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Impact of Bike Facilities on Residential Property Prices

Jenny H. Liu and Wei Shi

As many cities are investing in street improvements or transportation infrastructure upgrades to provide better bike access or more complete bike networks, many practitioners, planners, and policy makers are seeking more conclusive evidence about the economic value of bike infrastructure and bike facilities. With the use of residential property values as indicators of consumer preferences for bicycle infrastructure, many scholars have shown the importance of green space and off-street bike trails as amenities valuable to property owners. However, empirical evidence on the relationship of on-street bike facilities and property values remains relatively inconsistent. The unique focus of this study was advanced bike facilities that represented higher levels of bike priority or bike infrastructure investments shown to be more desirable to a larger portion of the population. Through the separate estimation of ordinary least squares hedonic pricing models and spatial autoregressive hedonic models of single and multifamily properties, it was found that proximity to advanced bike facilities (measured by distance) had significant and positive effects on all property values, which highlighted household preferences for high-quality bike infrastructure. Furthermore, the study showed that the extensiveness of the bike network (measured by density) was a positive and statistically significant contributor to the prices for all property types, even after proximity was controlled for with respect to bike facilities and other property, neighborhood, and transaction characteristics. Finally, estimated coefficients were applied to assess the property value impacts of the Green Loop (i.e., the proposed Portland, Oregon, signature bike infrastructure concept), which illustrated the importance of considering the accessibility and the extensiveness of bike facility networks.

Many cities across the country, as part of Complete Streets initiatives or to promote community livability, have engaged in street improvement or transportation infrastructure upgrade projects that increase access and mobility for pedestrians and bicyclists. In the determination of property value, the importance of public amenities (e.g., proximity to green spaces), transportation networks (e.g., airports, highways, rail stations) and school quality has been widely discussed in urban economics, planning, and real estate research. However, the specific contribution of bike infrastructure and facilities to residential property values is relatively undocumented or inconsistent, which presents difficulties in the justification of further allocations of resources to high-quality, bicycle-related infrastructure.

Relevant research in this area in general has focused on urban greenways, defined as "linear corridors of open space along rivers, streams, historic rail lines, or other natural or man-made features" (*1*), or "trails with greenbelts" (*2*). Proponents of urban greenways typically point to benefits from recreational use, active transportation-related public health benefits (*3*), or mode shift–related transportation benefits, as the result of new bike lanes or improvements in existing facilities (e.g., congestion relief, reductions in greenhouse gas emissions, reductions in noise) (*4–7*). Greenways may provide additional benefits in the form of environmental services (e.g., habitat conservation or carbon sequestration) and aesthetic value (*1*). Other researchers have focused on whether active transportation infrastructure investments generate positive returns on economic development and business activities (*8–10*). To the extent that residential properties serve as home bases for people's activities and provide access to nearby infrastructure, accessibility to desirable bike facilities and the extensiveness of a nearby bike facility network should be key determinants of residential property values. In other words, residential property values may serve as indicators of consumer preferences for bicycle infrastructure.

The present analysis served to quantify household preferences for better bicycle facilities. Property value increases may benefit existing homeowners as well as local governments through an increase in property tax revenue collection and overall economic development. However, a key consideration is that renters or other vulnerable populations may experience negative consequences if they are priced out of a burgeoning real estate market. The geographic distributions of accessibility to advanced bike facilities and the extensiveness of the bike facility network and their correlations to various socioeconomic characteristics are other important considerations within this context. It is clear that advanced bike facilities and other urban greenways that achieve complementarities with existing transportation infrastructure networks and city plans tend to produce better outcomes.

This study contributed to the existing literature not only by examining the relationship between advanced bike facilities (i.e., bike-priority facilities and separated bike lanes) and residential property values but also by focusing on two major components of bike priority facilities: (*a*) ease of access (distance) and (*b*) extensiveness of bike network (density). The paper begins with a brief summary of the relevant literature and methodologies. The results then are presented of a hedonic pricing model and of spatial autoregressive (SAR) models applied to Portland, Oregon. An illustration is presented of how the modeling results may be applied to estimate the property value impacts of Portland's proposed Green Loop concept. The paper concludes with a discussion of the policy implications of this research and future research directions.

