the buildings. In addition, the log likelihood, the corrected Akaike information criteria (AICc), and the Bayesian information criteria (BIC) are shown at the bottom of the table.

First, we look at the parameters of the accessibility measure. Overall, τ^1 and α^1 show the expected signs and are statistically significant, implying that a station with a new line has a positive effect on the neighboring housing rent, i.e., the housing rent is higher near a station with more lines and is lower as the housing is located farther from the station. In contrast, τ^0 and α^0 are not significantly different from zero. This means that stations without a new line

[19] One can construct $g(j, k=0) = j^{\theta^0}$ instead; however, doing so would hinder us from gaining a direct interpretation of the parameter, and the estimates of θ^0 and τ^0 would lose stability across different *J*.

have no influence on the surrounding housing rent.

If the model specification is accurate, addressing a greater number of stations in the estimation should give a better prediction of the housing rent. However, according to the result, the log likelihood, AICc, and BIC, adding more stations in the model worsens the estimation result, in which case we suspect a model misspecification. Another sign of the possibility of the misspecification can be seen in unstable parameters across *J*s. τ^1 and α^1 change from 0.39 to 0.26 and from -1.52 to -2.24, respectively, as *J* increases from 1 to 9. This implies that the marginal effect of the distance and of the number of lines may vary among stations with different proximity orders.

<< *insert Table 6, here* >>

Model B0: Table 7 shows OLS estimates of parameters in Model B0.[20] The positive signs of τ^1 and τ^0 imply that the housing rent is higher if the surrounding stations have a greater number of lines. The negative sign of α^1 means that the housing rent increases as the housing is located closer to a station with a new line. On the other hand, α^0 is not significantly different from zero, meaning that the housing rent is not influenced by the distance to a neighbor station without a new line. Unlike the previous model, Model B0 estimates the effect of the number of lines and the effect of the distance separately. The results based on this model reveal that the number of lines at a station without a new line has a positive effect on the nearby housing rent, which is not shown in Model A0, where the marginal effects of distance and number of lines are assumed to be positively correlated by construction of the model.

Similar to the results in Model A0, the estimation result becomes worse as *J* increases, as can be seen in the R^2, log likelihood, AICc, and BIC. In addition, the parameters are unstable with different *J*, which indicates that the marginal effects differ by the proximity order of a station. In particular, magnitudes of the parameters become smaller as *J* increases, implying that the marginal effects may be smaller for stations with lower proximity orders. These issues arise because of failing to account for assumption (A3), as can be confirmed in the following results of the proposed models.

<< *insert Table 7, here* >>

Model A1: The first proposed model, Model A1, introduces weighting parameters to Model A0 to address assumption (A3). The estimation results are shown in Table 8.

Note that the result in column [8-1] of Table 8 is identical to the result in column [6-1] of Table 6 for Model A0 because the functional forms of both models are the same when $J = 1$ (i.e., using only the closest station to construct a proximity measure). When $J = 2$, the results of the two models may differ because of a difference in the relative importance between the first and second closest stations. The traditional accessibility measure assumes that the first and second closest stations are equally important to residents, i.e., $\theta^1 = 0$. According to [8-2], θ^1 is –2.27 and the sign is statistically significant, implying that people perceive the closest station as being more important than the second closest station. In [8-3] to [8-5], θ^1 remains negative, whereas

[20] Hereafter, only the estimates of the parameters in the proximity measure are shown. Coefficients of the control variables, $\boldsymbol{X}$, are omitted from the result tables.

θ^0 is not statistically different from zero.

<< *insert Table 8, here* >>

In contrast to the results for Model A0, adding a greater number of neighboring stations in Model A1 improves the estimation result. According to the AICc and BIC, the estimation improves as we increase J to 5. Also, α^1 is relatively stable in Model A1 compared with Model A0. Another distinction from the result for Model A0 is that some of α^0 turn to be significant in Model A1. Because τ^0 is negative, the negative α^0 means that the rent increases as the housing is located farther from a station without a line.

Figure 3 illustrates the housing rent versus the distance to a station based on the result in [8-4]. Here, the number of lines leading to a station is fixed at one. Note that the levels of lines on the *y*-axis are not comparable across different proximity orders, because $c_{(j)}$ is absorbed by a constant in the hedonic function and thus cannot be identified. When the distance to the closest station increases from 0.2 miles (10th percentile) to 1.0 miles (90th percentile), the monthly rent decreases by approximately 2,200 yen ($22, with $1 = 100 yen) on average. In addition, when the distance to the second station with a new line increases from 0.5 miles (10th percentile) to 1.5 miles (90th percentile), the rent declines by approximately 500 yen ($5, with $1 = 100 yen). In contrast, the housing rent increases as the housing is located farther from the second closest station without a new line.

It is noted, however, that exponential-type models such as Models A0 and A1 impose a functional restriction, as mentioned earlier, in such a way that marginal effects of the distance and the number of lines are positively correlated (i.e., an increase in the number of lines is associated with an increase in the change of the marginal effect of the distance by construction of the measure). If this assumption is incorrect, Model A1 fails to give correct interpretations about the spatial effect.[21]

<< *insert Figure 3, here* >>

Model B1: The estimation results for the second proposed model, Model B1, are described in Table 9. Unlike the results for Model B0, the parameters become stable regardless of the choice of *J*. In addition, according to the AICc and BIC, the estimation result improves as we consider a greater number of stations in the model. As mentioned, adding more stations in the traditional accessibility measure worsens the estimation, which calls into question the credibility of using the traditional accessibility measure in our research. The two proposed models solve this problem by introducing weighting terms that assess different weights for the effects of stations by their proximity orders. Between the two proposed models, the performance of Model B1 is superior to that of Model A1, based on the information criteria (Figure 5). Both criteria decrease until *J* reaches 5. Therefore, we would take into account the first five stations closest to each housing unit to obtain a better prediction of the housing rent in Tokyo.

Now, let us interpret the result in [9-4].[22] Regarding a station with a new line, when τ^1 is 0.19,

[21] Unstable magnitudes of α^0 and τ^0 and their large standard errors can be signs of the misspecification of the spatial model.

[22] [9-4] is selected among [9-1] to [9-5] based on the AICc and BIC.

the rent appreciates by 1,900 yen ($19) when the number of lines at the closest station increases by one. When α^1 is –0.57, the rent decreases by 5,700 yen ($57) as the distance to the closest station increases by 1.0 mile. When θ^1 is negative, the marginal effects of the distance to and of the number of lines at a station with a new line diminish as its proximity order becomes lower. The marginal effects of these two variables are, respectively, 300 yen ($3) and 1,000 yen ($10) for the second closest station with a new line.

Regarding a station without a new line, α^0 and τ^0 are positive[23] but not statistically different from zero. The distance to and the number of lines at a station without a new line has no influence on the rent. This result implies that a line(s) that stops at a station is/are not important to residents as long as they have access to the line(s) at closer stations. Also, θ^0 shows a negative sign, but it is not statistically significant. Finally, ω^0 is –0.40, i.e., the rent of a hypothetical housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$, and $D^1_{i(2)} = 1$ is higher by 4,000 yen ($40) than the rent of a hypothetical housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$, and $D^1_{i(2)} = 1$. The rental difference, evaluated at the average distance to the second closest station (0.93 mile) and $q_{i(2)} = 1$ is approximately 1,100 yen ($11) between housing units with and without a new line at the second closest station. If we consider a closer distance, for example, 0.50 miles (approximately the 10th percentile of the distance to the second closest station), the rental difference will be approximately 2,500 yen ($25).

<< insert Table 9, here >>

Further estimations (Appendix 2)

In Appendix 2, we examine alternative models with some generalized specifications for the proposed proximity measures. We test two types of generalizations for each of the two proposed models, Model A1 and Model B1. In the first type, we set $g^k(j) = \theta^k_{(j)}$ such that the discounting weights are free from the functional form, which is restricted to $g^k(j) = j^{\theta^k}$ in Models A1 and B1. In the second type, we allow all parameters in $f^k(.)$ to vary by proximity order and by qualitative characteristics, i.e., $\tau^k_{(j)}$, $\alpha^k_{(j)}$, and $\omega^k_{(j)}$.

