Spatial Access to Metro Transit Villages and Housing Prices in Seoul, Korea

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Abstract: As many cities face traffic congestion, pollution, and urban sprawl, transit villages with transit-oriented development (TOD) and higher ridership have been a core theme for academics and professionals. Evaluating access to metro transit villages with higher transit demand is critical to assess how TOD and changed transit demand affect neighborhoods. Few studies have measured spatial access to metro transit villages by combining street configuration and metro ridership to identify its effects on property prices. This study used five newly developed accessibility and centrality measures to simultaneously capture street configuration and metro ridership within a neighborhood. The empirical models confirmed the effects of accessibility and centrality to metro transit villages on housing prices considering multiple walkable neighborhood scales. The models revealed that accessibility and centrality to metro transit villages with higher ridership were capitalized in higher housing prices within a 2-km network radius. However, prices of houses that were too close to metro stations obtained weaker premiums due to negative externalities such as crowdedness, congestion, and noise. Residents value housing in walkable neighborhoods with dense, interconnected streets directly routed to metro stations, and transit-oriented communities with higher metro ridership. **DOI: 10.1061/(ASCE)UP.1943-5444.0000516.**

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Introduction

Public transit has emerged as an alternative to relieve urban transport issues such as traffic congestion, air pollution, and urban sprawl. Particularly, metro transit has contributed significantly to providing efficient mobility, reducing congestion and energy consumption, and minimizing pollution in urban areas (Dai et al. 2016). Thus, academic and professional communities support creating transit villages through transit-oriented development (TOD) that encourage public transport use and discourage automobile use. Cervero (1998) called transit-oriented metropolitan areas transit metropolises. This study identifies neighborhoods surrounding metro stations as metro transit villages. TOD has evolved from nodes to places, and transit villages have become the hubs of transit service and urban development. Whereas the determinants of transit ridership have been the main interest of urban scholars and planners, there is limited understanding of how building transit villages will affect neighborhoods, which are considered the primary units of urban spatial structure (Wu et al. 2018). This study determined the value of spatial access to metro transit villages using housing market prices. The study used spatial accessibility and centrality metrics measuring metro ridership and street configuration concurrently.

Existing studies highlighted the theoretical and empirical relationship among TOD, metro ridership, and transit villages. TOD has been the main paradigm combining metro transit and urban development to create sustainable and livable cities and neighborhoods, because it reduces automobile use (Lewis and Baldassare 2010). Metro ridership represents the core indicator of TOD's performance, and also helps in identifying the trends of transit demand and transit-served neighborhoods (Bernick and Cervero 1997). The end goal of TOD is to create transit villages, defined as built forms and neighborhoods with higher ridership.

Previous studies have proved that metro transit access, TOD features, and street configuration are capitalized into higher property prices. Numerous studies have investigated the effects of metro access on property prices, controlling for physical properties, and environmental attributes (Bowes and Ihlanfeldt 2001). Most studies conducted empirical analyses of the value-added effects of metro access on property prices to understand the link between transport and land-use behavior, provide capitalization evidence for transportation investments, and capture property-market responses (Cervero and Susantono 1999; Bae et al. 2003; Feng et al. 2011; Dubé et al. 2013).

Some features of TOD account for variations in housing prices. Supportive design of a transit station area generates premium housing prices. For example, whereas station areas with park-and-ride features correlate with discounted housing prices, station areas with walk-and-ride features are associated with higher housing prices (Kahn 2007). The emerging relevant literature has focused on the synergistic effects of TOD on housing prices. A pedestrian-friendly urban setting combined with TOD generates higher condominium prices (Duncan 2011). Higher mixed-use land with walkable access to transit is positively associated with housing prices (Atkinson-Palombo 2010). Furthermore, Hong Kong's Rail + Property program revealed that transit service combined with well-designed property development generates a substantial premium in nearby housing prices (Cervero and Murakami 2009). Conversely, a Korean study found that ground-level subway stations have a negative effect on housing prices within 200 m (Lee and Kim 2015).

The TOD features of metro stations tend to attract higher transit demand and a subsequent increase in housing prices near stations. According to Sung and Oh (2011), favorable TOD settings that enhance metro ridership are good transit service networks, higher land-use mix, pedestrian-friendly street networks, and urban

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designs near stations. However, Lee et al. (2013) suggested that whereas density correlates positively with metro ridership in the central business district (CBD) and fringe areas, higher diversity tends to increase ridership in subcentral areas of Seoul. The relationship between density and TOD features such as land-use mix, design, transit supply, and road features varies with the type of metro station (Kim et al. 2014).

Street-level microaccessibility and centrality have been the core factors in explaining and predicting the locations of households and firms, land-use patterns, property prices, and transportation mobility in mature cities. Many relevant studies have proven that spatial accessibility to employment centers and retail stores along transportation networks substantially affects housing prices (Osland and Thorsen 2008). Furthermore, previous empirical studies have investigated spatial centrality's association with housing prices. For instance, concentrated nodes and detours along street networks are capitalized into higher housing prices because residents value higher accessibility to save transportation costs (Xiao et al. 2016).

Typical measurements of access to metro stations are straight-line and shortest path distance. However, recent studies have utilized more-advanced concepts of access to metro stations, encouraging more-reliable measurements. For example, route directness indicates the ratio of network distance to straight-line distance (Lin et al. 2014), whereas opportunity-based transit accessibility represents the total time-based opportunities, considering number of employees, network, and service (Lei et al. 2012). Furthermore, both bus transport availability to metro stations and the distance to stations influence access to public transit (Kim et al. 2007), whereas spatial affordance measures the task-relevant characteristics of the place (Fusco 2016).

Housing markets in Seoul have shifted from being supply-driven, indicating large-scale residential development, to being demand-driven, indicating a preference for convenient public transit and commuting (Yi and Lee 2014). These trends justify this empirical study regarding transit villages with higher metro ridership and changing housing prices.

Notably, few studies have examined how spatial access to metro transit villages with different ridership along street networks affects housing prices within walkable neighborhoods. We bridged the gap left by the individual studies of access to metro transit villages identified by metro ridership, street configuration to reach the villages, and walkable neighborhood housing markets. To provide new findings and insightful implications, this study captured the unexplored hypotheses linking access to metro transit villages and housing prices.

First, most studies have focused on the main determinants of transit ridership, whereas very few have studied how the transit villages influenced by TOD and changing transit demand affect neighborhoods along street networks. Clearly, metro transit villages are not identical in terms of transit ridership and other features (Debrezion et al. 2011). This study tested whether spatial access to metro transit villages substantially generates external effects on the neighborhood housing prices.