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LITERATURE REVIEW

Although this study focused on the property value impacts of bike facilities, it was important to understand various other determinants of residential home prices to appropriately account for them. In an application of Rosen's (*11*) hedonic (or implicit) pricing framework, Mohammad et al. categorized three classes of contextual factors that influenced property value: economic factors (e.g., supply and demand or economic conditions), internal factors (e.g., size, age, quality of the property), and external factors (e.g., location, surrounding amenities, transportation network) (*12*). The literature contains a large number of empirical studies that investigated how a combination of these factors might have affected residential property values (*13, 14*). Many documented the impacts of school district quality (*15*), neighborhood characteristics (*16*), environmental quality (*17*), and recreational amenities (*18*).

Transportation accessibility mainly enters the equation through variations of the bid-rent theory by which consumer and business willingness to pay for a property is inversely proportional to its distance to destinations such as the central business district (*19*). Researchers such as Ryan (*20*) and Duncan (*21*) illustrated the potential property value impacts of access to transportation facilities, but much of the research emphasis was placed on access to highways, heavy rail, or light rail. In general, the empirical evidence points to positive or neutral property value impacts as the result of proximity to green space or to off-street recreational trails (*1, 2, 22*). However, the present study found relatively scant empirical evidence from specific investigations of the property value impacts of on-street bike facilities (*23*).

Hedonic pricing analysis, a multivariate regression methodology, is the predominant technique used to estimate the marginal implicit prices of property characteristics and amenities. Lindsey et al. applied this methodology to three Indianapolis, Indiana, greenway corridors and found that, in two out of the three modeled corridors, the impact on values was significant and positive when the properties were located within a ½-mi buffer from the greenways (*1*). With the use of a similar methodological framework in San Antonio, Texas, Asabere and Huffman found homes that were near or that abutted trails, greenways, and trails with greenbelts were correlated with 2% to 5% price increases (*2*). Similar positive property value impacts were found when street network distance was used as an alternative measure for proximity and access to greenbelts in Austin, Texas (*24*). Recent studies have expanded on previous hedonic price models by controlling for spatial autocorrelation effects between green space and property values (i.e., the correlation between the values of neighboring homes or the likelihood of green space). Studies, such as ones by Conway et al. (*22*) and Parent and vom Hofe (*25*) found that proximity to green space or bike trailheads had a significant and positive impact on residential property values, even after they controlled for spatial autocorrelation effects.

Studies by Krizek (*26*) and Welch et al. (*23*) are examples in the scarce literature in which hedonic models were employed to examine the differential property value impacts of various types of bike facilities (e.g., off-street trails, on-street facilities, multiuse paths). Krizek's hedonic pricing models suggested that proximity to bike trails and on-street bike facilities in suburban areas of Minneapolis, Minnesota, had a negative impact on home values and that other types of bike facilities had no impact (*26*). Welch et al. used a longitudinal spatial hedonic model in Portland, Oregon, to show that shorter distances to off-street trails had a positive impact on property values, compared with the negative impact that stemmed from proximity to on-street bike lanes (*23*).

This present study aimed to fill the research gap in understanding the property value impacts of bike facilities by including not only a variable that measured proximity to the nearest bike facility but also a variable that described the density of bike facilities within a buffer zone around the property. Further, this unique study focused on advanced bike facilities, which represented higher levels of bike priority or bike infrastructure investments, and which have been shown to be more desirable to a larger portion of the population (*7, 27*). The study results provide essential information to assist policy makers, planners, community members, and other stakeholders to understand the potential property value impacts of bike infrastructure investments, particularly with respect to the decision-making and resource allocation processes.

METHODOLOGY AND DATA

In line with the existing literature, this present study first used a general hedonic price specification to characterize the impacts of various factors on residential property values with respect to data from Portland, Oregon. The model then was tested for spatial effects (i.e., the existence of spatial lag or spatial error), which may indicate greater influence of property sales in close proximity to the subject property than those that occur farther away. Finally, the coefficient estimates of the models were applied to a proposed bike infrastructure investment in Portland to illustrate the magnitude and distribution of property value impacts within a policy context.

