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Long-term impact of network access to bike facilities and public transit stations on housing sales prices in Portland, Oregon

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ABSTRACT

Planners and economists generally accept that housing market values increase with proximity to transportation facilities through the provision of improved access to activity locations. While the market benefits of rail station access are well-documented, inconsistent and insufficient methods have led to limited agreement on the true value associated with this locational amenity. Far fewer hedonic price studies have assessed the influence of bike facility access on housing sales prices, and those that have generally analyze cross-sectional data. In this study, we estimated a spatial hedonic model using a bootstrapped pseudo panel to determine the joint impact of network proximity to bike lanes and off-street multi-use paths, as well as light rail and streetcar stations, on housing sales in Portland, Oregon, from 2002 to 2013. Our findings revealed housing sales prices increased as network distance to the nearest light rail transit and streetcar station decreased. Likewise, owner-occupied single-family and multifamily housing sales rose in conjunction with reduced street network access to regional multi-use bike paths; however, improved proximity to on-street bike lanes negatively affected housing values. In sum, we believe these findings may help to inform non-automotive transportation infrastructure financing mechanisms that rely on rising property values.

1. Introduction

A commonly stated goal amongst regional transportation planners and decision makers is the diversification of the transportation system. Such diversification often includes the development of infrastructure supportive to both motorized and non-motorized travel modes. Inevitably, any conversation around infrastructure expansion turns immediately to project costs and benefits. While the direct mobility and monetary costs and benefits of these investments are easily discernable, the potential indirect and non-mobility benefits of a diverse transportation system often are made less apparent to decision makers. This set of non-mobility benefits relates to public health and safety as well as to environmental quality. A spate of still more elusive indirect monetary gains is believed to exist, and past hedonic studies have attempted to calculate them.

Urban planners and economists are interested in how the real estate market recognizes transportation improvements in the form of enhanced accessibility via non-automotive facilities. These enhancements often lead to increased housing market values (Armstrong and Rodriguez, 2006) by expanding the modal options available to residents for reaching workplaces and service facilities (Dubé et al., 2013). Despite this stated connection, few studies have linked the impact of bike facility proximity to changes in the housing market. By contrast, research into the impact of rail transit access on housing values has been commonly studied; however, findings from these studies have varied because of ranging methodologies and motivations (Debrezion et al., 2007).

A clearer understanding of the monetary contributions of transportation infrastructure expansions could assist researchers and practitioners interested in predicting the indirect effects of improved locational quality on the housing market (Can, 1990). Consequently, decision makers should be better informed when using limited resources to implement proposed visions. In the case of Portland, Oregon, the city adopted a bike plan for 2030 seeking to expand its pro-bike legacy by building more bike infrastructure to realize a number of stated goals, including the ability of residents to meet their daily transportation needs more efficiently (PBOT, 2010). Portland also welcomed an expansion of its streetcar network in 2012 and opened its fifth light-rail line (MAX Orange route) in the regional system in September 2015. Other American cities have also invested in light rail, streetcar, and bicycle infrastructure expansion with the intent of efficiently shaping the urban fabric and realizing the myriad benefits heralded by smart growth advocates.

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However, to achieve the identified goal of diversification in the transportation network, these cities must show that favorable housing market conditions arise from an extension of their bike and public transit networks (Knaap et al., 2001). To address this identified need, our study examines the monetary benefits of transportation system diversification by evaluating the long-term influence of improved bike and rail transit facility access from 2002 to 2013 on residential property sales prices in Portland, Oregon. Our working hypothesis is that increased distance to the nearest bike facility or public transit station has a negative influence on housing sales price.

2. Literature review

The seminal research of Lancaster (1966) and Rosen (1974) set the theoretical foundation for modern hedonic studies of residential market values. The former contribution to microeconomic theory introduced several assumptions, including that: (a) a single good such as the residence is composed of various characteristics reflecting its utility to the consumer, (b) the characteristics comprising this good may or may not be shared by more than one good, and (c) the overall set of goods may possess characteristics different from those pertaining to the goods separately. The latter study contributed to the conceptual framework of non-linear hedonic modeling techniques by addressing the complication of assuming a constant linear relationship between the price of a good and the price of its individual characteristics.

The representation of this good as a cohesive bundle of individual characteristics of a residential property has taken an assortment of functional forms. Sirmans et al. (2005) identified eight categories reflecting the bundling of different housing-related characteristics, including the construction and structure (e.g., square feet), internal features (e.g., full baths), and location or neighborhood (e.g., proximity to a metro station) associated with a house. Yet most studies focused on the potential impact of improved transportation facility access on residential property values have opted for more sparing functional forms. Mohammad et al. (2013) proposed three classes of contextual factors (internal, external, and economic) that affect property values, in which transport schemes (e.g., accessibility, distance) reflected a subgroup of external factors. In studying the effect that light-rail station proximity has on single-family home values in Portland, Chen et al. (1998) acknowledged four relevant categories describing the physical (e.g., lot size), neighborhood (e.g., median household income), locational (e.g., distance to central business district), and fiscal (e.g., property taxes) characteristics of a house.

In addition to these housing-specific characteristics, timing also has a significant influence on the realized impact of transportation improvements on property values. Knaap et al. (2001) found property transactions within one mile of a light-rail station in Portland sold for 9% more after the station locations were announced, with an even greater 36% premium if the property was located within one-half mile of a new station. Adopting a more refined approach to represent this temporal component, Golub et al. (2012) examined four distinct planning and implementation phases for Phoenix's light-rail line and found that property values increased over each successive phase. Welch (2010) investigated the impact of Atlanta's heavy rail system on property values for 35 years following the initial year of system operation and found an increase in property values with station proximity over time. This link between improved access to public transit stations and residential property sales has been well-documented in the literature (Hess and Almeida, 2007; Rodriguez and Mojica, 2009). Other hedonic price studies have found that close proximity to transit stations (Bowes and Ihlanfeldt, 2001) and transportation infrastructure (Seo et al., 2014) can also reduce property values, a phenomenon resulting from various nuisances (e.g., crime, air and noise pollution) associated with spatial adjacency to these facilities.