Although the estimation results and a detailed discussion are provided in Appendix 2, the results can be summarized as follows. First, the generalizations of Model A1 lead to an identification problem when we set J = 4 or more, preventing the maximum likelihood estimation from identifying the parameters. This is attributed to the fact that stations without a new line have too little effect on the housing rent when the ranking of the proximity order becomes lower than three. In such a case, the models fail to identify parameters between $\theta^0_{(j)}$ and τ^0 in the first type of generalization and between $\tau^0_{(j)}$ and $\alpha^0_{(j)}$ in the second type of generalization. In contrast, both of the generalized models for Model B1 identify every parameter, regardless of the choice of J. Between Model B1 and the corresponding two generalized models, the AICc shows the superiority of the generalized models, whereas the BIC prefers Model B1 to them. Although the model selection remains an open question, we

[23] One possible explanation of the positive α^0 is that the distance to the second closest station without a new line is likely positively correlated with the distance to a railway leading to the first two closest stations. A railway can be a disamenity to nearby housing because of the noise it generates (Andersson et al., 2010; Mrons et al., 2003; Diao et al., 2015; Poon, 1975). In future research, taking into account the distance to railways may provide further insights into our findings.

conclude that Model B1 holds an advantage to the other models in our applications in the sense that it provides meaningful interpretations (without suffering from a serious multicollinearity problem) of the spatial effect of the clustering stations on the housing rent.

4. Conclusion

The aim of this paper is to construct an empirical model to estimate the spatial effect of multiple sites that satisfies three general assumptions: (A1) the closer a site, the greater the effect may be, (A2) the impact of a site differs according to its characteristics, and (A3) the lower the proximity order of a site, the lower the impact may be. The last assumption (A3) in particular was not considered in previous empirical studies dealing with multiple sites. Thus, we propose two models, based on the exponential-type and linear-type gravity-base measure, by introducing an additional term that assigns different weights to the spatial effect of each site depending on its proximity order.

We employ the application of housing rent in relation to multiple surrounding train and subway stations in Tokyo. The estimation result is supposed to improve with the number of stations used in the proximity measure if the model is correctly specified. However, when we use the traditional accessibility measure in the hedonic model, the prediction power declines as we increase the number of stations in the model. This result suggests that the traditional accessibility measure, which does not account for the third assumption (A3), is not an appropriate model within the context of our application. In contrast, the proposed models solve this problem and obtain better results when we include a greater number of stations in the models. Although, to our knowledge, all the studies analyzing the housing market in Tokyo address only the closest station in the hedonic model, our study shows that the housing rent in Tokyo is influenced by at least the first three to five closest stations. It also shows that including more than the first five closest stations in the model does not improve the estimation result.

We also observe in the application that linear-type proximity measures (Model B0 and its extended models) perform better than exponential-type proximity measures (Model A0 and its extended models) based on the AICc and BIC. One of the advantages of the linear-type proximity measure is its ability to estimate marginal effects of distance and of quantitative characteristics independently. Because the exponential-type proximity measure imposes a positive correlation between these two marginal effects by construction of the functional form, it fails to give a valid interpretation of the result when its assumption is not true. Even more, it fails to give estimates when the marginal effect of the quantitative characteristics is too small and/or when the spatial effect actually takes a linear form. Among the three linear-type proximity measures (Model B1 and its generalized measures, presented in Appendix 2), the choice of the best model remains an open question, based on the AICc and BIC. Nevertheless, the simplest specification of Model B1 is practical in the sense that it gives clear interpretations about the spatial effect of clustering stations without facing the multicollinearity problem.

The proposed models are applicable to spatial analyses dealing with various types of multiple sites, such as crime scenes, foreclosures, and neighbor amenities. For each application, the proximity measure needs to be used with appropriate quantitative and qualitative characteristics of sites of interest. For instance, for a study of multiple crime scenes in neighborhood, a quantitative characteristic could be the time passed since an incident, and a qualitative characteristic could be a type of incident such as homicide, robbery or assault. For the examination of the effect of accessibility to grocery stores, the quantitative and qualitative characteristics could be replaced by the store’s floor area (or sales) and the type of store, respectively.

Lastly, we suggest that this methodology is worth testing with studies on polycentric urban structure, where one could examine whether or not the proximity order matters when assessing the effect of the accessibility to surrounding cities. Also, it would be interesting to construct a proposed proximity measure by using commuting time as the distance measure (instead of using the physical distance) to examine the effect of the introduction of a new transport system, such as high-speed rail, that may change the order of time distance from one city to another without changing the physical distance between them.

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Appendix 1: Traditional accessibility measure in a hedonic model

This appendix discusses the accessibility measure used in the hedonic analysis in the previous studies listed in Table 10. Table 2 summarizes most of the following discussion. The hedonic model accompanied with a traditional zone-to-zone accessibility measure is described as:

(8) $y_{i,z} = G(\{d_{zz'}, q_{z'}\}_{z' \in \mathbf{Z}}) + \mathbf{X}_i \boldsymbol{\beta} + e_i$,

where y_i is a property value of housing $i \in \{1, \ldots, N\}$ in a region $z \in \{1, \ldots, Z\}$, $G(.)$ is an accessibility measure, $\mathbf{X}_i$ is a vector containing a constant value and control variables affecting y_i, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and e_i is an error term.

The accessibility measure $G(.)$ is a function of distances from the region of housing i to all regions $\{d_{zz'}\}_{z' \in \mathbf{Z}}$ in the study area and of regional characteristics $\{q_{z'}\}_{z' \in \mathbf{Z}}$. A distance of two regions can be calculated as a Euclidian distance between central points of the two regions, or it can be calculated based on the transportation time and fees between major stations in two regions. Typically, the number of employees and jobs are used as the values for the regional characteristics.

Among various accessibility measures that have been examined in existing studies, types of gravity-base formulas, introduced by Hansen (1959), are recognized to perform better than other types of accessibility measures in terms of predictive power and the flexibility of functional form. The most commonly used gravity-base accessibility measure is a negative-exponential type, described as,

(9) $G_{i,z} = \sum_{z' \in \mathbf{Z}} \tau q_{z'} e^{\alpha d_{zz'}}$

where τ and α are parameters to be estimated. The previous studies find τ being positive and α being negative, that is, the region with more job opportunities has a positive influence on the housing value in surrounding regions, while the impact becomes lower with distance. Various extensions of measure (9) are possible as long as parameters can be identified. The other typical type of gravity-base accessibility measure is an inverse-power type, $G_{i,z} = \tau \sum_{z' \in \mathbf{Z}} q_{z'} d_{zz'}^{\lambda}$ where λ takes a negative sign (Song, 1996; Saize et al., 2011). The weighted sum of foreclosures used in Campbell et al. (2011) is equivalent to the inverse-power type of accessibility measure, where they impose $q_{z'} = 1$ and $\lambda = -1$.

A boundary condition is one of the issues of the accessibility measure. Since regions by which the accessibility measure is computed are censored in many studies, the measure tends to be underestimated near the boundary of the study area. Two approaches have been adapted to address this issue. One is to include surrounding regions to compute accessibility measures for the area of interest. However, the accessibility measure still tends to be overestimated in the center of study area even under such a treatment as long as the entire area is used to construct the measure. The other approach is to limit the regions from each housing to compute the accessibility measure (Gjestland et al., 2014).

Given the nonlinearity of the accessibility measure, three approaches have been used to estimate the hedonic model in the previous studies. The first approach is the maximum likelihood method, or nonlinear regression, which is practical in the sense that the estimation can be performed in a single step. It is also reliable, because it ensures the validity of the functional specification by obtaining a result. We suspect that the main reason some studies avoid using this approach is partly due to inappropriate specification of the model, which prevents the estimation from identifying parameters in the measure. The second approach, the grid-search method, may help obtain an estimation result in the presence of the identification problem, although it means that the estimates can be quite unstable. In the grid-search method, numbers of linear regressions with various combinations of parameters are employed to find the one that yields the highest likelihood or R-squared. Accordingly, the results using the grid-search method do not provide standard errors of the parameters, and thus, it is difficult to discern the stability of the parameters. The third approach is to assign specific values to parameters in the nonlinear terms and then to run the ordinary least squares to estimate the hedonic model. These values are typically taken from other studies or are estimated prior to the hedonic estimation.