The general ordinary least squares (OLS) specification is as follows:

$$P_i = \beta_0 + \beta_1 T_i + \beta_2 H_i + \beta_3 R_i + \beta_4 B_i + \varepsilon_i$$

where

- P_i = property sale price;
- T_i = vector that includes transaction characteristics (e.g., year and season of the sale), which serve as proxies for general economic factors;
- H_i = vector of internal property characteristics (e.g., age, size, and property tax liability of the property);
- R_i = vector of external neighborhood or regional characteristics (e.g., school quality, crime rate); and
- B_i = vector of bike facility characteristics.

This specification exclusively incorporates property tax characteristics, given the high level of heterogeneity in property tax liabilities generated through Oregon's Measure 5 and Measure 50, shown to be significantly capitalized into property values (*28*). Furthermore, neighborhood fixed effects were incorporated into the OLS specifications to capture inherent neighborhood differences that might have contributed to property value differences but had not been captured through the existing variables. Each of the estimated coefficients described the marginal value to the homeowner of amenities in each vector.

Although many of the variables used in residential property value hedonic models are spatial by definition, homebuyers, real estate professionals, and many scholars have asserted that home values often are heavily influenced and determined by the sale prices of nearby properties (*22, 29*). This spatial dependency effect can be incorporated into the modeling in the form of price correlations in a given location with prices in nearby locations. To ignore such spatial autocorrelation may lead to inefficient coefficient estimates in the OLS specification (*22*). Two commonly used SAR models that account for spatial autocorrelation are spatial lag and spatial error models: the first interprets spatial dependence as a consequence of omitted variable bias, whereas the latter interprets spatial dependence as the result of model misspecifications. The general spatial lag model form is

$$Y = \rho WY + X\beta + \varepsilon$$

where

ρWY = spatially lagged dependent variable that represents the omitted variable in the regression model,
ρ = spatial lag parameter,
W = spatial weighting matrix that represents the interaction between different locations (*22*), and
X = vector of all variables included in the OLS model.

The general spatial error model form is

$$Y = X\beta + \lambda W\varepsilon + v$$

where the original error term from the OLS specification is modeled as an autoregressive error term ($\varepsilon = \lambda W\varepsilon + v$) and

where

λ = spatial error parameter,
$W\varepsilon$ = spatial error, interpreted as the mean error from neighboring locations, and
v = independent model error (*22, 29*).

Lagrange multiplier tests were conducted to identify the appropriate SAR models. Another key consideration was the specification of the spatial weighting matrix, *W*, a matrix that describes the magnitude of impact of nearby property sales on the property in question. Two row-standardized methods were used to construct matrices for each residential property, *k*-nearest neighbors (i.e., 4-nearest neighbors) and specific distance-based neighbors (i.e., within 1-mi buffer zone). Figure 1 illustrates these two methods for a sample property sold in southwest Portland. Figure 1*a* shows that the sale price of the subject property was influenced most heavily by the nearest four or six properties sold in the specified time frame. Figure 1*b* shows the influence of all properties within a 1-mi or ½-mi buffer zone around the subject property. Again, statistical tests were performed to determine the spatial weighting methodology.

To construct the data set for the estimations, residential property tax roll data from 2010 to 2013 were collected from Multnomah County (i.e., where Portland, Oregon is located). This study focused on the impact of bike facilities on residential properties, including single-family homes (SFHs) and multifamily homes (MFHs) (e.g., condominiums). Thus other property types were excluded. Distressed transactions (e.g., foreclosures, short sales), or other types of transactions that were not at arm's length, also were excluded, because they would not have accurately reflected the actual property values. The distribution of property sale transactions and sale prices are shown in Figure 2. SFH transactions occurred relatively evenly throughout the City of Portland, whereas MFH transactions were much more concentrated in the city center with relatively higher sales prices.