Meanwhile, the use of hedonic price models to evaluate the potential impact of improved access to bike facilities on residential property values has received far less attention. Lindsey et al. (2004) examined housing sales price as a function of structural, tax and neighborhood, and three trail access variables. Defining access as a residence located within a one-half mile areal buffer, they estimated that housing sales prices had a positive association with access to the most popular trail in the Indianapolis greenway network, but no significant relationship with access to other trails in the system. Asabere and Huffman (2009) also used a log-linear model to estimate housing sales prices in San Antonio, Texas, as a function of the structural and property characteristics, as well as a set of amenity variables including the presence of a neighborhood trail. This presence of a trail in the neighborhood of the property transaction was related significantly and positively to housing sales prices, and interaction of this binary variable with the presence of a greenway in the neighborhood had a marginally positive relationship with housing sales prices. Recently, Parent and vom Hofe (2013) examined the link between assessed market value and network distance of a property to the nearest trailhead of an oft-traveled multi-use trail in Cincinnati, Ohio. Aside from the use of network distances, the study advanced prior ordinary least-squares (OLS) modeling efforts by testing three different spatial specifications. In all specifications, the network distance to the nearest trailhead was negatively related to the assessed market land value.

Krizek (2006) employed an OLS hedonic modeling approach to examine the connection between housing sales prices in the Twin Cities (Minneapolis-St. Paul, MN) and proximity to on-street bicycle facilities, in addition to off-street trails. Arguing that suburban and urban residents perceived the value of these bike facilities differently, Krizek (2006) stated that housing market prices were composed of the structural and neighborhood attributes of the house as well as its environmental location in the suburb or city. Study findings suggested a negative association between housing sales prices and suburban on-street bike lanes, but no clear indication concerning the directional impact of on-street facilities on housing sales prices for urban locations. Our study bolsters a sparse evidence base by using a non-parametric hedonic price model to estimate the longitudinal influence of segmented bike and public transit facilities on housing sales prices.

3. Methods

3.1. Panel construction

To examine the long-term influence of non-automotive infrastructure expansion on the Portland, Oregon, housing market, spatial information was collected from the metropolitan area's comprehensive Regional Land Information System (RLIS, 2015)) database. Foremost, a history of residential property sales for the City of Portland, based on annual updates between 2002 and 2013, was used to construct a spatial panel. The panel of sales data was recorded at the parcel-level and cleaned by limiting the longitudinal dataset to arms-length transactions of only single-family and owner-occupied multifamily units with a non-zero sales price. Further, properties with a building size of <300 and over 8000 square feet were removed from the final dataset. This resulted in a total of 146,311 candidate sales records in the City of Portland for the hedonic analysis. Sales data were temporally grouped by transaction year and spatially aggregated to a 300-meter grid cell system cast over the city. In total, 4483 grid cells covered the citywide study area.

The RLIS database also provided transportation data layers denoting the city's expansion of bike facilities and public transit stations over the 12-year study period. For this study, three bike facility types in which cyclists are separated from automotive traffic were explored (Fig. 1). From 2002 to 2013, the City of Portland increased bike-lane coverage from 148 to 191 miles, from two to 33 miles in local multi-use path expansion, and from 67 to 75 miles in regional multi-use path growth. Fig. 2 offers a map of the location of these bike lanes/paths in Portland at the beginning and end of this timeframe. An expansion of the region's light rail and streetcar network also occurred during the 12-year study

Fig. 1. Illustration of bike facility types used in analysis. Photos: S.R. Gehrke.

period. As a result, the number of light-rail stations in Portland increased from 30 in 2002 to 61 in 2013; moreover, the number of streetcar stations in the city more than doubled from 32 to 74 across the same period. Most station expansion during this timeframe resulted from the opening of the Yellow Line in 2004, Green Line in 2009, and Central Loop Line in 2012 (Fig. 2).

The network distance between the location of each residential property sales transaction and nearest bike facility (bike lane, local multi-use path, and regional multi-use path) and public transit station (light rail and streetcar) at the time of sale was calculated using ArcGIS Network Analyst. Beyond these transport scheme measures, a set of additional external factors affecting residential sales price was collected. Using block group-level socioeconomic and demographic data from the 2000 and 2010 US Decennial Census, as well as the 2005–09, 2006–10, 2007–11, and 2008–12 5-year American Communities Survey (ACS), locational characteristics were added to the full panel dataset. These socioeconomic data enabled development of a unique annual profile for each individual geographic unit of analysis. For those years of the timeframe not captured by the US Census or ACS data source, panel data were imputed using a standard straight-line projection method. The RLIS provided the requisite information to measure other external factors related to the location (e.g., median income, household density) and surrounding amenities (e.g., parks, land use entropy). The number of bedrooms and bathrooms in each sold residence was provided by an online real estate database (Trulia.com, 2015). More internal factors (e.g., size, age) as well as the listed sales price were offered by the RLIS. Table 1 lists variables included in the 12-year panel.