Second, many studies measure spatial access to metro stations and transit villages merely in terms of straight-line or shortest path distance. Furthermore, many relevant studies fail to identify the connection between spatial access to metro stations and street configuration. However, access to transit villages and street layout synergistically affect neighborhood housing prices (Bartholomew and Ewing 2011). Thus, this study captured a more sophisticated measure of spatial access to metro station, combining metro ridership with street configuration to reach the metro stations. Furthermore, many studies have failed to compare the similar and different effects of access to metro transit villages with spatial accessibility and centrality under a consistent conceptual structure. A few empirical studies have confirmed the significant effects of street configuration to explain and predict the externalities of metro transit in housing prices and spatial patterns of land-use intensity, retail location, and walking volume (Bartholomew and Ewing 2011; Liu et al. 2016; Wang et al. 2014; Sevtsuk 2014; Kang 2015).

Third, the debate over the spatial scope of externalities from metro transit villages attracts considerable attention in TOD and policies. This study traced the spatial trade-off between positive and negative effects of metro transit villages over walkable neighborhood scales in housing prices. We expected the effects to vary when it comes to the spatial scope of walkable neighborhoods as catchment areas for metro transit (Guerra et al. 2012). Various radius-focused studies found that the neighborhood scale of metro effects varies widely, from 200 m at the closest to 900 m at the farthest (Lyu et al. 2016; Lee et al. 2014; Choi et al. 2012; Jun et al. 2015). Considering metro transit ridership as well as street configuration generates a more accurate and reliable neighborhood scale of metro transit externalities. This study compared multiple walkable neighborhood scales to identify the spatial scope of the externalities and provide inputs regarding urban planning and design.

Finally, existing hedonic price models in housing studies failed to properly control the differently aggregated data units such as individuals and groups. We used multilevel hedonic price models to capture how explanatory variables at the individual housing and neighborhood levels affect housing prices (Law 2017).

This study made key assumptions in evaluating the spatial access to metro transit villages by measuring street configuration and metro ridership of walkable neighborhoods. First, metro transit villages are defined as neighborhoods with higher metro ridership (Yang et al. 2016). Second, metro ridership is the core index for identifying transit villages, because metro transit villages strongly correlate with higher ridership. Third, the beneficial effects of access to metro transit villages, along with street configurations, are capitalized in higher housing prices. Therefore, this study measures access to metro transit villages, street configuration, and metro ridership simultaneously. Finally, a metro station is the centerpiece of a transit village, as confirmed by the studies of metro catchment areas (Cervero et al. 2017). The effects of spatial access should therefore be stronger the closer one is to metro stations. Thus, we set the walkable neighborhood scale of externalities from metro stations to up to 2 km and validated the scale with multilevel hedonic price models.

This paper consists of six sections. Section "Study Context and Data Sources" describes the local context of the housing markets, public transit in the study areas, and the data sources. Section "Methods" introduces key variables used in empirical models, whereas section "Description of Variables" addresses the empirical models and model specifications. Section "Empirical Models and Model Specification" interprets and discusses key findings. Lastly, section "Results and Discussion" summarizes the key findings and suggests policy implications.

Study Context and Data Sources

Based on this study's main focus, the author introduces the context of housing markets and public transit in Seoul, Korea. Seoul had a resident density of 18,000 people/km^2 in 2013 (Jang and Kang 2015), and condominiums are the dominant housing type in the residential market. Statistics confirm the market share for condominiums at 58.8% and that of single-family housing at 16% in 2010 (Seoul Statistics 2014).

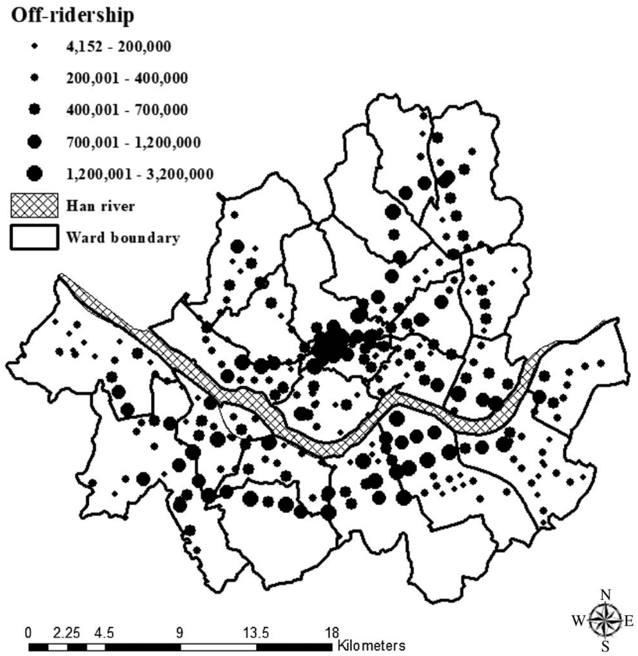

Fig. 1. Spatial pattern of monthly average off-ridership in Seoul, Korea, 2010. (Data from Korea Railroad Corporation 2011.)

Seoul is a transit-oriented city in terms of volume of transit service, use of public transit, and public transit policy. In 2014, public transport and passenger cars accounted for 72.8% and 22.8% of all modes of transportation, respectively. Specifically, bus transit and subways (including rail) accounted for 27.0% and 39.0% of transportation, respectively. In 2015, the average daily ridership was 7,234,000 for the subway and 4,403,282 for buses, with the average time taken to access public transit being 8.69 min (Seoul Statistics 2016).

The primary data for the core hypotheses are housing transaction information. Since 2006, the Ministry of Land, Infrastructure, and Transport has provided sales data on condominiums (called apartments in Korea). The data incorporate transaction price, location, floor number, size, year built, and month of sale. This study geocoded the 2010 data using location information. Additionally, the study geocoded the location of metro stations and their monthly average on- and off-ridership in 2010 to measure the metrics of spatial accessibility and centrality weighted by ridership. On-ridership represents the number of passengers getting onto metro transit and off-ridership the number of passengers getting off (Korea Railroad Corporation 2011). Moreover, geographical information on urban core, urban subcore, bus stops, parks, schools, retail centers, roads, streets, and building use was obtained. Finally, to measure the neighborhood features, this study utilized the boundaries of the Korean census tract from Statistics Korea (2010). Fig. 1 shows the spatial pattern of monthly average off-ridership in Seoul in 2010, when metro ridership was mainly concentrated in CBDs.