<< insert Table 10, here >>

Appendix 2: Additional estimations

This appendix discusses extended versions of the proposed proximity measure examined in the text. Let us start with extended specifications of Model A1 as follows:

Model A2

$$G_i = \sum_{j=1}^{J} D_{i(j)}^1 \theta_{(j)}^1 \tau^1 q_{i(j)} e^{\alpha^1 d_{i(j)}} + D_{i(j)}^0 \theta_{(j)}^0 \tau^0 q_{i(j)} e^{\alpha^0 d_{i(j)}} + c_{(j)}$$

Model A3

$$G_i = \sum_{j=1}^{J} D_{i(j)}^1 \tau_{(j)}^1 q_{i(j)} e^{\alpha_{(j)}^1 d_{i(j)}} + D_{i(j)}^0 \tau_{(j)}^0 q_{i(j)} e^{\alpha_{(j)}^0 d_{i(j)}} + c_{(j)}$$

Recall that the general function of a proposed proximity measure is given as $G_i = \sum_{j=1}^{J}(\sum_{k=1}^{K} g^k(j) f^k(.)) + c_{(j)}$. Although the $f^k(.)$ in Model A2 is the same as that in Model A1, $g^k(j)$ is generalized in such a way that the weights are free from functional restrictions. Model A3 eases the functional restrictions even further such that all parameters in $f^k(.)$ can vary by proximity orders and types of station; thus, $g^k(j)$ has no room to intervene. In both extended models, a greater J is associated with more parameters, whereas the number of parameters does not go beyond six in Model A1.

Table 11 describes estimation results for Model A2. The results of the model with $J = 4$ or more are not shown in the table because these maximum likelihood estimates fail to converge. We suspect that τ^0 and some of $\theta_{(j)}^0$ are no longer statistically different from zero for j = 4, preventing the parameters from being identified.

<< *insert Table 11, here* >>

Table 12 shows results for Model A3. We are also unable to estimate the models with $J = 4$ or more. By construction of this model, $\tau_{(j)}^0$ and $\alpha_{(j)}^0$ cannot be identified if $\tau_{(j)}^0$ is zero. We suspect that $\tau_{(4)}^0$ is close enough to zero.

<< *insert Table 12, here* >>

Next, the following two models are examined as extensions of Model B1:

Model B2

$$G_i = \sum_{j=1}^{J} D_{i(j)}^1 \theta_{(j)}^1 \left(\tau^1 q_{i(j)} + \alpha^1 d_{i(j)}\right) + D_{i(j)}^0 \theta_{(j)}^0 \left(\tau^0 q_{i(j)} + \alpha^0 d_{i(j)}\right) + D_{i(j)}^0 \theta_{(j)}^2 \omega^0 + c_{(j)}$$

Model B3

$$G_i = \sum_{j=1}^{J} D_{i(j)}^1 \left(\tau_{(j)}^1 q_{i(j)} + \alpha_{(j)}^1 d_{i(j)}\right) + D_{i(j)}^0 \left(\tau_{(j)}^0 q_{i(j)} + \alpha_{(j)}^0 d_{i(j)}\right) + D_{i(j)}^0 \omega_{(j)}^1 + c_{(j)}$$

As with the previous cases, only $g^k(j)$'s in Model B2 are generalized from Model B1, and Model B3 allows all parameters to vary by proximity orders and qualitative characteristics. We employ OLS for Model B3, which now turns to be a linear function. Table 13 shows the results for Model B2. In contrast to Model A2, we are able to obtain results for all J from 1 to 9, because the parameters are independent of one another in this model. We observe that τ^0 and α^0 are close to zero, as with the results for Model B1.

<< insert Table 13, here >>

In [13-5], $\theta^1_{(2)}$ = 0.22 means that the effect of the second closest station with a new line is 22% as significant as the effect of the closest station. It turns out that $\theta^1_{i(2)}$ is the only weighting parameter with a significant sign. $\omega^0_{(2)}$ = –0.41 implies that the rent is higher by 4,100 yen ($41) for a housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$ and $D^1_{i(2)} = 1$ compared with the rent of a housing unit with $d_{i(2)} = 0$, $q_{i(2)} = 0$ and $D^1_{i(2)} = 1$. If we assess the rental difference by using the mean distance to the second closest station (0.93 mile) and $q_{i(2)} = 1$, the rental gap will be approximately 1,300 yen ($13).

The AICc declines as J increases and hits the minimum at J = 5, suggesting that the estimation improves by adding the first five closest stations to the model, while adding more than five stations does not contribute to a better prediction. On the other hand, the BIC hits the minimum at J = 3 and increases as we add more stations to the model, suggesting that only the three closest stations should be considered in the model. This is because the BIC penalizes the number of parameters more than the AICc does.

Lastly, we look at the result for Model B3. Table 14 shows variance inflation factors (VIFs) of hedonic models using all independent variables, including those in Model B3, for each J from 1 to 5. Based on the commonly used rule of thumb, where the multicollinearity is considered high regarding a variable with a VIF of 10 or greater, it is observed that the multicollinearity becomes severe once the third closest stations are added to the model. In particular, distances are highly correlated with one another.

<< insert Table 14, here >>

Table 15 shows the corresponding estimation results using J = 1 to 5. The shadows of cells indicate degrees of VIFs of variables of the corresponding parameters. Although the unbiasedness still holds as long as the model is correctly specified, magnitudes of parameters for variables with high VIFs should be carefully interpreted.

Let us first look at the spatial effect of a station with a new line. The marginal effect of the number of lines, $\tau^1_{(j)}$, decreases as the proximity order becomes lower, and the number of lines at the third closest station no longer has a significant effect on the rent. However, the fourth and fifth closest stations show the same magnitude of effects as the second closest station, which is difficult to interpret in the presence of the serious multicollinearity. The marginal effect of the distance, $\alpha^1_{(j)}$, is only significant for the closest station.

Now, we look at the spatial effect of a station without a new line. First, $\tau^0_{(j)}$ are not different from zero in all models. The number of lines at a station without a new line does not matter to people because they already have access to these lines at closer stations. On the other hand, $\alpha^0_{(j)}$ shows some positive and significant signs for models with J = 2 and 3, while the signs are no longer significant after including distances to three stations or more. Lastly, the sign of $\omega^1_{(j)}$

is statistically significant only for j = 2. As with previous models, $\omega_{(j)}^{1}$ needs to be interpreted with other parameters by taking into account the distance to the jth closest station. The rental difference of housing located in the average distance from the second closest station (0.93 miles) with and without a new line, having single lines, is approximately 1,800 yen ($23). When evaluated at the distance of 0.50 miles (the 10^{th} percentile of the distance to the second closest station), the rental difference is approximately 2,400 yen.

<< *insert Table 15, here* >>

Figure 9 compares the AICc and the BIC of the originally proposed models as well as the two generalized models. Model B3 is the preferable specification according to AICc, while the BIC chooses Model B1 over the other two models. Although the model selection remains an open question for the future research, we suggest in general that researchers compare several models with different levels of functional flexibility. The advantage of a flexible model, such as Models A3 and B3, is in its ability to discern a general idea of what the $g(.)$ would look like. However, such models come with the cost of high multicollinearity among variables, which hinders us from having a valid interpretation of parameters of the proximity measures, and there is a high penalty in the information criteria. Once one has some understanding of a general relationship between the proximity orders and the weights, one can construct a specific function for $g(.)$ to have a simplified proximity measure. The significant advantage of such a simplified measure is that it allows us to give a clear interpretation of the spatial effect for every site without having increasing penalties on information criteria.

<< *insert Figure 6, here* >>

Table 1. Proximity measures and implications for the spatial effect of multiple sites

		Proximity measure			
		(i) Distance to the closest site	(ii) Number of sites within a range	(iii) Indicator of sites within a range	(iv) Traditional accessibility measure
General assumptions about the spatial effect of multiple sites					
(A1)	The closer a site, the greater the impact may be.	○	×	×	○
(A2)	The impact may differ by the characteristics of the sites.	○[a]	○[a]	○[a]	○[a]
(A3)	The higher the ranking of proximity of a site, the higher the impact may be.	△[b]	×	△[b]	×

○: The proximity measure addresses the assumption. ×: The proximity measure does not address the assumption. ○[a] : All proximity measures are able to address different impacts of heterogeneous sites by introducing distinct parameters and dummy variables. △[b] : These measures are extreme cases in which no weights are assigned to the effects of any sites except the closest one.