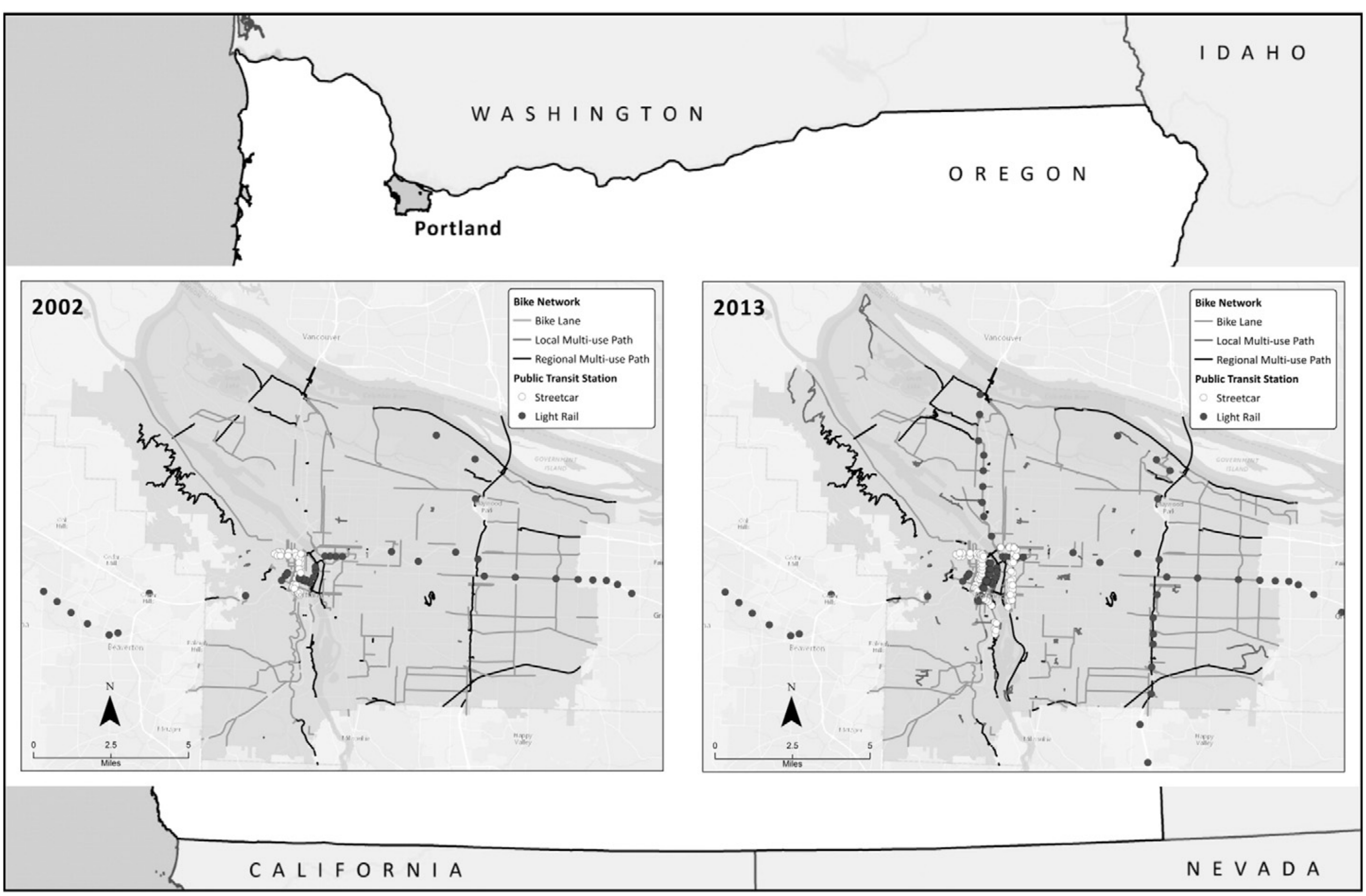

Fig. 2. Bike facility and public transit station expansion in Portland, Oregon from 2002 (left) to 2013 (right). Source: Created by the authors.

Table 1
Variables within spatial panel dataset.

Variable	Description
Dependent	
Sale price	Total sale price of a unit within the grid cell (inflation adjusted 2013 $US)
Independent	
Internal	
Age	Age of housing unit at the time of sale
Bathrooms	Sum of full (1) and half (0.5) bathrooms
Bedrooms	Total number of bedrooms
Lot acres (ln)	Number for acres for property sale, in log form
Neighborhood	
Household density	Household density within the grid cell
Land use entropy	Mean land use entropy (residential, commercial, industrial)
Median income	Median household income within the grid cell (inflation adjusted 2013 $US)
Percent rented	Percent of rented housing units within the grid cell
Percent white	Percent White households within the grid cell
Distance	
CBD distance	Feet in network distance to central business district
Bike lane distance	Feet in network distance to nearest bike lane
Local multi-use path distance	Feet in network distance to nearest local multi-use path
Regional multi-use path distance	Feet in network distance to nearest regional multi-use path
Light rail station distance	Feet in network distance to nearest MAX light rail station
Streetcar station distance	Feet in network distance to nearest streetcar Station
<1/8 mile from light rail track (dummy)	1 = property located within 1/8 mile of a light rail track
<1/8 mile from streetcar track (dummy)	1 = property located within 1/8 mile of a streetcar track
<1/8 mile from major road (dummy)	1 = property located within 1/8 mile of a major road
Between 1/8 and 1/4 mile from light rail track (dummy)	1 = property located >1/8 mile and <1/4 mile of a light rail track
Between 1/8 and 1/4 mile streetcar track (dummy)	1 = property located >1/8 mile and <1/4 mile of a streetcar track
Between 1/8 and 1/4 mile from major road (dummy)	1 = property located >1/8 mile and <1/4 mile of a major road
Temporal	
Years light rail open	Years between light rail station opening and observed sale
Years streetcar open	Years between streetcar station opening and observed sale
Property sold in 2002 (dummy)	0 = observed sale occurred in the year 2002
Property sold in 2003 (dummy)	1 = observed sale occurred in the year 2003
Property sold in 2004 (dummy)	1 = observed sale occurred in the year 2004
Property sold in 2005 (dummy)	1 = observed sale occurred in the year 2005
Property sold in 2006 (dummy)	1 = observed sale occurred in the year 2006
Property sold in 2007 (dummy)	1 = observed sale occurred in the year 2007
Property sold in 2008 (dummy)	1 = observed sale occurred in the year 2008
Property sold in 2009 (dummy)	1 = observed sale occurred in the year 2009
Property sold in 2010 (dummy)	1 = observed sale occurred in the year 2010
Property sold in 2011 (dummy)	1 = observed sale occurred in the year 2011
Property sold in 2012 (dummy)	1 = observed sale occurred in the year 2012
Property sold in 2013 (dummy)	1 = observed sale occurred in the year 2013