Methods

Motivation for Measuring Accessibility and Centrality Metrics for Metro Access

Few studies of the effects of spatial access to transit villages on property prices have considered the two key factors of metro ridership and street configuration that connects residential sites to metro stations. It is highly probable that the street configuration surrounding metro stations and level of metro ridership should generate local variations in housing prices. More sophisticated metrics utilizing street configuration and metro ridership for each metro station will provide more relevant and precise information on residents' metro access. Two benefits justify the use of the Urban Network Analysis (UNA) toolbox developed by Sevtsuk, Mekonnen, and Kalvo of the City Form Lab (Sevtsuk and Mekonnen 2012). First, previous methods focused mainly on the straight-line and/or shortest-path distances to metro stations, failing to capture the spatial configuration to reach metro stations along street networks. UNA calculates spatial accessibility and centrality using morphological information of the streets. Second, most empirical studies of metro access ignore the metro demand variation, separating the effects of street geometry and metro demand. Using the UNA toolbox, the street-level indexes of spatial accessibility and centrality are weighted by metro ridership. Hence, the metrics indicate a more accurate and reliable variation of local metro access. The empirical tests that value metro access considering housing prices therefore provide more insightful and detailed policy implications for urban and transportation planners as well as urban designers. A few recent empirical models tested the validity of the metrics using the UNA toolbox in explaining retail location patterns and retail sales (Sevtsuk 2014; Kang 2016).

Description of Variables

The empirical models used housing price as a dependent variable and the following independent variables: (1) five metrics for accessibility of and centrality to metro stations, (2) housing attributes, (3) location and transportation, (4) neighborhood land use, and (5) time of housing sales.

Metro Accessibility and Centrality Metrics

The UNA toolbox produces reach and gravity index as accessibility measures and betweenness, closeness, and straightness as centrality metrics. Whereas accessibility indexes indicate the ease of reaching potential destinations, centrality indexes represent the relative importance of the origin along streets (Geurs and van Wee 2004). Measuring these metrics requires three main types of information—street geometry from origins (condominium sites) to destinations (metro stations), destination features (on- or off-ridership), and network radius. The condominium sites were the centroid of each parcel with a unique address. Spatial accessibility and centrality with street configuration, weighted by on- or off-ridership, was calculated based on mathematical formulas (Fig. 2).

To capture the neighborhood-scale effects and decompose the local variations of effects, the network radii were set to 500–750, 750–1,000, 1,000–1,500, and 1,500–2,000 m after confirming that the residents in Seoul walk 2.6 km per day (Park et al. 2016). While testing the empirical models, the author also used below 500 m and beyond 2,000 m as radii, but excluded them from the final models owing to the statistical insignificance of metro access within these two radii.

This study defines reach and gravity index as the spatial accessibility to metro stations. Reach is the total on- or off-ridership along the shortest network distance between condominium site i and metro station j within a given network radius. More metro ridership within a given network radius generates a higher value of reach. Therefore, reach, represents neighborhood on- or off-ridership. The gravity index indicates reach combined with distance friction. The gravity index is measured by summing the values of on- or off-ridership (weight) divided by distance friction (Fig. 2). Higher transit ridership with the same distance friction leads to a higher gravity index. The beta value of 0.00217 was selected as

$$\mathrm{Reach}^{r}[i] = \sum_{j \in G-\{i\}; d[i,j] \le r} W[j]$$

$$\mathrm{Gravity}^{r}[i] = \sum_{j \in G-\{i\}; d[i,j] \le r} \frac{W[j]}{e^{\beta \cdot d[i,j]}}$$

$$\mathrm{Betweenness}^{r}[i] = \sum_{j \in G-\{i\}; d[i,j] \le r} \frac{n_{jk}[i]}{n_{jk}} \cdot W[j]$$

$$\mathrm{Straightness}^{r}[i] = \sum_{j \in G-\{i\}; d[i,j] \le r} \frac{\delta[i,j]}{d[i,j]} \cdot W[j]$$

$$\mathrm{Closeness}^{r}[i] = \frac{1}{\sum_{j \in G-\{i\}; d[i,j] \le r} (d[i,j] \cdot W[j])}$$

Note:
i = residential sites (origins)
j = metro stations (destinations)
G = network
r = network radius (500–750 m, 750 m–1 km, 1–1.5 km, 1.5–2 km)
$d[i,j]$ = shortest-network distance between origin i and destination j (meters)
$\delta[i,j]$ =straight-line distance between origin i and destination j (meters)
$n_{jk}[i]$ = number of paths passing through node i with j and k in the network radius r from i
n_{jk} = number of paths between nodes j and k
Beta (β) = 0.00217
$W[j]$ = on- or off- ridership in metro station j (persons).

Fig. 2. Mathematical formulas for measuring accessibility and centrality. (Data from Sevtsuk and Mekonnen 2012; Kang 2015, 2018a, b.)

distance friction, referring to Handy and Niemeier (2017). This value was used for two reasons. First, there is no other empirically tested value for walking behavior to metro stations in Seoul. Second, the value obtained from the cited study on walking travel fits into the theme of this study. Empirical tests have verified that the gravity index correlates with the spatial pattern of land use, stores, and local employment (Waddell and Ulfarsson 2003).

The centrality metrics include betweenness, straightness, and closeness. Betweenness measures the volume of detouring a site, weighted by on- or off-ridership. In this study, the value of betweenness indicates the ratio of total passing at origin i to total available travel between destination j and another condominium site k. After measuring all passing between and all origin-destination pairs, betweenness metrics identify the fraction of detours between the pairs that pass condominium sites i. Betweenness was measured by summing each fraction multiplied by the on- or off-ridership for each destination within the given network radius. Therefore, a site i with increased detouring and higher transit ridership has a higher betweenness value. Straightness calculates how closely the shortest-network distance between condominium site i and metro station j within a specific network radius resembles the Euclidian distance, weighted by on- or off-ridership (Porta et al. 2006). Straightness was calculated as follows. After measuring the shortest-network and straight-line distance of each pair of condominium site i and metro station j within a specific network, the ratio of the two distances between the straight-line distance and the shortest-network distance was calculated. Then, the ratio was multiplied by the on- or off-ridership of metro station j. Finally, the measured values were added to generate the straightness value. Therefore, a more direct route between pairs of origins and destinations with higher transit ridership tends to increase the value of straightness. A higher value of straightness represents direct access to metro stations with more ridership located along direct routes from condominium sites. Finally, closeness represents how close each site is to the surrounding metro stations, weighted by the on- or off-ridership within a given network radius. Therefore, the value of closeness is more likely to increase if metro stations with more ridership are located close to housing. A lower closeness value implies more on- or off-ridership for closer metro stations in terms of calculating methods, leading to higher premium effects on housing prices. Fig. 2 shows the mathematical formulas for calculating each accessibility and centrality metric.

Housing Attributes

Our empirical models also controlled for housing attributes such as size, floor number, and age of housing, which are typical values for explaining housing price variation. The Korean central government has provided relevant information since 2006 (Ministry of Land, Infrastructure, and Transport 2017). Size is measured in square meters for each unit, whereas the floor number represents the vertical position of each unit in a high-rise apartment building. Age is based on the year in which the house was built.