Table 2. Assumptions of and potential issues related to proximity variables in the hedonic model

Proximity variable	Assumptions of the functional forms and issues
Distance to the closest site	• *Assumption*: Only the distance to the closest sites matters. *Issue*: Distances to the second and third closest sites may matter. • *Potential bias*: The effect of the closest site can be overestimated because of its positive correlations with the second closest site, the third closest site, and so forth.
Number of sites within a range	• *Assumption*: Every site within a boundary has the same magnitude of spatial effect regardless of distances to the sites. *Issue*: The effect may be greater for a closer site. • *Assumption*: It imposes a clear-cut neighborhood boundary on the spatial effect of sites. *Issue*: The effect may be continuously decreasing in distance. • *Issue*: Decision on the construction of boundaries can be arbitrary. • *Potential bias*: The effect of a site near the housing or border within the boundary can be underestimated or overestimated.
Indicator of sites within a range	• *Assumption*: Whether or not there exists at least one site within a boundary is all that matters. The second closest site, the third closest site, and so forth, within the boundary have no additional effect. *Issue*: The effect may be greater with a greater number of sites within a boundary. • *Assumption*: The closest site within a boundary has a constant spatial magnitude effect regardless of the distance to the site. *Issue*: The effect may be greater for a closer site. • *Issue*: Decision on the construction of boundaries can be arbitrary. • *Potential bias*: The effect of a site near the housing or border within the boundary can be underestimated or overestimated.
Traditional accessibility	• *Assumption*: Every site has the same importance (weight of the spatial effect) regardless of its order of proximity. *Issue*: People may care more about the closest site than the second closest site. • *Potential bias*: The effect of sites with lower order proximity can be overestimated because of negative correlations between the order of proximity to a site and its significance.

Table 3. Definitions of variables

Variable	Definition
$d_{(j)}$	Distance (miles) to the *j*th closest station, $s_{(j)}$
$q_{(j)}$	Number of train/subway lines at $s_{(j)}$
$D^1_{(j)}$	New-line dummy, i.e., 1 = if $s_{(j)}$ has a line that does not stop at $s_{(1)\ldots}$ $s_{(j-1)}$; 0 = otherwise
$D^0_{(j)}$	1 = if $D^1_{(j)} = 0$, i.e., all lines at $s_{(j)}$ stop at either one of $s_{(1)\ldots}$ $s_{(j-1)}$; 0 = otherwise
Rent	Rental price per month (10,000 yen per month)
FSpace	Floor space (square foot)
Bedrooms	Number of bedrooms
FLevel	Floor level
Age	Age of the building (year)
Story	Total number of floor levels in a building
Shop	Number of retail stores within 1 mile
CBD	Distance (miles) to the closest major station: major stations are Shinjuku, Ikebukuro, Shibuya, Shinagawa, Tokyo, Ueno, Musashikosugi
AC	1 = air conditioner equipped; 0 = otherwise
FL1	1 = unit located on the first floor of the building; 0 = otherwise
Corner	1 = unit located at a corner of the building; 0 = otherwise
Propan	1 = propane gas; 0 = otherwise
IH	1 = stove with induction heating equipment; 0 = otherwise
AutoLock	1 = building entrance with an autolock system; 0 = otherwise
Box	1 = apartment with parcel lockers; 0 = otherwise
Apartment1	1 = standard apartment; 0 = otherwise
Terraced	1 = terraced house; 0 = otherwise
Apartment2	1 = luxury apartment; 0 = otherwise
House	1 = family home; 0 = otherwise
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 structures; 0 = otherwise

Table 4. Basic statistics (dependent variable, control variables)

Variable	Mean	SE	Minimum	Maximum
Dependent variable				
Rent	8.96	3.58	4.00	26.50
Independent variable				
FSpace	30.73	15.23	5.00	145.21
Bedrooms	1.34	0.61	1.00	6.00
Flevel	2.96	2.42	1.00	38.00
Age	16.74	10.87	0.00	45.00
Story	4.76	3.67	1.00	99.00
Shop	4.16	4.41	0.00	61.00
CBD	6.09	3.07	0.00	13.13
AC	0.88	0.32	0	1
FL1	0.26	0.44	0	1
Corner	0.38	0.49	0	1
Propan	0.03	0.17	0	1
IH	0.06	0.24	0	1
AutoLock	0.36	0.48	0	1
Box	0.22	0.41	0	1
Apartment1	0.34	0.47	0	1
Terraced	0.00	0.06	0	1
Apartment2	0.66	0.48	0	1
House	0.00	0.05	0	1
PC	0.00	0.05	0	1
RC	0.43	0.49	0	1
SRC	0.07	0.26	0	1
Others	0.01	0.11	0	1
Steel	0.26	0.44	0	1
Wooden	0.22	0.42	0	1

Table 5. Basic statistics (distance, number of lines, new-line dummy)

Variable	Mean	SE	Minimum	Maximum
Distance: $d_{(j)}$				
$d_{(1)}$	0.56	0.36	0.01	2.62
$d_{(2)}$	0.93	0.43	0.13	3.06
$d_{(3)}$	1.20	0.49	0.26	3.55
$d_{(4)}$	1.42	0.54	0.38	3.69
$d_{(5)}$	1.59	0.56	0.49	3.85
$d_{(6)}$	1.75	0.60	0.52	4.14
$d_{(7)}$	1.89	0.63	0.60	4.42
$d_{(8)}$	2.03	0.66	0.69	4.65
$d_{(9)}$	2.16	0.69	0.82	4.79
Number of train/subway lines: $q_{(j)}$				
$q_{(1)}$	1.45	0.93	1	10
$q_{(2)}$	1.42	0.97	1	12
$q_{(3)}$	1.38	0.90	1	12
$q_{(4)}$	1.42	0.95	1	12
$q_{(5)}$	1.43	0.93	1	12
$q_{(6)}$	1.46	1.02	1	12
$q_{(7)}$	1.47	1.16	1	12
$q_{(8)}$	1.46	1.15	1	12
$q_{(9)}$	1.49	1.16	1	12
New-line dummy: $D^1_{(j)}$				
$D^1_{(1)}$	1	0	1	1
$D^1_{(2)}$	0.51	0.50	0	1
$D^1_{(3)}$	0.44	0.50	0	1
$D^1_{(4)}$	0.41	0.49	0	1
$D^1_{(5)}$	0.35	0.48	0	1
$D^1_{(6)}$	0.31	0.46	0	1
$D^1_{(7)}$	0.30	0.46	0	1
$D^1_{(8)}$	0.29	0.45	0	1
$D^1_{(9)}$	0.27	0.44	0	1

Table 6. Model A0: Traditional accessibility measure

	[6-1]	[6-2]	[6-3]	[6-4]	[6-5]
J =	1	2	3	5	9
Parameters in the proximity measure					
τ_1	0.39***	0.34***	0.29***	0.24***	0.26***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)
α_1	–1.52***	–1.92***	–1.71***	–1.54***	–2.24***
	(0.19)	(0.19)	(0.26)	(0.37)	(0.68)
τ_0		-1.15	0.04	0.03	0.02
		(2.00)	(0.03)	(0.02)	(0.01)
α_0		-7.06	0.00	-0.02	-0.06
		(6.25)	(0.37)	(0.31)	(0.18)
X					
FSpace	0.21***	0.21***	0.21***	0.21***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bedrooms	–0.41***	–0.42***	–0.42***	–0.42***	–0.42***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
FLevel	0.08***	0.08***	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	–0.05***	–0.05***	–0.05***	–0.05***	–0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Story	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CBD	–0.16***	–0.15***	–0.15***	–0.15***	–0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AC	0.4***	0.41***	0.41***	0.41***	0.41***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
FLevel1	–0.11***	–0.11***	–0.11***	–0.12***	–0.11***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Corner	–0.06**	–0.05*	–0.05*	–0.05*	–0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AutoLock	0.27***	0.27***	0.27***	0.27***	0.28***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Box	0.65***	0.65***	0.65***	0.65***	0.65***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Log likelihood	–23,630	–23,641	–23,658	–23,672	–23,700
AICc	47,352	47,379	47,412	47,441	47,497
BIC	47,700	47,742	47,776	47,804	47,861
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in the traditional accessibility measure, Model A0. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of building-structure dummies (*PC*, *RC*, *SRC*, *Others*, *Steel*, *Wooden*), apartment-type dummies (*Apartment1*, *Terraced*, *Apartment2*, *House*), and three variables that do not have significant effects (*Shop*, *Propan* and *IH*) are not shown in the table.