3.2. Analytic approach

While spatial panel modeling has been established in econometric analyses, the approach has been rarely used in transportation planning and geography studies. The limited application of the methodology may be attributed to implementation barriers related both to significant data collection efforts and computational requirements. However, when compared to cross-sectional data analyses, use of a spatial panel and constituent analysis method enables the estimation of a more robust hedonic price regression model with greater variation and less collinearity among specified variables (Elhorst, 2003). Moreover, estimation of a hedonic price model with a spatial panel allows the specification and testing of more complicated behavioral hypotheses than those tested with conventional hedonic models (Hsiao et al., 1999).

Although an addition of temporal information marks a clear methodological advantage to using a spatial panel modeling approach, two problems related to the joint incorporation of a locational component must be addressed going forward. First, spatial dependence, where an event at one location may be influenced by the occurrence and magnitude of a similar event at a spatially proximate location, must be addressed adequately to prevent spurious model results in the form of spatial error. Second, model parameters may not be homogeneous across spatial locations (Armstrong and Rodriguez, 2006; Elhorst, 2003). Merely adjusting for any temporal autocorrelation would not adequately overcome these potentially confounding modeling errors. Consequently, a spatiotemporal autocorrelation model specification should be employed.

The spatial panel data model used in this hedonic study was a random effects spatial panel model incorporating both spatial lag and spatial error effects (Elhorst, 2003). Model estimation was performed in the R statistical software program (R Core Team, 2014) using the splm package (Millo and Piras, 2012). Eq. (1) shows the structural form of the spatial panel model, which can be taken as a combination of a panel and spatial regression model (Millo and Piras, 2012).

$$y = \lambda(I_T \times W_N)y + X\beta + u \tag{1}$$

Here, y is an $NT \times 1$ vector of observations on the dependent variable, X is a $NT \times k$ matrix of observations on the non-stochastic exogenous variables, I_T is an identity matrix of dimension T, W_N is an $N \times N$ spatial weights matrix with diagonal elements set to zero, λ represents the corresponding spatial parameter, and u is a disturbance vector representing the sum of the temporal autocorrelation (Eq. (2)) and spatial autocorrelation (Eq. (3)) terms.

$$u = (\iota_T \times I_N)\mu + \varepsilon \tag{2}$$

In Eq. (2), ι_T is a $T \times 1$ all-ones vector and I_N is an $N \times N$ identity matrix in which the product of the terms is multiplied by a vector of time-invariant individual specific effects μ and then summed with ε the vector of spatial autocorrelation innovations. In Eq. (3), $\rho(|\rho|<1)$ is a spatial autoregressive parameter and W_N is a spatial weights matrix.

$$\varepsilon = \rho(I_T \times W_N)\varepsilon + v \tag{3}$$

In this study, the suite of random effects spatial panel models used a maximum likelihood estimator and developed a spatial weights matrix using the "rook contiguity" method. That is, for the purposes of constructing the spatial weight matrix, each neighboring grid cell was defined as an adjacent cell with a shared side. Previous spatial panel models commonly rely on multiple observations within an arbitrary boundary that average observations for each panel time period to produce one value for each item located in the chosen spatial boundary. However, this approach likely biases any parameter estimate by allowing a single outlying observation to have a large influence in a panel of averaged values. To avoid sample bias, a bootstrap approach was adopted, which constructed a pseudo spatial panel dataset from a single observation for every grid cell, each year of the study period.

Using the constructed pseudo spatial panel, nonparametric bootstrapping was employed to derive 1000 sample datasets of residential sales transactions from 2002 to 2013. The repeated balanced panel datasets were composed of randomly selected observed residential property sales within the City of Portland, where only one time-specific property-level sale was randomly selected (with replacement) for each grid cell with a housing sales transaction. By bootstrapping

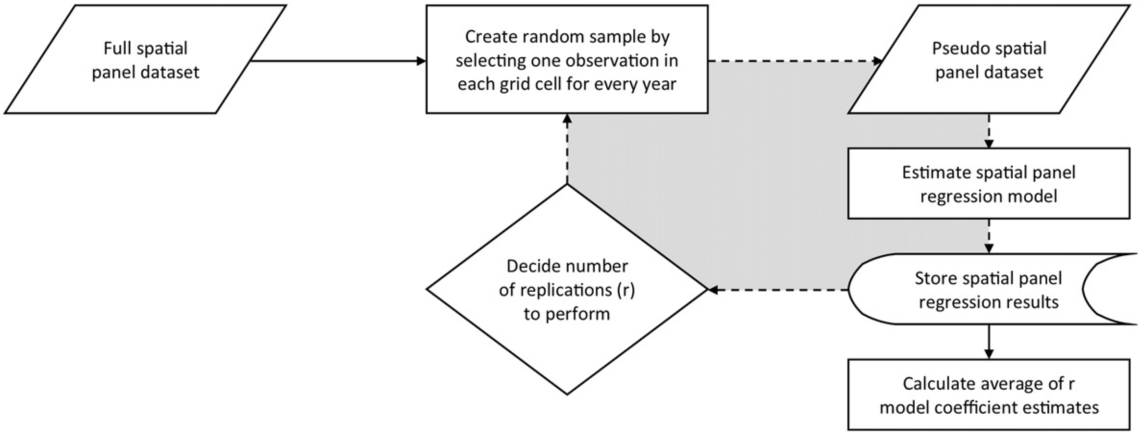

Fig. 3. Flow diagram of bootstrapped pseudo spatial panel construction and model fitting.