Location and Transportation Attributes

Housing prices vary with relative location and access to transportation. Prior studies confirmed that distance to CBDs, subCBDs, roads and streets, public transit access points such as metro stations and bus stops, commercial centers, schools, parks, and the nearest land use substantially change residential property prices (Hartell 2017). Therefore, the straight-line distances to these amenities were measured to control their influence on housing prices.

Neighborhood Land-Use Attributes

The composition of neighborhood land use also affects the value that residents place on their dwellings. Because the locations of metro stations consider neighborhood land use, econometric models face endogeneity. Therefore, this study considered neighborhood residential and commercial-office density as typical urban land use, occupying 90.12% of the total built areas in Seoul. Whereas residential density was measured as total residential built area per hectare for each census tract, commercial-office density was measured by total built area for retail and offices per hectare of the tract.

A few studies have verified whether the land-use mix and the balance of land use generate premiums or discounts in housing prices (Koster and Rouwendal 2012). Consequently, land-use mix and the total floor area by land use type in each neighborhood (Korean census tract) were measured using mathematical formulas adopted from related studies (Cervero and Kockelman 1997). This study applied the entropy index to calculate the neighborhood land-use mix. If the value is closer to 1, it represents evenly mixed land use as

$$\mathrm{Mix}_i = \frac{\sum_{i=1}^{n} P_i \ln(P_i)}{\ln(n)} \quad (1)$$

where n = number of land-use categories; and P_i = proportion of each type of land use i.

This study also calculated the balance indexes of residential and nonresidential land use from available data (Seoul Metropolitan Government 2010). The balance index of the two land-use indexes indicates a higher balance if the value is close to 1 for balance between residential (Resi) and nonresidential (Nonresi) land use in region i (Cervero and Duncan 2003):

$$\text{Balance index}_i = 1 - \left| \frac{\mathrm{Resi} - \mathrm{Nonresi}_i}{\mathrm{Resi} + \mathrm{Nonresi}_i} \right| \quad (2)$$

Timing of Housing Sales

The timing of housing sales also influences the housing prices due to seasonal supply and demand (Quigley 1995). Therefore, dummy variables were set for the quarter in which houses were sold. In the empirical models, the reference group of the time variable was the first quarter of the year 2010.

Empirical Models and Model Specification

Aggregate units of data are important in selecting analytic methods. Prior studies of the effects of individual features and place attributes tended to face atomistic and ecological fallacies (Duncan and Jones 2000). Whereas the atomistic fallacy refers to a failure to capture the local contexts surrounding individual behavior, the ecological fallacy refers to a failure to infer individual attributes (Fotheringham et al. 2003). Furthermore, the data composition of different aggregate units requires econometric models beyond general regression, due to the deviation of the assumption of regression analysis (Rabe-Hesketh and Skrondal 2008). Alternatively, multilevel regression models could identify the effects of individual- and place-level factors separately (Fotheringham et al. 2003). Because multilevel regression models use data from discrete spatial units, the econometric methodology cannot capture the potential spatial autocorrelation of variables in continuous spatial units (Chasco Yrigoyen and Le Gallo 2012). Despite the potential spatial autocorrelation issue, multilevel regression models are widely used, and their effectiveness and robustness for analyzing spatial data are confirmed (Duncan 2011; Wang et al. 2015; Jang and Kang 2015). An alternative is to use spatial econometrics and geographically weighted regression (GWR) if the spatial variables fit in these models.

Because this study used data on individual condominiums nested within Korean census tracts, multilevel modeling was applied to the available data. For a variable composition, whereas individual condominium-level data (Level 1) contain accessibility and centrality metrics, housing attributes, location and transportation attributes, and time of sales, the Korean census-tract-level data (Level 2) include residential and commercial-office density, land-use mix, and the balance index of land use. The equation for the multilevel regression is as follows:

$$P_{ij} = \gamma_{00} + \beta_1 \mathbf{M}_{ijk} + \beta_2 \mathbf{H}_{ijk} + \beta_3 \mathbf{L}_{ijk} + \beta_4 \mathbf{N}_{ijk} + \beta_6 \mathbf{T}_{ijk} + \mu_{0j} + \varepsilon_{ij} \quad (3)$$

where P_{ij} = sales price of housing i in neighborhood j; β_k represents the parameters of each independent variable ($k = 1, 2, 3, 4, \ldots, m$), γ_{00} denotes constants; $\mathbf{M}_{ijk}$ = vector of each of the five spatial accessibility and centrality metrics to metro ridership of housing i and neighborhood j; $\mathbf{H}_{ijk}$ = vector of the size, floor number, and age of housing i and neighborhood j; $\mathbf{L}_{ijk}$ = vector of the relative location and transportation features of housing i and neighborhood j; $\mathbf{N}_{ijk}$ = vector of land-use features in neighborhood j; $\mathbf{T}_{ijk}$ = vector of transaction time in housing i; and μ_{0j} and ε_{ij} = error terms of neighborhoods and residential sites, respectively. Vectors **M**, **H**, **L**, **N**, and **T** and the variable denotations are indicated in Tables 1–3.

After testing the models, a log-log functional formula was selected in which both dependent and independent variables were the natural logarithms. The final model results justified the use of multilevel analysis as an intraclass correlation value

Table 1. Descriptive statistics (network radius: 750–1,000 m, off-ridership)

Variable description	Mean	Minimum	Maximum
Housing price (KRW)	500,000,000	80,000,000	4,700,000,000
Accessibility and centrality metrics (Vector **M**, Level 1)			
Reach to off-ridership	704,785.00	0.00	6,191,723.00
Gravity index to off-ridership	112,104.60	0.00	1,773,420.00
Betweenness to off-ridership	103,415.40	0.00	4,468,715.00
Straightness to off-ridership	549,336.20	0.00	5,224,615.00
Closeness to off-ridership	0.00000002	0.00	0.00004
Housing attributes (Vector **H**, Level 1)			
Housing size (m^2)	81.99	19.4	268.05
Housing floor number	8.61	1.00	39.00
Housing age	13.07	0.00	40.00
Location and transportation attributes (Vector **L**, Level 1)			
CBD access	9,938.57	1,318.19	17,001.40
Sub-CBD access	4,795.92	376.56	11,993.91
Bus stop access	122.89	12.82	431.95
Park access	540.10	31.53	2,635.61
Retail center access	875.05	104.67	3,508.85
School access	177.19	2.67	1,365.01
Road access	93.42	9.65	565.65
Street access	63.71	0.95	1,039.00
Access to nearest residential property	28.49	0.01	460.22
Access to nearest commercial property	67.39	0.01	365.37
Access to nearest office property	305.22	3.49	1,288.34
Access to nearest industrial property	276.31	0.01	1,518.87
Neighborhood land use attributes (Vector **N**, Level 2)			
Density of residential use (built area/ha)	157,551.00	0.00	36,500,000.00
Density of commercial-office use (built area/ha)	4,523.80	0.00	401,813.80
Land-use mix	0.14	0	0.86
Balance index of land use	0.14	0	1
Time of sale (vector **T**)			
First quarter (reference group)	0.30	0	1
Second quarter	0.15	0	1
Third quarter	0.15	0	1
Fourth quarter	0.39	0	1

Note: CBD = central business district.