Table 7. Model B0

	[7-1]	[7-2]	[7-3]	[7-4]	[7-5]
J =	1	2	3	5	9
τ_1	0.16***	0.10***	0.07***	0.06***	0.04***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
α_1	–0.48***	–0.29***	–0.17***	–0.09***	–0.03***
	(0.09)	(0.04)	(0.04)	(0.02)	(0.02)
τ_0		0.15***	0.13***	0.06***	0.04**
		(0.05)	(0.04)	(0.02)	(0.02)
α_0		0.16	0.03	0.03	0.00
		(0.15)	(0.05)	(0.04)	(0.01)
ω^0		–0.48***	–0.29***	–0.14**	–0.02
		(0.11)	(0.08)	(0.06)	(0.04)
R^2	0.8788	0.8787	0.8776	0.8772	0.8766
Log likelihood	–23,607	–23,612	–23,675	–23,699	–23,736
AICc	47,307	47,323	47,449	47,496	47,569
BIC	47,655	47,694	47,820	47,867	47,940
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows ordinary least squares estimates using a different number of closest stations (J) in Model B0. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, $\boldsymbol{X}$, are not shown in the table.

Table 8. Model A1

	[8-1]	[8-2]	[8-3]	[8-4]	[8-5]
J =	1	2	3	5	9
τ^1	0.39***	0.42***	0.43***	0.44***	0.43***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
α^1	-1.52***	-1.53***	-1.49***	-1.43***	-1.43***
	(0.19)	(0.16)	(0.16)	(0.15)	(0.17)
τ^0		-0.79*	-0.41	-0.24	-0.32
		(0.41)	(0.55)	(0.24)	(0.22)
α^0		-3.36***	-2.16	-1.57**	-1.92***
		(0.65)	(2.00)	(0.70)	(0.50)
θ^1		-2.27***	-2.23***	-1.79***	-1.82***
		(0.82)	(0.68)	(0.52)	(0.56)
θ^0			-0.49	0.07	-0.42
			(2.46)	(0.51)	(0.39)
Log likelihood	–23,630	–23,606	–23,603	–23,596	–23,598
AICc	47,352	47,310	47,306	47,292	47,296
BIC	47,307	47,230	47,208	47,198	47,200
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model A1. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, $\boldsymbol{X}$, are not shown in the table.

Table 9. Model B1

	[9-1]	[9-2]	[9-3]	[9-4]	[9-5]
J =	1	2	3	5	9
τ^1	0.16***	0.16***	0.18***	0.19***	0.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
α^1	–0.48***	–0.52***	–0.56***	–0.57***	–0.55***
	(0.09)	(0.08)	(0.07)	(0.11)	(0.14)
τ^0		0.06	0.03	0.01	0.02
		(0.05)	(0.05)	(0.07)	(0.06)
α^0		0.30**	0.29**	0.24	0.28
		(0.14)	(0.14)	(0.24)	(0.23)
ω^0		–0.45***	–0.43***	–0.40*	–0.45**
		(0.11)	(0.12)	(0.22)	(0.19)
θ^1		–2.77***	–3.22***	–2.57***	–2.62***
		(0.88)	(0.78)	(0.59)	(0.68)
θ^0			–2.48	–1.10	–1.99
			(1.99)	(2.17)	(3.12)
θ^2			–1.14	–0.71	–1.18
			(0.70)	(1.10)	(1.03)
Log likelihood	–23,607	–23,565	–23,552	–23,547	–23,548
AICc	47,307	47,230	47,208	47,198	47,200
BIC	47,655	47,609	47,601	47,591	47,594
Observations	14,404	14,404	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (*J*) in Model B1. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, ***X***, are not shown in the table.

Table 10. Previous literature studies using accessibility measures in the hedonic approach

[1] Paper	[2] Study area (years of data)	[3] Accessibility measure	[4] Bdy	[5] Distance (zone)	[6] q_z	[7] Sample (zones)	[8] Mth
Adair et al. (2000)	Belfast Urban Area (1996)	$\sum_z \tau(q_z/Q_z)e^{\alpha d_{iz}}$	*4	ZtoZ (TAZ)	People	2,648 (182)	given
Ahlfeldt (2011)	Berlin, Germany (2000–2008)	$\tau \log \sum_z q_z e^{\alpha d_{iz}}$	C	ZtoZ (VP)	Worker	33,843 (1,201)	GS
Ahlfeldt and Wendland (2010)	Berlin, Germany (1881–1936)	$\sum_z \tau q_z e^{\alpha d_{iz}}$	C	ZtoZ (CP)	LV	1,470 (1,470)	NLS
Franklin and Waddell (2003)	King County, WA (1995–1998)	$\sum_z \tau q_z e^{\alpha d_{iz}}$	*3	ZtoZ (TAZ)	C/E/I	41,600 (938)	GS
Giuliano et al. (2010)	Los Angeles, CA	$\sum_z \tau q_z e^{\alpha d_{iz}}$	C	ZtoZ (TAZ)	Job	22,552 (308)	given
Lin and Cheng (2016)	Taipei, Taiwan (2009)	$\tau_m \log \sum_z \frac{q_z d^{\gamma}_{m,iz} e^{\alpha d_{m,iz}}}{\sum_z \sum_m \tau_m q_z d^{\gamma}_{m,iz} e^{\alpha d_{m,iz}}}$	C	ZtoZ (district)	Worker	7,077 (41)	given
McArthur et al. (2012)	Southwest Norway	$\tau \log \sum_z q_z^{\gamma} e^{\alpha d_{iz}}$	C	ZtoZ (zip code)	Job	4,479 (153)	ML
Osland and Thorsen (2008)	Southwest Norway (1997–2001)	$\tau \log \sum_z q_z e^{\alpha d_{iz}}$, $\tau \log \sum_z q_z^{\gamma} e^{\alpha d_{iz}}$, $\tau \log \sum_z (q_z/Q_z) d_{iz}$, $\tau \log \sum_z q_z^{\gamma} d_{iz}^{\sigma}$,	C	ZtoZ (zip code)	EO	2,788 (98)	ML
Osland (2010)	Southwest Norway (1997–2002)	$\sum_z \tau[q_z^1 \exp(\alpha^1 d_{iz}/h) + q_z^2 \exp(\alpha^2 d_{iz}/h)]^h$	C	ZtoZ (zip code)	Worker	1,691 (55)	ML
Osland and Pryce (2012)	Glasgow, Scotland (2007)	$\sum_z \tau q_z^{\gamma} d_{iz}^{\sigma} e^{\alpha d_{iz}}$	*1	PtoZ	Worker	6,269 (6,501)	GS
Osland et al. (2016)	Southwest Norway (1997-2007)	$\sum_z \tau q_z e^{\alpha d_{iz}}$	C *2	ZtoZ (zip code)	EO	7,180 (98)	*5
Wang and Minor (2002)	Cleveland, OH (1980–2000)	$\sum_z \tau(q_z/Q_z)d_{iz}^{\sigma}$	C	ZtoZ (CT)	Job	193 (193)	given

[1] Paper, [2] Study area and years of data, [3] Accessibility measure: d_{iz} = distance from housing i to zone z, q_z= value of attractiveness of zone z, $Q_z = \sum_z q_z$, parameters = $\tau, \alpha, \gamma, \sigma, h$, [4] Boundary condition: C = censored by study area, *1 = includes extra 60 km, *2 = the authors argue that the study area is surrounded by natural barriers that create a delimitation to other areas, *3 = includes Puget Sound region, *4 = includes 36 extra zones, [5] Distance calculations and zone type: ZtoZ = zone-to-zone, PtoZ = point-to-zone, TAZ = traffic analysis zone, VP = voting precincts, CP = commercial post defined in Bruno Aust (1986), CT = census track [6] q_z (value of

attractiveness in zone z): EO = the number of employment opportunities, Worker = the number of workers, Job = the number of jobs, C/E/I = the number of commercial, educational, industrial employment opportunities, LV = land value, People = the number of people commuting from zone i to zone s, Q_z = attractiveness/access measures of zone s from other areas, [7] Sample size and the number of zones in the study area, [8] Estimation method: ML = maximum likelihood, NL = nonlinear least squares, GS = grid search, given = conducting ordinary least squares with pre-estimated accessibility parameters. *5 = the paper does not explain how α is obtained, while it presumably applies the same method as in Osland and Thorsen (2008).

Table 11. Model A2

	[11-1]	[11-2]	[11-3]
J =	1	2	3
τ^1	0.39***	0.39***	0.4***
	(0.05)	(0.05)	(0.05)
α^1	−1.52***	−1.59***	−1.47***
	(0.19)	(0.17)	(0.19)
τ^0		0.03	0.00
		(0.02)	(0.00)
α^0		0.83***	3.44***
		(0.20)	(1.08)
$\theta^1_{(2)}$		0.23**	0.15***
		(0.10)	(0.06)
$\theta^1_{(3)}$			0.10**
			(0.05)
$\theta^0_{(3)}$			0.92***
			(0.10)
Log likelihood	−23,630	−23,612	−23,604
AICc	47,352	47,323	47,309
BIC	47,700	47,694	47,695
Observations	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model A2. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, $\boldsymbol{X}$, are not shown in the table.