With the geolocation of each property, other regional and bike facility characteristics were joined spatially. To capture school quality,

Row-standardized weighting matrix for property

ID #	1	2	3	4	5	6
K = 4	0.25	0.25	0.25	0.25	0	0
K = 6	0.17	0.17	0.17	0.17	0.17	0.17

(a)

Row-standardized weighting matrix for property

ID #	1	2	3	....	85	...	372
D = 0.5 mi	0.012	0.012	0.012	0.012	0.012	0	0
D = 1 mi	0.003	0.003	0.003	0.003	0.003	0.003	0.003

(b)

FIGURE 1 Spatial weighting matrix diagrams for two neighboring methods: (*a*) *k*-nearest neighbors and (*b*) specific distance-based neighbors (• = properties sold, 2010 to 2013).

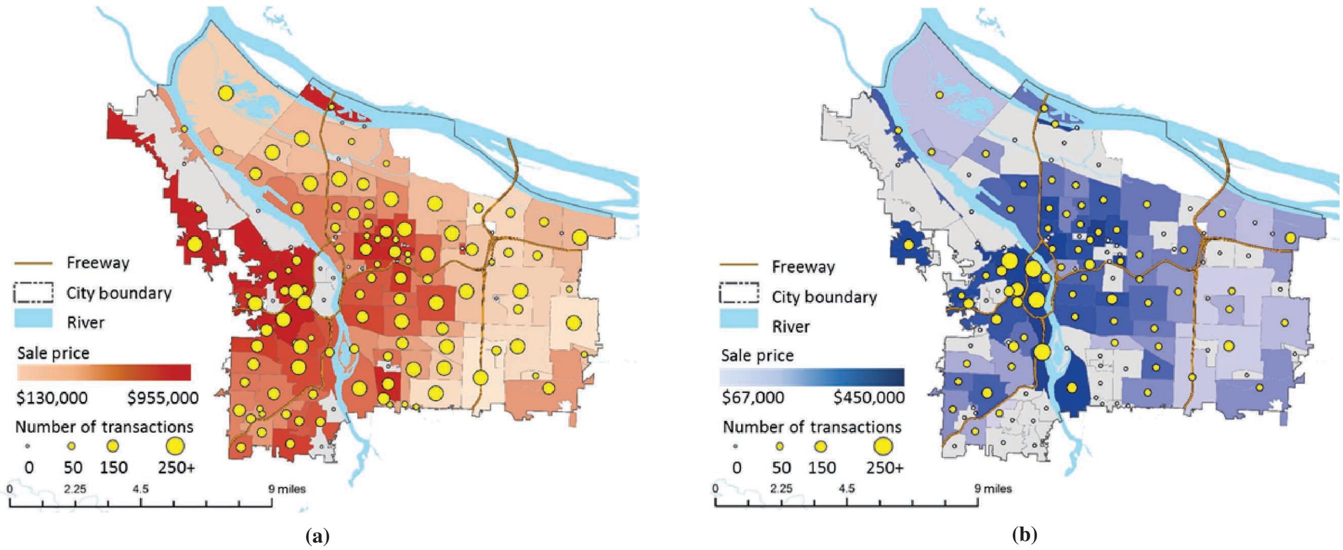

FIGURE 2 Distribution and values of property transactions by neighborhoods (2010 to 2013): (*a*) SFHs and (*b*) MFHs.

each property was assigned an elementary school catchment area in which the average was adjoined of state-published reading and math scores (measured by the percentage of students who exceeded state standards in the catchment area). Safety was represented by crime rates (i.e., number of crimes per 1,000 residents in 2012), and was incorporated from a neighborhood incidence of crime data set from the Portland Police Bureau. Each property was matched spatially with (*a*) the distance to the central business district, which represented access to jobs and other central city amenities, and measured as the distance from each neighborhood centroid to Portland downtown, and (*b*) the access to walking-distance neighborhood amenities from a proprietary source (i.e., walk score application). Because residential property sales were affected not only by overall economic and market conditions but also by seasonality, a sale year and a sale season variable (i.e., June to September nonrainy season) were incorporated to capture these trends in the market (*30*).