Table 2. Multilevel regression results for reach, gravity index, and betweenness (network radius: 750–1,000 m, off-ridership)

Variables	Reach model		Gravity index model		Betweenness model	
	Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Accessibility and centrality metrics (Vector **M**)						
Log (reach to off-ridership)	0.0256^{a}	1.17	—	—	—	—
Log (gravity index to off-ridership)	—	—	0.0256^{a}	1.18	—	—
Log (betweenness to off-ridership)	—	—	—	—	-0.00303^{b}	1.05
Housing attributes (Vector **H**)						
Log (housing size)	0.922^{a}	1.13	0.922^{a}	1.13	0.922^{a}	1.13
Log (housing floor number)	0.0364^{a}	1.06	0.0364^{a}	1.06	0.0364^{a}	1.06
Log (housing age)	-0.00441^{c}	1.18	-0.00442^{c}	1.18	-0.00440^{c}	1.18
Location and transportation attributes (Vector **L**)						
Log (CBD access)	−0.00967	1.72	−0.011	1.72	−0.0155	1.71
Log (sub-CBD access)	-0.129^{a}	1.76	-0.129^{a}	1.76	-0.133^{a}	1.76
Log (bus-stop access)	0.0796^{a}	1.46	0.0792^{a}	1.46	0.0840^{a}	1.46
Log (park access)	-0.0849^{a}	1.22	-0.0845^{a}	1.22	-0.0858^{a}	1.2
Log (retail center access)	-0.0562^{c}	1.3	-0.0563^{c}	1.31	-0.0757^{b}	1.29
Log (school access)	0.0206	1.23	0.0204	1.23	0.0244^{c}	1.22
Log (road access)	−0.0132	1.65	−0.0135	1.65	−0.0133	1.65
Log (street access)	0.0620^{a}	1.39	0.0620^{a}	1.39	0.0641^{a}	1.38
Log (access to nearest residential property)	0.0156^{c}	1.91	0.0152^{c}	1.91	0.0137	1.91
Log (access to nearest commercial property)	−0.0135	1.78	−0.0134	1.78	−0.00648	1.78
Log (access to nearest office property)	0.0187	1.63	0.0181	1.63	0.0135	1.62
Log (access to nearest industrial property)	-0.0323^{a}	1.3	-0.0318^{a}	1.29	-0.0313^{a}	1.21
Neighborhood land-use attributes (Vector **N**)						
Log (density of residential use)	−0.00615	1.71	−0.00626	1.71	−0.00638	1.73
Log (density of commercial-office use)	0.00972^{b}	2.95	0.00983^{b}	2.95	0.0101^{b}	2.95
Land-use mix	0.0123	4.87	0.0129	4.87	0.0408	4.9
Balance index of land use	-0.258^{a}	3.53	-0.258^{a}	3.53	-0.268^{a}	3.55
Time of sale (Vector **T**)						
Second quarter, 2010	-0.0446^{a}	1.28	-0.0446^{a}	1.28	-0.0449^{a}	1.28
Third quarter, 2010	-0.0646^{a}	1.28	-0.0646^{a}	1.28	-0.0647^{a}	1.28
Fourth quarter, 2010	-0.0506^{a}	1.41	-0.0506^{a}	1.41	-0.0508^{a}	1.41
Constant	16.97^{a}	—	17.02^{a}	—	17.47^{a}	—
Proportion of variance						
Level 2	0.37		0.37		0.34	
Level 1	0.07		0.07		0.07	
ICC	0.95		0.95		0.95	
AIC	−9,772.64		−9,770.07		−9,768.19	
Number of cases	5,509		5,509		5,509	
Number of groups	696		696		696	

Note: ICC = intraclass correlation.
[a] $p < 0.001$.
[b] $p < 0.01$.
[c] $p < 0.05$.

exceeding 0.05. Furthermore, variance inflation factors (VIFs) were used to test collinearity among explanatory variables (Gujarati and Porter 2009).

Table 1 presents the variables and the descriptive statistics for the case of off-ridership within a 750–1,000-m network radius. The housing prices ranged from USD 66,722 to USD 3,919,933 (USD 1 = KRW 1,199). It also lists the range of the two accessibility and three centrality metrics. Regarding housing attributes, housing size was up to 268.05 m^2, the floor number was up to 39, and the housing age was up to 40 years. Condominium sites were most likely to be located close to residential properties, followed by streets, retail property, roads, bus stops, schools, industrial property, office, parks, retail centers, subCBDs, and CBDs. Neighborhood land-use attributes showed residential density, commercial-office density, the mixture of land-use, and the balance between residential and nonresidential property. Finally, the timing of sales indicates the quarterly dummy variable for transaction time within the reference group (first quarter of 2010).

Results and Discussion

Preliminary Analysis

Before the modeling, this study attempted some preliminary analyses. The correlation testing between housing attributes and the accessibility and centrality metrics indicated no sample selection bias. Furthermore, to test whether adding accessibility and centrality metrics improved the empirical model fit, the models were compared with and without accessibility and centrality metrics as per Akaike's information criterion (AIC). The lower AIC values of the models with accessibility and centrality metrics indicated that these models were a better fit than those without the metrics (Antipova et al. 2011).