Table 12. Model A3

	[12-1]	[12-2]	[12-3]
J =	1	2	3
$\tau^1_{(1)}$	0.39***	0.42***	0.44***
	(0.05)	(0.04)	(0.04)
$\tau^1_{(2)}$		0.08	0.08
		(0.06)	(0.05)
$\tau^1_{(3)}$			0.01
			(0.02)
$\alpha^1_{(1)}$	-1.52***	-1.53***	-1.47***
	(0.19)	(0.16)	(0.17)
$\alpha^1_{(2)}$		-1.48**	-1.27*
		(0.70)	(0.66)
$\alpha^1_{(3)}$			0.21
			(0.29)
$\tau^0_{(2)}$		-0.79**	-0.70**
		(0.4)	(0.34)
$\tau^0_{(3)}$			-0.03
			(0.06)
$\alpha^0_{(2)}$		-3.36***	-2.82***
		(0.65)	(0.52)
$\alpha^0_{(3)}$			0.79
			(0.95)
Log likelihood	−23,630	−23,606	−23,586
AICc	47,352	47,311	47,281
BIC	47,700	47,690	47,690
Observations	14,404	14,404	14,404

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model A3. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and the coefficients of control variables, $\boldsymbol{X}$, are not shown in the table.

Table 13. Model B2

	[13-1]	[13-2]	[13-3]	[13-4]	[13-5]		
J =	1	2	3	5	9		
τ^1	0.16***	0.16***	0.17***	0.19***	0.18***		
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)		
α^1	–0.48***	–0.52***	–0.58***	–0.59***	–0.59***		
	(0.09)	(0.08)	(0.08)	(0.08)	(0.07)		
τ^0		0.06	0.01	-0.01	0.03		
		(0.05)	(0.05)	(0.05)	(0.11)		
α^0		0.30**	0.23*	0.23	0.20		
		(0.14)	(0.13)	(0.15)	(0.16)		
$\theta^1_{(2)}$		0.15*	0.19**	0.22***	0.22***	$\theta^1_{(6)}$	0.03
		(0.09)	(0.08)	(0.08)	(0.08)		(0.11)
$\theta^1_{(3)}$			–0.16	–0.10	–0.10	$\theta^1_{(7)}$	–0.02
			(0.10)	(0.10)	(0.11)		(0.08)
$\theta^1_{(4)}$				0.08	0.07	$\theta^1_{(8)}$	–0.11
				(0.08)	(0.13)		(0.12)
$\theta^1_{(5)}$				0.07	0.11	$\theta^1_{(9)}$	–0.01
				(0.13)	(0.15)		(0.1)
$\theta^0_{(3)}$			0.58	0.57	0.52	$\theta^0_{(6)}$	–0.12
			(0.53)	(0.49)	(0.46)		(0.42)
$\theta^0_{(4)}$				0.19	0.16	$\theta^0_{(7)}$	0.06
				(0.34)	(0.49)		(0.38)
$\theta^0_{(5)}$				0.43	0.17	$\theta^0_{(8)}$	0.24
				(0.56)	(0.72)		(0.41)
						$\theta^0_{(9)}$	0.33
							(0.72)
$\omega^0_{(2)}$		–0.45***	–0.4***	–0.38***	–0.41***	$\omega^0_{(6)}$	0.02
		(0.11)	(0.12)	(0.13)	(0.13)		(0.15)
$\omega^0_{(3)}$			–0.22***	–0.24***	–0.24**	$\omega^0_{(7)}$	–0.01
			(0.08)	(0.09)	(0.09)		(0.14)
$\omega^0_{(4)}$				-0.12	-0.12	$\omega^0_{(8)}$	–0.09
				(0.10)	(0.12)		(0.16)
$\omega^0_{(5)}$				–0.24**	-0.19	$\omega^0_{(9)}$	–0.12
				(0.09)	(0.19)		(0.23)
Log likelihood	–23,607	–23,565	–23,546	–23,533	–23,523		
AICc	47,307	47,230	47,198	47,185	47,190		
BIC	47,655	47,609	47,599	47,631	47,727		
Observations	14,404	14,404	14,404	14,404	14,404		

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model B2. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and coefficients of the control variables, $\boldsymbol{X}$, are not shown in the table.

Table 14. Variance inflation factors (VIFs) in Model B3

[14-1]		[14-2]		[14-3]		[14-4]		[14-5]	
Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
$D^1{}_{(1)}\times d_{(1)}$	3.44	$D^1{}_{(2)}\times q_{(2)}$	3.08	$D^1{}_{(2)}\times q_{(2)}$	3.12	$D^1{}_{(2)}\times q_{(2)}$	3.17	$D^1{}_{(2)}\times q_{(2)}$	3.19
$D^1{}_{(1)}\times q_{(1)}$	4.13	$D^1{}_{(1)}\times q_{(1)}$	4.30	$D^1{}_{(3)}\times q_{(3)}$	3.26	$D^1{}_{(4)}\times q_{(4)}$	3.28	$D^1{}_{(3)}\times q_{(3)}$	3.29
		$D^1{}_{(1)}\times d_{(1)}$	7.11	$D^1{}_{(1)}\times q_{(1)}$	4.68	$D^1{}_{(3)}\times q_{(3)}$	3.28	$D^1{}_{(4)}\times q_{(4)}$	3.32
		$D^0{}_{(2)}\times q_{(2)}$	8.24	$D^1{}_{(1)}\times d_{(1)}$	7.21	$D^1{}_{(1)}\times q_{(1)}$	4.79	$D^1{}_{(5)}\times q_{(5)}$	3.49
		$D^0{}_{(2)}\times d_{(2)}$	9.40	$D^0{}_{(3)}\times q_{(3)}$	8.26	$D^1{}_{(1)}\times d_{(1)}$	7.32	$D^1{}_{(1)}\times q_{(1)}$	4.82
		$D^1{}_{(2)}\times d_{(2)}$	9.99	$D^0{}_{(2)}\times q_{(2)}$	8.84	$D^0{}_{(3)}\times q_{(3)}$	8.68	$D^1{}_{(1)}\times d_{(1)}$	7.38
		$D^0{}_{(2)}$	16.07	$D^1{}_{(2)}\times d_{(2)}$	16.42	$D^0{}_{(4)}\times q_{(4)}$	9.07	$D^0{}_{(5)}\times q_{(5)}$	7.79
				$D^0{}_{(2)}\times d_{(2)}$	17.58	$D^0{}_{(2)}\times q_{(2)}$	9.34	$D^0{}_{(3)}\times q_{(3)}$	8.97
				$D^0{}_{(2)}$	17.76	$D^1{}_{(2)}\times d_{(2)}$	16.46	$D^0{}_{(4)}\times q_{(4)}$	9.23
				$D^1{}_{(3)}\times d_{(3)}$	18.48	$D^0{}_{(2)}\times d_{(2)}$	18.06	$D^0{}_{(2)}\times q_{(2)}$	9.72
				$D^0{}_{(3)}$	18.55	$D^0{}_{(2)}$	19.02	$D^1{}_{(2)}\times d_{(2)}$	16.68
				$D^0{}_{(3)}\times d_{(3)}$	21.33	$D^0{}_{(3)}$	19.34	$D^0{}_{(2)}\times d_{(2)}$	18.15
						$D^0{}_{(4)}$	20.08	$D^0{}_{(5)}$	19.14
						$D^1{}_{(4)}\times d_{(4)}$	33.11	$D^0{}_{(3)}$	19.74
						$D^1{}_{(3)}\times d_{(3)}$	33.83	$D^0{}_{(2)}$	19.87
						$D^0{}_{(4)}\times d_{(4)}$	41.71	$D^0{}_{(4)}$	20.61
						$D^0{}_{(3)}\times d_{(3)}$	42.69	$D^1{}_{(3)}\times d_{(3)}$	34.10
								$D^0{}_{(3)}\times d_{(3)}$	43.88
								$D^1{}_{(5)}\times d_{(5)}$	55.32
								$D^1{}_{(4)}\times d_{(4)}$	67.25
								$D^0{}_{(4)}\times d_{(4)}$	92.15
								$D^0{}_{(5)}\times d_{(5)}$	94.97
Mean VIF	5.08	Mean VIF	6.08	Mean VIF	7.82	Mean VIF	10.65	Mean VIF	15.61
		$5 \leq$ VIF <10		$10 \leq$ VIF < 20		$20 \leq$ VIF < 50		$50 \leq$ VIF	