regression estimates with a nonparametric approach, any distribution assumptions concerning the population of residential property sales in the study area, where such information may not be easily obtained over a 12-year period, were not required to be met. A hedonic spatial panel regression model was then fitted in order to predict the housing sales price of randomly selected residential transactions within the pseudo panel as a function of internal and external factors. Adoption of a bootstrap approach enabled estimation of a coefficient mean, standard error, and p-values resulting from 1000 model estimations (Efron and Tibshyrani, 1993). Fig. 3 shows a flow diagram of the described modeling approach.

4. Results

4.1. Spatial panel descriptive characteristics

During panel construction, the inflation-adjusted housing sales price and internal factors describing each single-family and owner-occupied

Table 2
Descriptive statistics for full panel of variables in final model specification.

Variable	Mean	Standard Deviation	Minimum	Maximum
Sale price (2013$)	285,405.50	144,104.90	25,266.00	1,284,139.00
Internal				
Age	57.70	32.90	0.00	148.00
Bathrooms	1.90	1.10	0.00	18.00
Bedrooms	2.70	1.20	0.00	18.00
Lot acres (ln)	0.10	8.80	0.01	2500.00
Neighborhood				
Household density	21.60	10.70	1.40	66.20
Land use entropy	38.10	25.10	0.00	97.30
Median income	59,153.00	23,769.40	11,095.70	204,573.00
Percent rented	38.40	15.30	7.50	89.40
Percent white	78.10	14.40	26.10	100.00
Distance				
CBD distance	26,538.40	10,237.40	1911.20	61,021.40
Bike lane distance	2332.80	2797.60	5.30	23,301.40
Local multi-use path distance	9090.90	7568.30	4.00	45,144.50
Regional multi-use path distance	5442.70	3367.00	0.00	20,798.10
Light rail station distance	10,850.10	7328.50	170.30	40,321.30
Streetcar station distance	22,820.90	11,463.20	17.10	56,685.70
<1/8 Mile from light rail track (dummy)	0.03	0.20	0.00	1.00
<1/8 Mile from streetcar track (dummy)	0.02	0.20	0.00	1.00
<1/8 Mile from major road (dummy)	0.40	0.50	0.00	1.00
Between 1/8 and 1/4 mile from light rail track (dummy)	0.05	0.20	0.00	1.00
Between 1/8 and 1/4 mile from streetcar track (dummy)	0.02	0.10	0.00	1.00
Between 1/8 and 1/4 mile from major road (dummy)	0.30	0.50	0.00	1.00
Temporal				
Years light rail open	13.80	8.10	0.00	27.00
Years streetcar open	3.40	2.90	0.00	12.00
Property sold in 2003 (dummy)	0.10	0.30	0.00	1.00
Property sold in 2004 (dummy)	0.10	0.30	0.00	1.00
Property sold in 2005 (dummy)	0.10	0.30	0.00	1.00
Property sold in 2006 (dummy)	0.10	0.30	0.00	1.00
Property sold in 2007 (dummy)	0.10	0.30	0.00	1.00
Property sold in 2008 (dummy)	0.10	0.20	0.00	1.00
Property sold in 2009 (dummy)	0.10	0.20	0.00	1.00
Property sold in 2010 (dummy)	0.10	0.20	0.00	1.00
Property sold in 2011 (dummy)	0.10	0.20	0.00	1.00
Property sold in 2012 (dummy)	0.10	0.20	0.00	1.00
Property sold in 2013 (dummy)	0.04	0.20	0.00	1.00

multifamily residence sold over the 12-year study period were spatially matched to the grid cell network. Similarly, external factors describing the location, surrounding amenities, and transport scheme of each grid cell were spatially joined to each sales transaction. Table 2 provides a descriptive summary of these internal and external factors within the full panel of 80,182 observations.

The close proximity of most housing sales transactions to bike infrastructure described in Table 2 is visualized in Fig. 4. The average residence sold was located two miles from a local multi-use bike path, one mile from a regional multi-use path, and one-half mile from a bike lane. Residential properties located near the city center, with its diverse network of bike facilities, were among the sales observations with the greatest access to the city's extensive bike network. This network of bike lanes and local/regional multi-use paths extends across most city neighborhoods; thus, providing strong bike facility access for a majority of Portland's housing units.