After these preliminary analyses, the core hypotheses—that access to metro stations combining two main factors (street configuration and metro ridership) significantly explains the spatial variation in housing prices—were tested. To test the hypotheses, spatial accessibility and centrality with street configuration and

Table 3. Multilevel regression results for straightness and closeness (network radius: 750–1,000 m, off-ridership)

Variables	Straightness model Coefficient	Straightness model VIF	Closeness model Coefficient	Closeness model VIF
Accessibility and centrality metrics (Vector **M**)				
Log (straightness to off-ridership)	0.0256[a]	1.18	—	—
Log (closeness to off-ridership)	—	—	−0.0191[a]	1.15
Housing attributes (Vector **H**)				
Log (housing size)	0.922[a]	1.13	0.922[a]	1.13
Log (housing floor number)	0.0364[a]	1.06	0.0364[a]	1.06
Log (housing age)	−0.00441[b]	1.18	−0.00442[b]	1.18
Location and transportation attributes (Vector **L**)				
Log (CBD access)	−0.00999	1.72	−0.00753	1.72
Log (sub-CBD access)	−0.130[a]	1.76	−0.132[a]	1.76
Log (bus-stop access)	0.0797[a]	1.46	0.0806[a]	1.46
Log (park access)	−0.0848[a]	1.22	−0.0849[a]	1.21
Log (retail center access)	−0.0561[b]	1.31	−0.0579[b]	1.3
Log (school access)	0.0204	1.23	0.0209[b]	1.23
Log (road access)	−0.013	1.65	−0.0129	1.65
Log (street access)	0.0620[a]	1.38	0.0622[a]	1.39
Log (access to nearest residential property)	0.0156[b]	1.91	0.0156[b]	1.91
Log (access to nearest commercial property)	−0.0136	1.78	−0.013	1.78
Log (access to nearest office property)	0.0188	1.63	0.0175	1.62
Log (access to nearest industrial property)	−0.0323[a]	1.3	−0.0328[a]	1.31
Neighborhood land-use attributes (Vector **N**)				
Log (density of residential use)	−0.00616	1.71	−0.00614	1.71
Log (density of commercial-office use)	0.00972[c]	2.95	0.00975[c]	2.95
Land-use mix	0.0124	4.87	0.013	4.87
Balance index of land use	−0.258[a]	3.53	−0.258[a]	3.53
Time of sale (Vector **T**)				
Second quarter, 2010	−0.0446[a]	1.28	−0.0446[a]	1.28
Third quarter, 2010	−0.0646[a]	1.28	−0.0646[a]	1.28
Fourth quarter, 2010	−0.0506[a]	1.41	−0.0506[a]	1.41
Constant	16.98[a]	—	16.93[a]	—
Proportion of variance				
Level 2	0.37		0.37	
Level 1	0.07		0.07	
ICC	0.95		0.95	
AIC	−9,772.45		−9,773.99	
Number of cases	5,509		5,509	
Number of croups	696		696	

Note: ICC = intraclass correlation.
[a] $p < 0.001$.
[b] $p < 0.05$.
[c] $p < 0.01$.

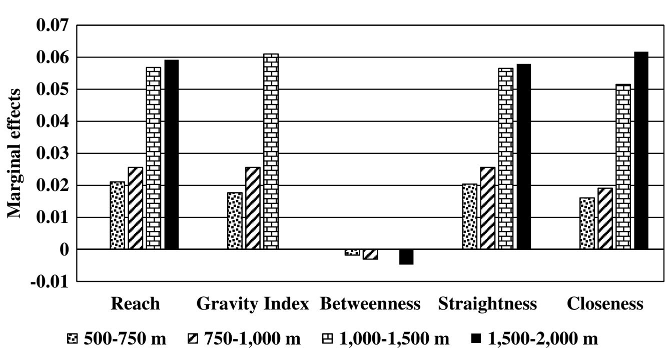

Fig. 3. Marginal effects of metro access on housing prices (off-ridership).

on- or off-ridership were measured. Next, the empirical models captured the effects of spatial accessibility and centrality weighted by on- or off-ridership, controlling the same variables (Figs. 3 and 4). Although all the results from empirical models of spatial accessibility and centrality capturing street configuration and on- and off-ridership are available, for conciseness, the variable composition and the results for reach, gravity index, betweenness, straightness, and closeness are provided for 750–1,000-m radii of off-ridership (Tables 2 and 3). The models include only the explanatory variables with VIF values below 5. The author interprets and discusses only the variable coefficients significant at the 5% level.

Effects of Metro Accessibility and Centrality Metrics

The main research question related to metro accessibility and centrality to metro transit villages. Figs. 3 and 4 provide the estimation results for the effect of metro accessibility and centrality—considering on- or off-ridership—on housing prices within each neighborhood scale. Each model of spatial accessibility and centrality generated similar results among the models. Therefore, the overall patterns regardless of on-ridership or off-ridership in terms of network radius were compared. The empirical models confirmed that greater accessibility and centrality to metro stations generate a premium in housing prices, excluding the betweenness variable.

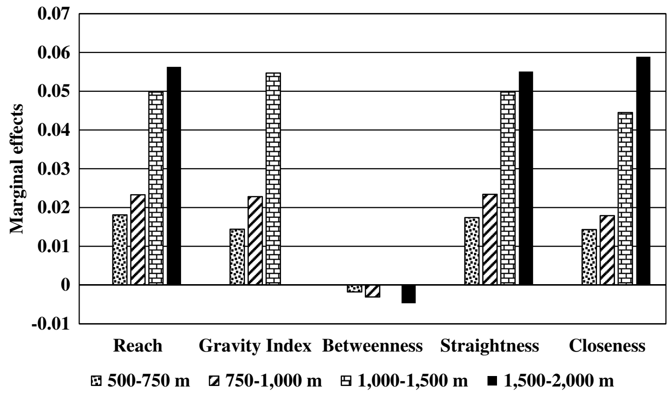

Fig. 4. Marginal effects of metro access on housing prices (on-ridership).

Two accessibility metrics—reach and gravity index—influenced housing price appreciation. A higher reach value was positively capitalized in residential property prices. A higher gravity index value—considering distance friction—was also positively associated with housing prices, except for the 1,500–2,000-m network radius. This pattern implies that residents value houses with easy access to metro stations with higher ridership along dense street networks within walkable neighborhoods, confirming the results of previous studies (Duncan 2008). This also indicates that homebuyers in Seoul value easier access to metros for commuting, as well as higher resident and worker density using public transit.

Concerning centrality metrics, higher betweenness discounts the residential property prices within the 500–1,000 and 1,500–2,000-m radii. This implies that condominium sites not having easy access to metro stations are not favorable to housing prices. Generally, residents prefer a residential location with direct access to high-ridership metro stations to save on transport costs and enjoy higher mobility convenience. This result coincides with that of a study of Chinese cities which found that higher betweenness discounts nearby residential property prices owing to noise and crowdedness from the frequent passing of commuters (Xiao et al. 2016). Conversely, retail properties favor sites with higher betweenness within specific street networks (Wang et al. 2014). These contrasting results are rooted in the different features of housing and retail properties.

Additionally, higher straightness and closeness values generated premiums on housing prices. The effects of straightness were similar to those of reach within each neighborhood scale. These patterns of effects may indicate that the residents highly prefer housing near neighborhoods with better street layouts and more directly reachable high-ridership metro stations. Therefore, urban settings with high street density, direct access, and proximity to nearby metro stations with higher transit use command higher premiums in housing prices. Specifically, because higher straightness indicates trip efficiency for visiting metro stations, being located along straight-line street networks is positively associated with higher housing prices. Furthermore, a higher closeness value implies that highly valued housing is located on street networks with higher connectivity to metro stations serving transit villages, confirming the results of the previous studies (Matthews and Turnbull 2007). Other studies also found that centrality indexes—such as the straightness and closeness of street networks—are highly relevant to clustering retail activities and housing prices (Wang et al. 2014).