In addition to property characteristics (e.g., square footage and building age), a property tax measure was calculated, which was an assessed value to real market value (AV/RMV) ratio that described the percentage of a property's real market value on which property taxes were assessed. For example, a property with a 0.60 AV/RMV ratio will be assessed property taxes only on 60% of its real market value, which represents a significant tax advantage over that of a similar property with a ratio of 0.90. Liu and Renfro showed that the AV/RMV ratio was a significant determinant of property sale prices (*28*).

In general, there are two broad categories of bike facilities: (*a*) off-street paths, which include exclusively off-road bicycle facilities and multiuse paths used jointly by all nonmotorized modes; and (*b*) on-street facilities (e.g., simple striped bike lanes, separated bike lanes, bike boulevards). Studies have shown that cyclists prefer separated bike lanes to striped bike lanes (with simple striping and no additional separation between cyclists and vehicular traffic), and more advanced bike facilities may attract bicyclists to detour from the most direct route to take advantage of such facilities (*7, 27, 31*). The present study focused on the property value impacts of advanced bike facilities, including cycle tracks (i.e., separated bike lanes), buffered bike lanes, and bike boulevards within the context of Portland.

Two key variables were constructed to represent advanced bike facility characteristics at each property: (*a*) the distance to the nearest advanced bicycle facility and (*b*) the advanced bike facility density within a ½-mi radius [½ mi is a commonly used buffer zone distance used to measure bike facility accessibility in bike and greenway studies (*1*)]. The first variable represented the availability and ease of access from each property, and the second variable represented the extent of the network around the property. Figure 3 shows the geographic distribution of these facilities in Portland (i.e., distance to nearest facility and density of bike facilities). On average, the properties were only 0.68 mi (3,602 ft) away from the nearest advanced bike facility and had access to more than 0.74 mi (3,896 ft) facilities within a ½-mi radius. However, the spatial distribution was uneven within the city boundaries and dropped off significantly along the edges of the city.

Table 1 presents descriptive statistics on characteristics with respect to transactions, property, the region, and bicycle facilities. During the 2010 to 2013 time period, 20,122 residential property sales transactions occurred in Portland, at an average price of $303,834. SFHs tended to garner higher prices and were larger, older, and had lower AV/RMV ratios than MFHs. The MFHs that sold tended to be located in the central part of the city, with better walkability and access to city center amenities but with higher crime rates. In large part because of the concentration of MFHs in central locations with higher density, MFHs tended also to have better access to advanced bike facilities (i.e., at a shorter distance) and a denser network of facilities.

FINDINGS

A pooled OLS hedonic price regression was first conducted on all residential property sales. However, the Chow test ($F = 53.05$, $p < .01$) indicated the existence of structural change between the determinants of SFH and MFH values, and supported separate SFH and MFH property type restricted models. As shown in Table 2, in Models 1 and 2 (SFH.1 and MFH.1), the specifications included transaction characteristics (i.e., sale year and seasonality fixed effects),