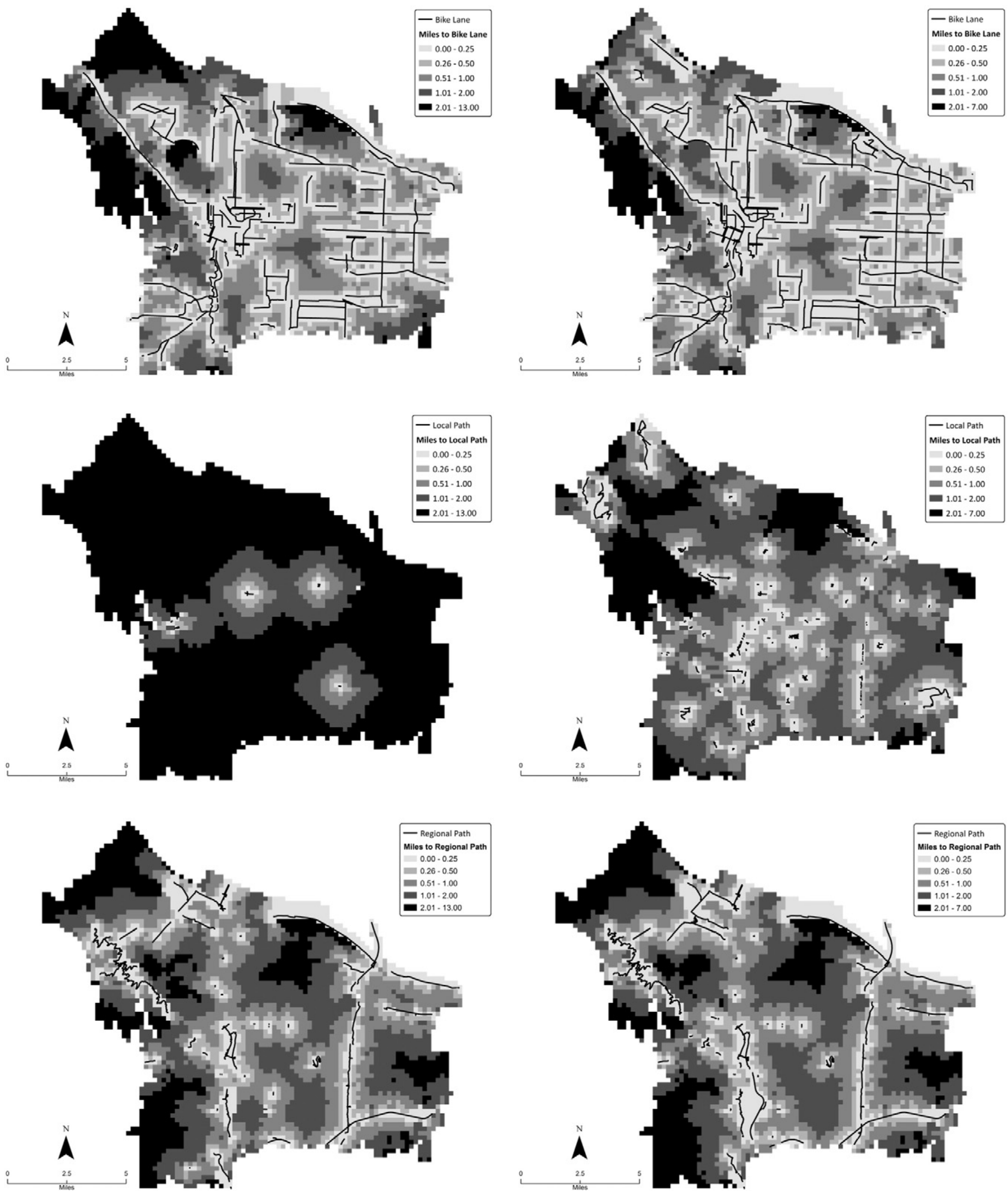

Fig. 4. Change in grid-based street network distance to nearest bike facility from 2002 (left) to 2013 (right).

By contrast, Fig. 5 shows that street network access to light rail transit and streetcar stations was not nearly as ubiquitous across the city. The majority of streetcar stations in Portland are located within the city center; while light rail transit station locations extend outward from the city center along the region's major arterials. As such, the average sales transaction was located over four miles from a streetcar station and two miles from the nearest light rail station.

4.2. Spatial panel model results

The nonparametric bootstrapped estimation results of the hedonic spatial panel model are shown in Table 3. Final regression results are based on an averaging of estimated coefficients and standard errors from the 1000 model estimations. Overall, an increased distance to the nearest rail station tended to decrease the average housing sales price in Portland over the 12-year study period. Model estimates revealed for each additional foot along the street network that a single-family or owner-occupied multifamily residence was located from the nearest light rail station, the dwelling unit sold for \$0.46 less. By comparison, increased network distance to the nearest Portland Streetcar station had a much greater negative impact on housing sales price at \$4.45 per foot. Accordingly, the average Portland residence sold between 2002 and 2013 was located 4.32 miles from a streetcar station; thus, a home situated one-half mile from the nearest streetcar station sold for a premium of \$89,755 due to station proximity, all else held constant.

Regarding the temporal component of housing sales, the length of time between a rail station's inaugural year of operation and the observed year of a succeeding housing sale had a significant impact on a property's realized market value. After controlling for annual fluctuations in the housing market during the 12-year study period, increased proximity to a light-rail station was associated with an additional \$1361 per year in housing sales price appreciation. Similarly, improved proximity to a streetcar station was linked to an annual property value appreciation of \$4113. These values reflect an increasing bid rent for station proximity as the utility of rail station access continues to gain greater market recognition in the City of Portland.

As for the benefit of improved bike facility access on housing sales, the findings were divided based on whether the nearest facility provided off-street or on-street access. Proximity to regional multi-use paths had a substantial and sustained positive impact on long-term housing sales prices. A decrease in housing sales price of \$0.86 was attributed to each additional foot the residence was located from the nearest regional path. For each additional foot in distance that a residence was located from the nearest off-street local multi-use path, the dwelling unit sold for \$0.01 less. Although, due to additional compounding factors not fully specified in the model, this distance variable was not significant. Taken together, the average Portland home sold during the