Figs. 3 and 4 indicate that the effects of accessibility and centrality—excluding betweenness—on housing prices were higher with network radii up to 1,500–2,000 m. There are two reasons for this pattern. First, owing to their large-scale development and relatively low land prices, most condominiums are developed away from metro stations. Therefore, residents reach the nearest metro station by bus or on foot. Second, issues such as noise, crowdedness, traffic, vibrations, and other safety concerns from metro stations and trips to commercial facilities near the stations discount housing prices, all other variables being equal. Therefore, being too accessible or adjacent to metro stations influences housing prices negatively. Fig. 5 shows the spatial pattern of the mean predicted housing price by each model. These prices were converted from the predicted log values of housing prices from each model. The five maps—by models—illustrate that the mean predicted housing price was higher in the residential areas near the Han River and Kang-nam areas, where higher-priced housing is mainly concentrated.

The locality and travel behaviors of Seoul residents also supported the key findings of the empirical models. As previously described, residents and workers in Seoul tend to use metro transit for their commuting and noncommuting trips, as indicated by its 39.0% modal share. Easy and convenient transfers between metro and bus transit accelerate the rising premiums related to transit access concerning housing prices. Notably, the average time to reach public transit is around 9 min, suggesting that many metro stations and bus stops are located within walking distance from residential areas. Therefore, street configuration is a critical factor in determining metro access. The core findings are rooted in residents' travel behavior, spatial contexts to reach metro stations, and travel patterns across Seoul City. Finally, as previously introduced, higher metro ridership and pedestrian-friendly and dense streets simultaneously determine the level of accessibility and centrality to metro stations. Therefore, this study confirms that transit neighborhoods with higher demand for metro transit also command premiums on housing prices.

Effects of Other Variables

Other variables also affect housing prices, but with inconsistent statistical significance. Regarding housing attributes, residents value larger housing with scenic high-rise views. Older housing has lower prices within the 750–1,000- and 1,500–2,000-m network radii. The effects of housing size and floor number were stable within the same network radii. The results showed that homeowners consistently consider housing attributes as factors of housing prices. Whereas housing prices are lower when farther from sub-CBDs, parks, and retail clusters within the 1,000-m network radius, they are higher with longer distances to bus stops, roads, and street networks within a 750-m radius. From the empirical results, locational and transportation features significantly explain the spatial variation of housing prices, which is substantiated by the results of the previous studies (Xiao et al. 2016). Regarding nearby land use, whereas being close to residential use discounts housing price within a 1,500-m radius, access to industrial land use was negatively associated with housing price within all radii. Higher access to commercial use generated premiums in housing price within a 750-m radius. Regarding land-use density, housing prices in neighborhoods with higher residential density tended to be lower, except for the 750–1,000- and 1,500–2,000-m network radii, whereas the prices were higher in the commercial- and office-dense areas, except for the 1,500–2,000-m network radius. Increased local competition among residential and nonresidential land use near metro stations was more likely to raise neighborhood housing prices. However, land-use mixture and balance between residential and nonresidential land use erratically affected housing prices owing to the local contexts. Finally, housing prices decreased over

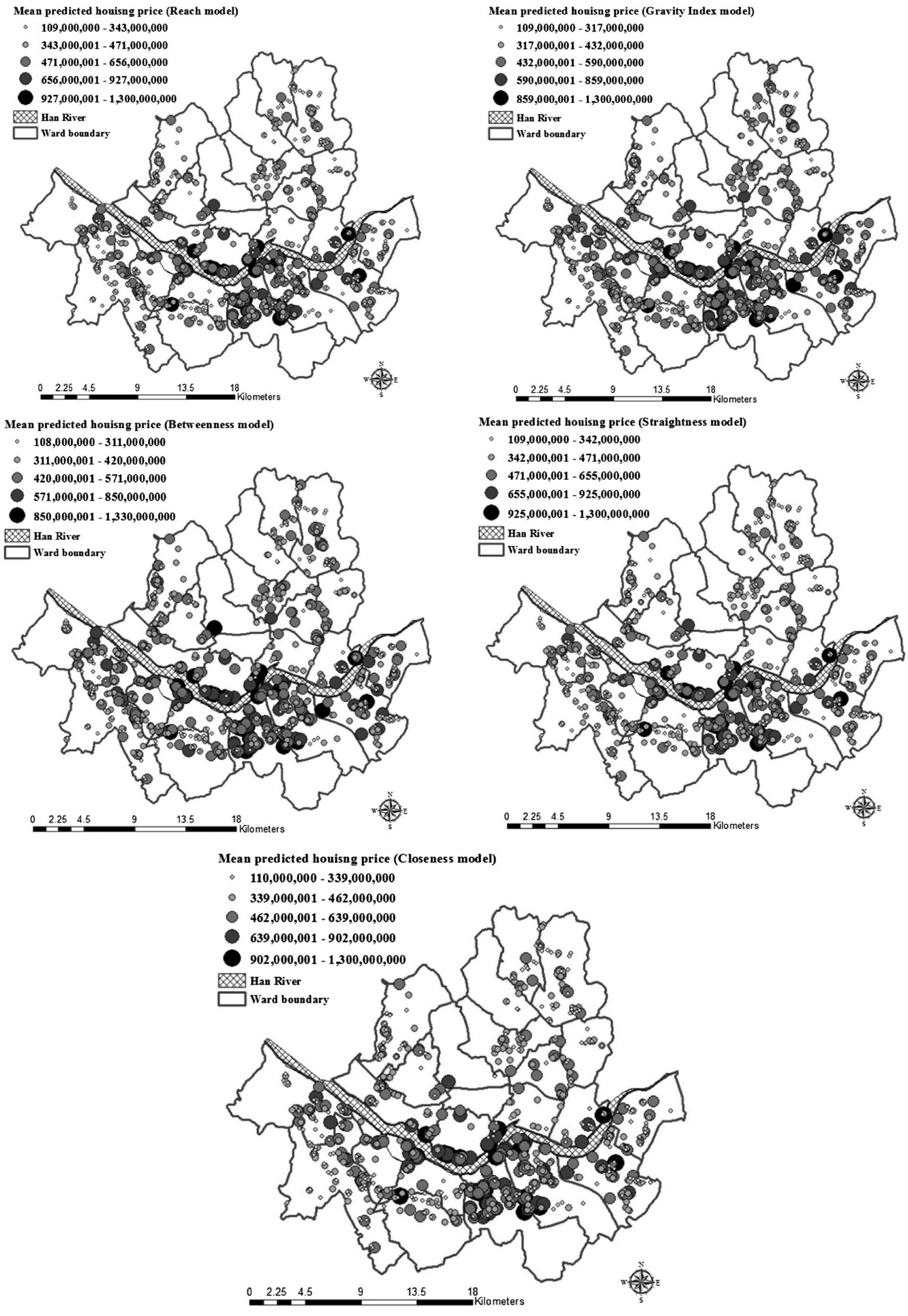

Fig. 5. Spatial pattern of mean predicted housing price by each model.

the second to fourth quarters, compared with the prices in the first quarter of 2010.