Table 15. Model B3

	[15-1]	[15-2]	[15-3]	[15-4]	[15-5]
J =	1	2	3	4	5
$\tau^1_{(1)}$	0.16***	0.16***	0.17***	0.18***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\tau^1_{(2)}$		0.04**	0.04**	0.04**	0.04**
		(0.02)	(0.02)	(0.02)	(0.02)
$\tau^1_{(3)}$			0.00	0.01	0.01
			(0.02)	(0.02)	(0.02)
$\tau^1_{(4)}$				0.05***	0.05***
				(0.02)	(0.02)
$\tau^1_{(5)}$					0.04*
					(0.02)
$\alpha^1_{(1)}$	–0.48***	–0.56***	–0.59***	–0.59***	–0.6***
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
$\alpha^1_{(2)}$		–0.01	–0.15	–0.15	–0.15
		(0.07)	(0.09)	(0.09)	(0.09)
$\alpha^1_{(3)}$			0.22**	0.13	0.13
			(0.09)	(0.10)	(0.11)
$\alpha^1_{(4)}$				0.13	0.15
				(0.10)	(0.12)
$\alpha^1_{(5)}$					–0.10
					(0.15)
$\tau^0_{(2)}$		0.06	0.03	0.03	0.03
		(0.05)	(0.05)	(0.05)	(0.05)
$\tau^0_{(3)}$			–0.01	–0.01	–0.01
			(0.05)	(0.05)	(0.05)
$\tau^0_{(4)}$				0.03	0.03
				(0.05)	(0.05)
$\tau^0_{(5)}$					–0.04
					(0.04)

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	[15-1]	[15-2]	[15-3]	[15-4]	[15-5]
J =	1	2	3	4	5
$\alpha^0_{(2)}$		0.33**	0.17	0.15	0.17
		(0.14)	(0.17)	(0.17)	(0.18)
$\alpha^0_{(3)}$			0.2**	0.11	0.12
			(0.09)	(0.09)	(0.10)
$\alpha^0_{(4)}$				0.12	0.17
				(0.09)	(0.12)
$\alpha^0_{(5)}$					–0.02
					(0.13)
$\omega^1_{(2)}$		0.39***	0.39***	0.38***	0.38***
		(0.12)	(0.11)	(0.12)	(0.12)
$\omega^1_{(3)}$			0.07	0.06	0.08
			(0.12)	(0.12)	(0.12)
$\omega^1_{(4)}$				–0.04	–0.03
				(0.12)	(0.12)
$\omega^1_{(5)}$					0.04
					(0.14)
R^2	0.8788	0.8795	0.8799	0.8801	0.8803
Log likelihood	–23,607	–23,563	–23,540	–23,530	–23,519
AICc	47,307	47,229	47,193	47,170	47,164
BIC	47,655	47,615	47,617	47,670	47,814
Observations	14,404	14,404	14,404	14,404	14,404

$5 \leq$ VIF <10	$10 \leq$ VIF < 20	$20 \leq$ VIF < 50	$50 \leq$ VIF

Dependent variable: *Rent* ($100/month). Each column shows maximum likelihood estimates using a different number of closest stations (J) in Model B3. ***, **, and * indicate, respectively, 1, 5, and 10% significance levels based on a two-tailed test. Numbers in parentheses are building-cluster-robust standard errors. Results for municipality fixed effects and coefficients of the control variables, ***X***, are not shown in the table. VIF: Variance Inflation Factor.

Figure 1. Train and subway stations around Tokyo's 23 wards in 2011.

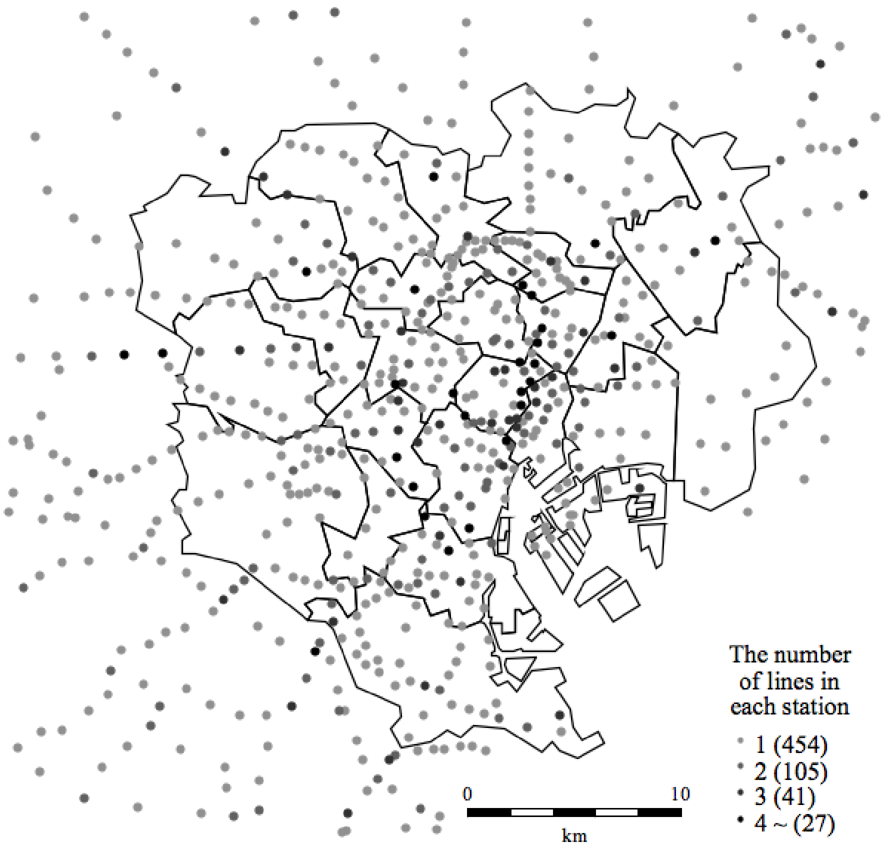
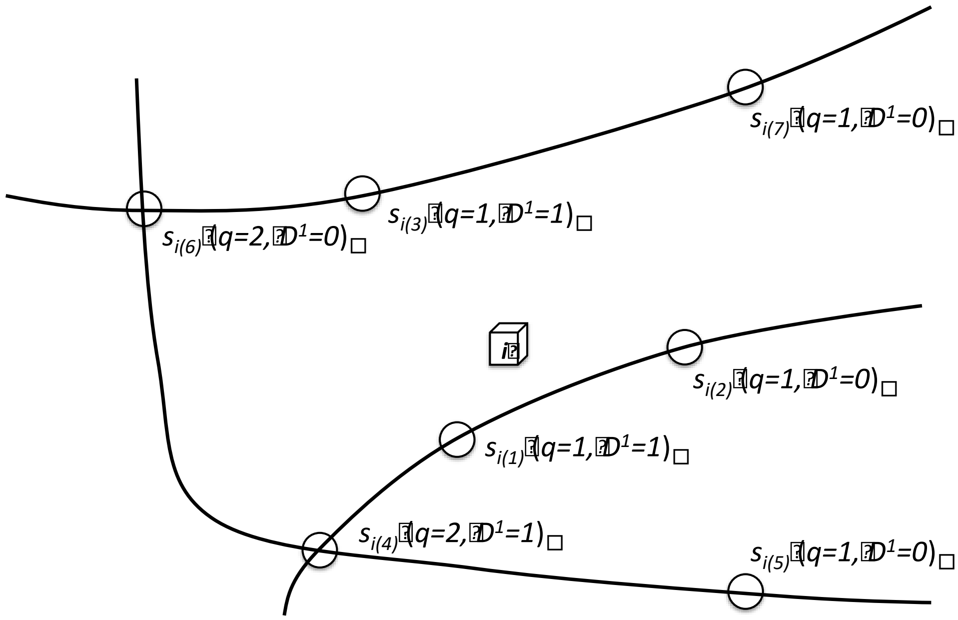
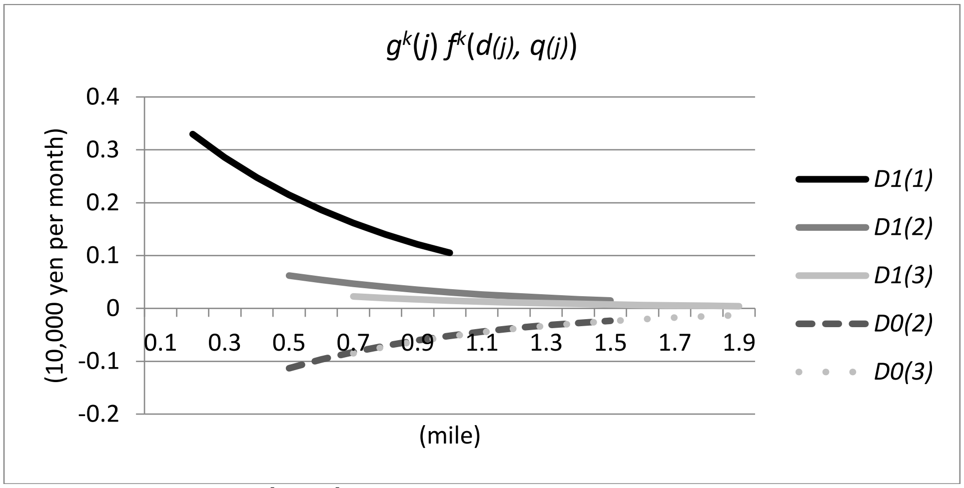