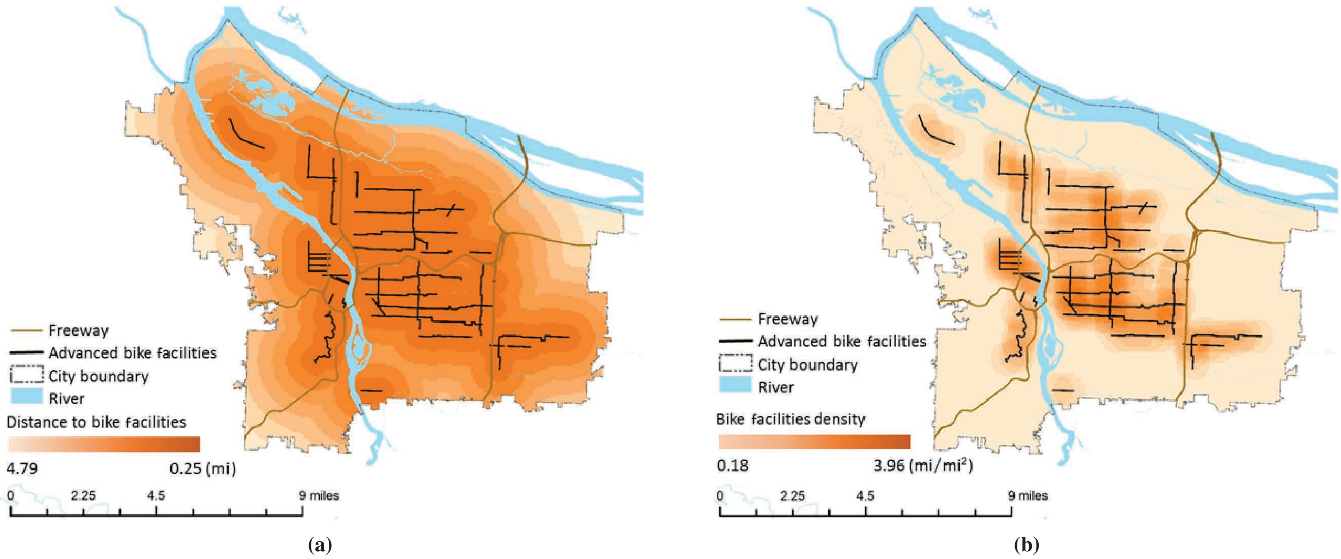

FIGURE 3 Distribution of advanced bike facilities in Portland: (*a*) distance to nearest advanced bike facilities and (*b*) density of advanced bike facilities.

property characteristics, regional characteristics, and bicycle facility characteristics. In Models 3 and 4 (SFH.2 and MFH.2), neighborhood fixed effects were introduced to control for any unobserved heterogeneity across neighborhoods as an alternative to the regional variables that were calculated at the neighborhood scale (e.g., crime rate, walk score, distance to central business district). The *R*-squared values ranged from 0.728 to 0.821 for these estimated models, which indicated that the specifications described approximately between 72.8% and 82.1% of the property sale price variation.

As expected, residential property values were affected positively and were statistically significant with respect to property size, proximity to the central business district, and better school districts. Each additional square foot contributed between $128 and $231 of additional value, depending on the property type and model specification. Age contributed positively to property values in SFHs but was shown to have a negative impact on MFHs, possibly because of the inherent value of historical building structures, and also because older homes might be associated with larger lot sizes. The estimated coefficient for the AV/RMV ratio was statistically significant and negative for SFHs, which indicated that consumers were willing to pay higher prices for properties that had relatively lower property tax liabilities. The property tax effect did not appear to be significant for MFHs, possibly because of the much smaller range of AV/RMV ratios that existed in this property type, which tended to be newer

TABLE 1 Descriptive Statistics

Variable	Overall Average	SFH	MFH
Number of observations, *n*	20,122	17,163	2,959
Transaction characteristics			
Sale price ($)	303,834 (20,000–2,700,000)	312,639 (20,000–2,700,000)	252,764 (23,834–1,560,000)
Sale year (mode)	2013	2013	2012
Seasonality—transactions between June and September (%)	36.9	37.2	35.3
Property characteristics			
Age of property (years)	60.27 (0–148)	65.13 (0–148)	32.04 (1–130)
Size of property (ft^2)	1,636 (275–9,552)	1,726 (339–9,552)	1,110 (275–4,830)
AV/RMV ratio	65.19 (8–100)	62.83 (8–100)	78.61 (27–100)
Regional characteristics			
School quality—out of 100	71.07 (27–93)	69.35 (27–93)	81.04 (27–93)
Distance to CBD (mi)	4.2 (1–9.5)	4.5 (1–9.5)	2.8 (1–9.5)
Walk score—out of 100	63.82 (6–97)	61.73 (6–97)	75.93 (6–97)
Crime rate per 1,000 residents	81.87 (10–1270)	70.3 (10–1270)	148.6 (10–1270)
Bicycle facility characteristics			
Distance to nearest bike facility (ft)	3,602 (29–21,206)	3,755 (40–21,206)	2,713 (29–20,523)
Bike facility length (ft)	3,896 (0–18,896)	3,661 (0–18,796)	5,260 (0–18,896)

NOTE: CBD = central business district. Values in parentheses represent the minimum and maximum values of each variable.