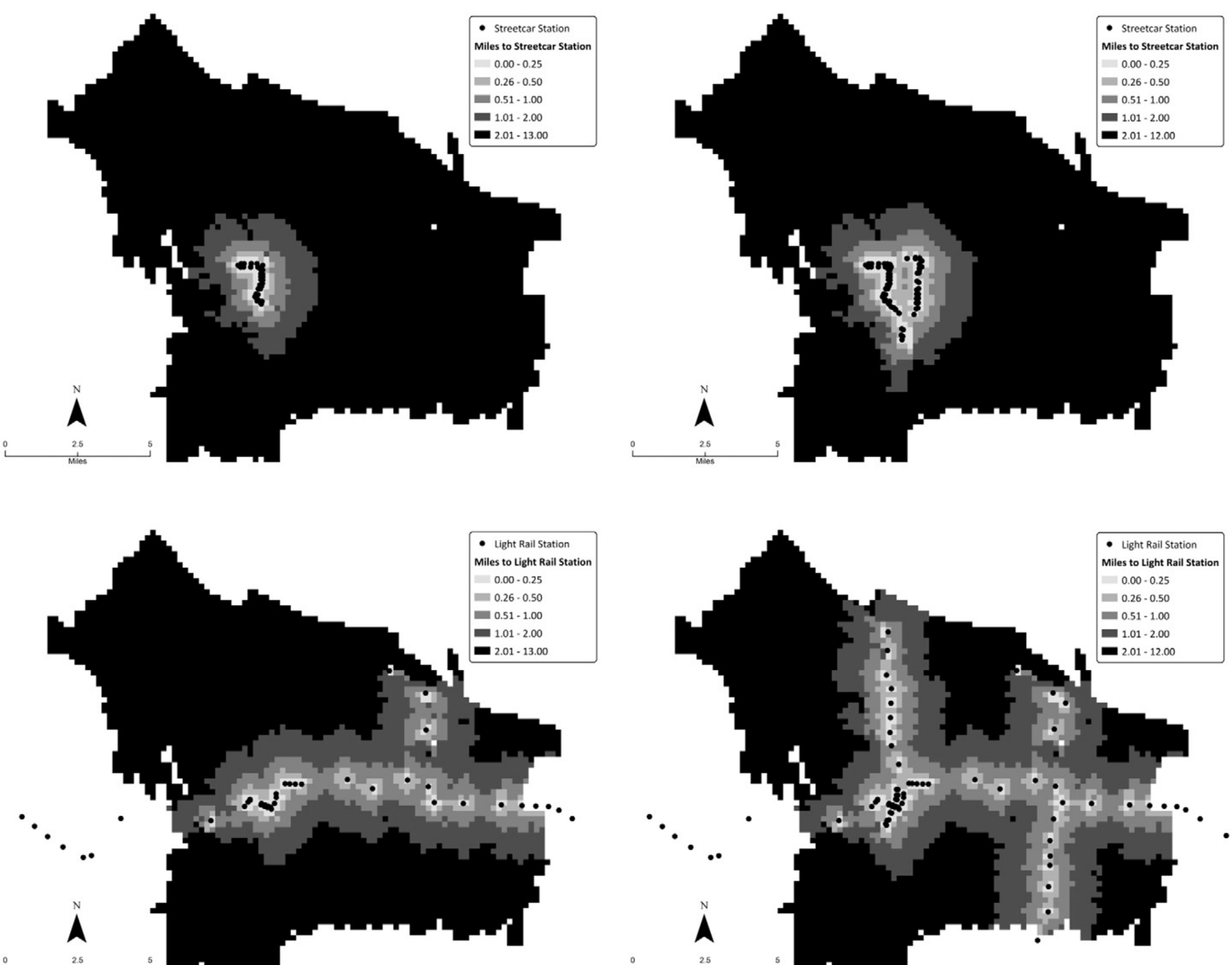

Fig. 5. Change in grid-based street network distance to nearest rail transit station from 2002 (left) to 2013 (right).

Table 3
Spatial panel model results for bootstrap regression estimates ($r = 1000$).

Variable	Mean Estimate	Standard Error	*p*-Value
Constant	130,468.902	9520.283	0.000
Internal			
Age	−27.445	30.844	0.374
Bathrooms	27,836.543	1248.142	0.000
Bedrooms	18,961.730	1017.141	0.000
Lot acres (ln)	32,043.795	1419.476	0.000
Neighborhood			
Household density	580.835	78.712	0.000
Land use entropy	171.229	33.764	0.000
Median income	1.807	0.055	0.000
Percent rented	−577.072	72.364	0.000
Percent white	836.777	50.651	0.000
Distance			
CBD distance	−0.558	0.125	0.000
Bike lane distance	2.470	0.378	0.000
Local multi-use path distance	−0.013	0.121	0.915
Regional multi-use path distance	−0.862	0.189	0.000
Light rail station distance	−0.462	0.115	0.000
Streetcar station distance	−4.450	0.126	0.000
<1/8 Mile from light rail track (dummy)	−24,091.585	3400.697	0.000
<1/8 Mile from streetcar track (dummy)	82,027.396	16,371.040	0.000
<1/8 Mile from major road (dummy)	−10,789.912	1703.075	0.000
Between 1/8 and 1/4 mile from light rail track (dummy)	−16,489.798	3147.580	0.000
Between 1/8 and 1/4 mile streetcar track (dummy)	45,548.206	14,303.923	0.001
Between 1/8 and 1/4 mile from major road (dummy)	−1364.450	1749.410	0.435
Temporal			
Years light rail open	1361.427	80.719	0.000
Years streetcar open	4112.991	350.386	0.000
Property sold in 2003 (dummy)	7024.502	3036.970	0.021
Property sold in 2004 (dummy)	58,364.474	3486.357	0.000
Property sold in 2005 (dummy)	99,112.984	3806.547	0.000
Property sold in 2006 (dummy)	118,169.243	3535.974	0.000
Property sold in 2007 (dummy)	98,248.312	3758.736	0.000
Property sold in 2008 (dummy)	69,385.550	3657.399	0.000
Property sold in 2009 (dummy)	45,031.905	3666.662	0.000
Property sold in 2010 (dummy)	28,748.127	3820.637	0.000
Property sold in 2011 (dummy)	−1870.970	3889.975	0.643
Property sold in 2012 (dummy)	22,490.074	3402.957	0.000
Property sold in 2013 (dummy)	30,406.756	3262.999	0.000

12-year study period would have sold for $4541 and $53 less if the residence was located one mile from the nearest regional and local multi-use path, respectively.