Figure 2. Quantitative (q) and qualitative (D^l) characteristics



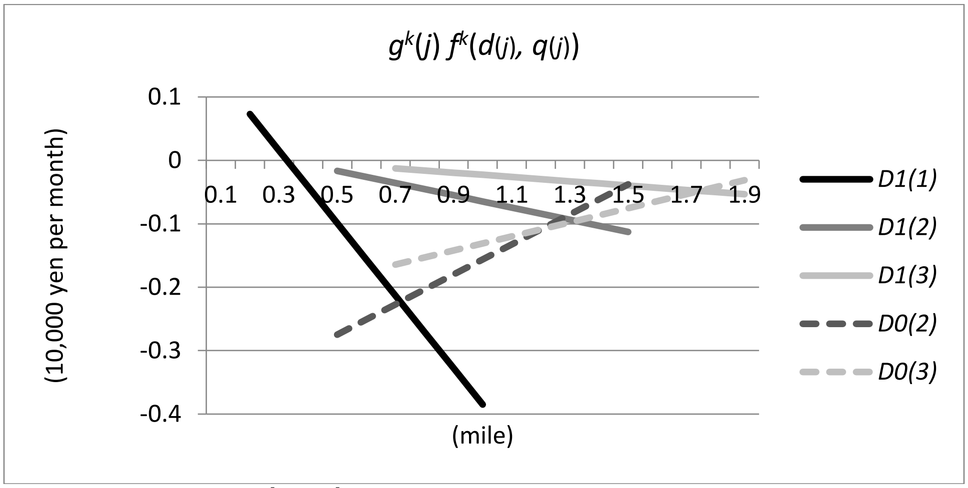
$s_{i(j)}$ indicates the jth closest station from housing i. q is the number of lines and D^l is a new-line dummy. The closest station, $s_{i(1)}$, has one line, i.e., $q = 1$, and it is the closest station from housing i to take the line, i.e., $D^l = 1$. The second closest station, $s_{i(2)}$, also has one line, i.e., q=1, while this line leads to the closer station, which is $s_{i(1)}$, i.e., $D^l = 0$; in other words, the resident of housing i can go to $s_{i(1)}$ to take the line instead of going to $s_{i(2)}$. The new-line dummy for the third closest station $s_{i(3)}$ is one because it is the closest station from housing i to take the line that leads to the station. On the other hand, the new-line dummy for the sixth closest station, $s_{i(6)}$, is zero because the resident can go to closer stations, $s_{i(3)}$ and $s_{i(4)}$, to take all lines that lead to the station.

Figure 3. Model A1



This figure illustrates $g^k(j)f^k(.)$ in Model A1 with respect to distance, based on the result in [9-4] of Table 9. The quantitative value $q_{(j)}$, i.e., the number of lines, is fixed at one. Each line is drawn between the 10th percentile and the 90th percentile of distances to stations with a corresponding proximity order. Note that the levels of $g^k(j)f^k(.)$ illustrated in this figure are not comparable between different proximity orders because $c_{(j)}$s are not included in these measures. $D^1{}_{(1)}$ is the closest station, $D^1{}_{(2)}$ is the second closest station with a new line, $D^1{}_{(3)}$ is the third closest station with a new line, $D^0{}_{(2)}$ is the second closest station without a new line, and $D^0{}_{(3)}$ is the third closest station without a new line.

Figure 4. Model B1



This figure illustrates $g^k(j)f^k(.)$ in Model B1 with respect to distance, based on the result in [10-4] of Table 10. The quantitative value $q_{(j)}$, i.e., the number of lines, is fixed to one. Each line is drawn between the 10th percentile and the 90th percentile of distances to stations with a corresponding proximity order. Note that the levels of $g^k(j)f^k(.)$ illustrated in this figure are not comparable between different proximity orders because $c_{(j)}$s are not included in these measures. $D^1_{(1)}$ is the closest station, $D^1_{(2)}$ is the second closest station with a new line, $D^1_{(3)}$ is the third closest station with a new line, $D^0_{(2)}$ is the second closest station without a new line, and $D^0_{(3)}$ is the third closest station without a new line.

Figure 5. Akaike and Bayesian information criteria.

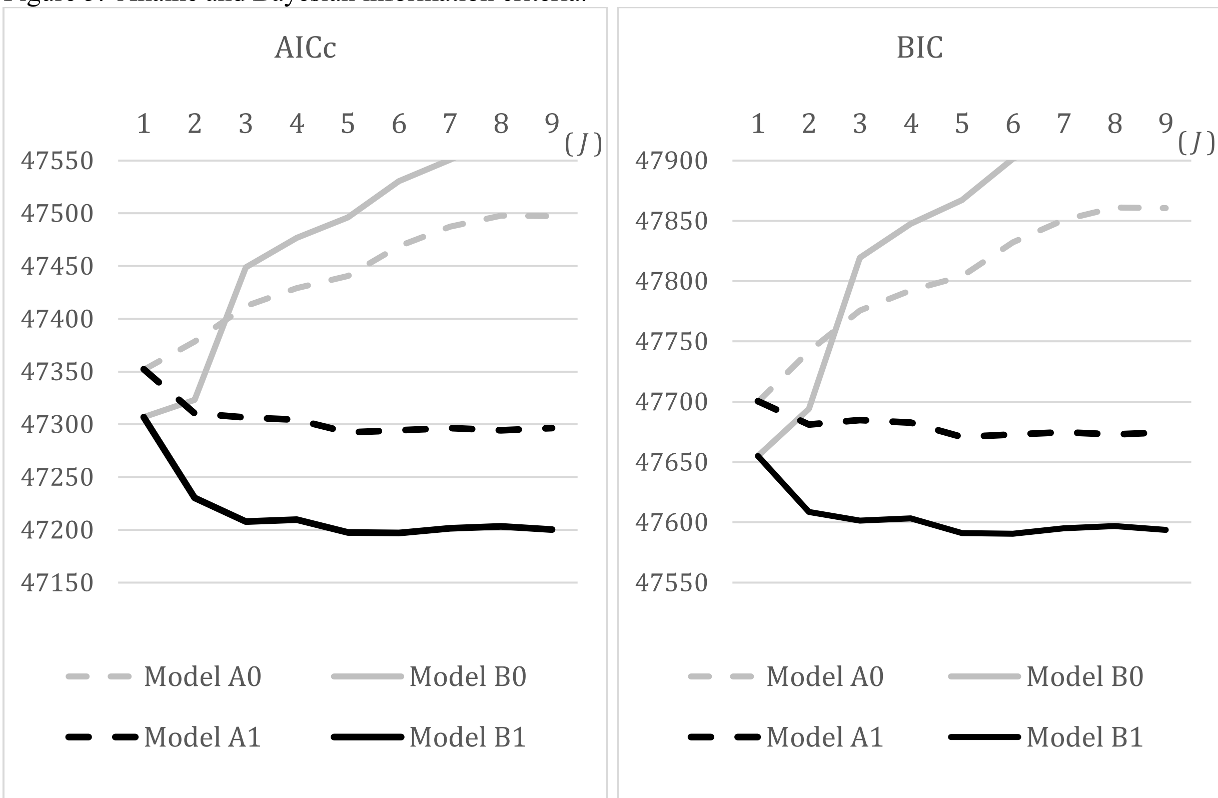


Figure 6. Akaike and Bayesian information criteria. (Appendix 2)