Conclusion and Policy Implications

This study estimated the value of spatial accessibility and centrality to metro transit villages—simultaneously capturing street layout and metro ridership—concerning housing prices. Most previous studies focused only on the proximity between housing sites and metro stations (Debrezion et al. 2011). Few studies focused on how metro transit villages with TOD and change of transit ridership affect housing prices. Furthermore, there is limited understanding of the synergistic effects of the two main factors of street configuration and metro ridership on walkable neighborhood housing prices. Therefore, it is necessary to identify the spatial accessibility and centrality metrics, including both street geometry and metro ridership. The empirical analysis revealed that higher accessibility and centrality, excluding betweenness, commanded premiums on housing prices within a 2-km walkable network radius. Clearly, transit-oriented neighborhoods with higher metro ridership, easier access to metro stations through dense streets, and directly connected street networks have significant positive effects on housing prices.

Beyond the empirical results of existing studies, our key findings expand the relevant discussion and suggest insightful policy implications. First, the effects of access to metro transit villages measured by metro transit ridership on housing prices verified that residents greatly value housing located in a transit-oriented community owing to lower commuting times, transportation costs, and traffic congestion, as well as increased safety from traffic accidents and better access to destinations. These results imply that creating metro transit village by TOD is highly acceptable for housing market and residents. Second, the results of the accessibility and centrality models stated that the synergetic features of both street configuration and metro transit village substantially explain the spatial variations in housing prices, implying that housing markets value a pedestrian-friendly street layout as well as metro stations with higher ridership. These approaches are helpful in determining the specific design of transit village–friendly streets. Thus, urban planning and design authorities should meticulously create street configurations to connect residential sites and metro stations. This will ensure metro transit villages with well-organized streets. Third, the evaluation of spatial accessibility and the centrality metrics presented the specific street morphology that residents prefer for public transit usage and access. Therefore, urban professionals need to build denser, more interconnected, and more directly routed streets to reach metro stations with more transit demand. The spatial accessibility and centrality indexes suggest the effective strategies and systematic design for minimizing negative effects and maximizing positive externalities of public transit. Fourth, the empirical tests confirmed that the maximum network radius for capitalizing metro access in housing prices is 2 km, which is a walkable distance, although the prices of housing too close to metro stations obtained weaker premium due to negative externalities from the stations such as crowdedness, congestion, and noise. Thus, improving street settings and TOD through measures such as higher density, mixed land use, and street design should occur within 2 km of metro stations in Seoul to create metro transit villages. Fifth, this study verified that metro stations being too accessible, i.e., within 500 m, discounts housing prices owing to noise, crowdedness, congestion, and other nuisances from the stations and the surrounding land use. These findings imply that urban planners and design authorities should allocate commercial land use instead of residential land use in neighborhoods adjacent to metro stations that welcome crowdedness and endure noise and other nuisances from the stations. This tested relationship between access to metro transit villages and residential developments is fundamental to resetting land use, transportation systems, and urban design for more-sustainable cities and neighborhoods. Sixth, valuing the housing premium from the mixed features of street configuration and metro ridership could be a cornerstone for identifying areas with insufficient affordable housing, predicting residential gentrification and displacement, and executing value capture of the windfall of homeowners that gain unexpected benefits from public investment (Zuk et al. 2018; Kang and Cervero 2009; Cervero and Murakami 2009). Finally, as shown by the synergetic effects of access to metro transit villages along street networks on housing prices, residents value the holistic externalities of public transit and street layout within walkable neighborhoods. Thus, close collaboration among urban planning and design, land-use planning, and transportation planning is required for creating transit-oriented cities and neighborhoods.

Key findings and lessons of this study are transferable to other cities in the developed and developing worlds. First, the effects of spatial access to metro transit villages on housing prices vary depending on urban growth and local contexts of street configuration, urban form, travel behavior, metro ridership, and housing markets. The available data allow other cities to test how spatial access to metro transit villages change neighborhood housing markets and prices. In particular, relevant geographical data are effective for finding the relation between metro transit villages and housing prices. Second, other studies can measure spatial accessibility and centrality to metro stations using our methodology if they have microlevel street maps and other relevant materials. The newly developed spatial accessibility and centrality indexes will measure multiple and synergetic features of metro transit villages and street configuration in simple numbers to be intuitive and understandable. However, residents' valuation of the access to metro transit villages along street networks depends on their preference of metro transit and travel behavior. Third, although this study recommended the spatial range of housing premium from metro stations up to a 2-km network radius, the spatial range in other cities varies with the locality surrounding metro transit such as urban development, socioeconomic features, centrality of the stations, travel behavior, and street layout. Other studies can find the specific neighborhood scale by applying our analytic methods to the relevant geographical and quantitative data. Fourth, our multilevel hedonic price models will be applicable to other cases if they have the suitable data of individual and neighborhood units in addition to other methodologies such as general regression and spatial econometrics. Finally, the accessibility and centrality indexes as well as econometric models of this study are a reference to formulate and evaluate urban policy and design regarding metro transit villages and neighborhood property markets for other studies. Notably, city leaders are interested in creating transit villages and monitoring their effects on neighborhoods. Thus, the methodology and findings from this study can allow them to understand the deep connection between metro transit villages and neighborhood property markets, and support creating urban policy and design for transit-oriented cities. Furthermore, the approach of this study could be used to identify the similarities and differences among global cities with different local contexts. Comparing diverse cases may lead to more-generalized principles to create transit-oriented and pedestrian-friendly neighborhoods.

This study has several limitations that the author hopes to address in future work. First, it is difficult to predict how access to planned metro stations along street networks affects the prices of nearby housing in the long run. If the panel data relevant to this topic become available, it may be possible to test the spatial-temporal dynamics between public transit access and housing prices. Second, it is necessary to develop more-sophisticated ways of measuring metro access. The methodology can be improved and better variables can be obtained through more-advanced analytics and data. Lastly, expanding the analysis to compare other contexts or comparison over time would be valuable in enhancing the understanding of the effects of metro access.

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