In terms of proximity to an on-street facility, the average Portland home sold for $2.47 more with each additional foot that the residential property was located away from a bike lane. While a potentially counterintuitive finding, the large negative impact of bike lanes on housing sales price may be attributed to the correlation of this external factor with undesirable features of a home's location (e.g., noise and air pollution, traffic safety) that are not fully captured by the specification of the model's nuisance variables. Many bike lanes are located along busy roads, several of which serve as major arterials; thus, the effect of being located near this road facility type would appear to outweigh the accessibility benefits of a separated, on-street bike lane.

5. Conclusions

This study estimated a hedonic spatial panel model to determine the long-term impact of improved network access to bike and public transit facilities on housing sales prices in Portland, Oregon. Findings from this 12-year study revealed a substantial and negative effect of increased distance to the nearest regional off-street bike facility or rail station on residential market values. Accordingly, the closer a sold residence was to a regional multi-use path, light-rail station, or streetcar station, the greater the structure's observed housing sales price. However, our findings have also shown the residential market benefits associated with an increased diversification of the transportation network are complex when the joint influence of these improvements are considered along with proximity to a major arterial. Case in point: the impact of local multi-use path and bike lane access on housing sales price was either negligible or counterintuitive to prior findings in the literature.

Yet, to the best knowledge of the authors, this work represents the first hedonic price analysis of bike infrastructure to utilize a longitudinal dataset. Additionally, studies of the impact of light rail transit access on housing sales prices in the oft-studied Portland metropolitan region and the majority of other locations have typically adopted a cross-sectional study design or non-spatial longitudinal analytic methods to measure longer-term trends in the dynamic housing market. Table 4 provides a standardized comparison of this study's findings to the results of other hedonic price studies that have measured the monetary impact of proximity to a bike facility or Portland's rail-based transit network.

Beyond use of a 12-year panel to study a long-term phenomenon, this research presented a spatial panel modeling approach previously not implemented in planning studies to identify the contribution of improved access to bike and public transit facilities on housing sales price. Of the few studies to have employed time series hedonic regression methods, even when controlling for spatial autocorrelation, most have been hampered by their short-term measurement of the effect size of improved facility access. The diversification of a transportation system

Table 4
Comparison of findings from past relevant hedonic price studies.

Study	Facility type	Location	Proximity per foot (2013 $US)
Al-Mosaind et al. (1993)	Light rail transit	Portland, OR	$10.86
Lewis-Workman and Brod (1997)	Light rail transit	Portland, OR	$1.21
Chen et al. (1998)	Light rail transit	Portland, OR	$14.24
Dueker and Bianco (1999)	Light rail transit	Portland, OR	$12.57 to $15.10
This paper	Light rail transit	Portland, OR	$0.46
	Streetcar		$4.45
Lindsey et al. (2004)	Multi-use paths	Indianapolis, IN	$6.95
Krizek (2006)	Multi-use paths	Twin Cities, MN	Positive effect
	Bike lanes		No significant effect
Asabere and Huffman (2009)	Multi-use paths	San Antonio, TX	$3107.64*
Parent and vom Hofe (2013)	Multi-use paths	Miami, OH	$4.19
This paper	Local multi-use paths	Portland, OR	$0.01
	Regional multi-use paths		$0.86
	Bike lanes		$-2.47

* Applicable only to houses abutting a trail.

through the expansion of rail-based transit and bicycle networks represents a long-term investment in which the residential market value associated with an increased proximity to such infrastructure cannot be accurately portrayed by a single year of observations. The long-term view of the housing value and non-automotive infrastructure proximity relationship taken in this study, as well as the new findings highlighted by an innovative analytical approach, has the potential to better inform those transportation infrastructure financing mechanisms that rely on rising property values.

Additionally, this research measured the joint impact of network access to both bike and public transit facilities on housing sales price. Past analyses have not simultaneously measured the effect of improved accessibility to these facilities on housing value, despite growing evidence underscoring a synergistic link between cycling and public transit (Krizek and Stonebraker, 2010). The prospective for household members to substitute one non-automotive travel mode for another may be viewed as a desirable locational feature for a household purchasing a new residence. Also, by calculating transportation facility access as street network distance instead of the commonly used straight-line measurements or the simple adoption of a series of areal buffer approximations, our study provides a more realistic understanding of how improved bike and public transit access affects housing values.

While this work presents conceptual and methodological advancements to the literature on hedonic price studies, there are several study caveats that warrant further clarification and consideration. First, this study assesses the market impact of transportation infrastructure improvement at a regional scale instead of a local assessment (e.g., corridor) where the external factors of housing market value may exert a stronger impact. Future efforts should also consider the addition of economic factors (e.g., land supply, regional market conditions) or other internal (e.g., stories) and external (e.g., school quality, congestion) factors that were not tested because of limitations in data availability. Finally, the nonlinear effects of bike and transit facility proximity also warrants future examination, as recent evidence suggests that, as distance from a public transit station increases, the property value benefits for this proximity decrease at an accelerating rate (Kay et al., 2014; Seo et al., 2014). Nonetheless, despite these considerations and others, this study has addressed many notable methodological shortcomings of previous hedonic price studies in finding that increased access to off-street bike facilities and rail transit stations has a sustained and often substantial positive impact on residential property values.

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