TABLE 2 OLS Hedonic Regression Model Results

Variable	SFH.1, Model 1	MFH.1, Model 2	SFH.2, Model 3	MFH.2, Model 4
Number of observations, *n*	17,163	2,959	17,163	2,959
Property characteristics				
Age of property (years)	281.04***	−377.60***	52.53*	−307.91***
	(29.65)	(45.91)	(27.83)	(44.09)
Size of property (ft^2)	151.26***	230.53***	128.31***	228.18***
	(1.02)	(2.93)	(1.02)	(2.75)
AV/RMV ratio	−410.67***	−64.70	−325.38***	90.90
	(61.92)	(114.75)	(75.96)	(114.26)
Regional characteristics				
School quality—out of 100	1,274.47***	639.54***	694.55***	735.34***
	(59.42)	(177.81)	(84.54)	(309.19)
Distance to CBD (mi)	−22,880.47***	−23.982.46***	na	na
	(645.19)	(1,477.44)		
Walk score—out of 100	−678.66***	531.40***	na	na
	(72.82)	(102.22)		
Crime rate per 1,000 residents	−141.28***	−31.67***	na	na
	(17.53)	(10.01)		
Bicycle facility characteristics				
Distance to nearest bike facility (ft)	−0.52**	−0.05	−0.08	−0.12
	(0.27)	(0.53)	(0.519)	(1.46)
Bike facility length (ft)	3.06***	3.57***	2.60***	0.46
	(0.23)	(0.36)	(0.36)	(0.51)
Transaction characteristics				
Sale year (2011)	−13,524.15***	−16,680.44***	−16,236.90***	−19,900.66***
	(2,229.85)	(4,006.72)	(2,032.73)	(3,644.53)
Sale year (2012)	−4,232.12**	−10,207.24**	−6,162.62***	−15,395.83***
	(2,139.88)	(4,076.16)	(1,999.65)	(3,783.18)
Sale year (2013)	25,370.05***	10,082.32***	24,134.58***	6,779.81*
	(2,090.80)	(3,935.21)	(1,925.55)	(3,643.04)
Nonrainy season	11,919.76***	10,489.90***	10,227.27***	9,958.70***
	(1,486.17)	(2,692.89)	(1,321.68)	(2,428.24)
Constant	107,871.30***	−24,196.06	155,495.40***	−17,785.11
	(9,279.54)	(20,469.20)	(10,827.44)	(68,827.13)
R^2	.728	.767	.788	.821
Adjusted R^2	.728	.766	.786	.816

NOTE: na = not applicable; dependent variable is property sale price. Neighborhood fixed-effect coefficients are omitted for space in Models 3 and 4. Chow test is an econometric test that determines whether the coefficients in two linear regressions have differential impacts on different subgroups of the population. Chow test of the SFH and MFH models is significant, which indicates that the independent variables do have differential impacts on SFH and MFH property values. Therefore, this indicates the need to separate residential property sales into two groups to model the exact magnitude of impacts of each independent variable for the two residential types.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

and less subject to large variations in property tax liabilities. Higher crime rates were negatively associated with property values, which indicated a clear preference for neighborhood safety. Higher walk scores, however, were negatively correlated with SFH property values and positively correlated with MFH property values. This finding revealed an inherent difference in the preferences for the density of neighborhood amenities within walking distance (e.g., SFH buyers put higher value on privacy near their homes) or in differences in transportation patterns (e.g., SFH owners may drive more) between buyers of the two property types. Sale year fixed-effect coefficients showed that the real estate market dipped in 2011 compared with 2010 (base year) but indicated a recovery in property prices, which started in 2012 and 2013. Homes that sold between June and September (i.e., Portland's nonrainy season) tended to garner a price premium of $9,959 to $11,920 above those sold during the rainy season.

Closer proximity to advanced bike facilities and access to a denser network of these facilities within a ½-mi radius tended to contribute positively to property values. Each ¼ mi closer to the nearest facility represented a $686 premium for SFHs and $66 for MFHs (although for MFHs the effect was not statistically significant in this specification). In addition, an increase in the density of advanced bike facilities by a ¼ mi within a ½-mi radius of a property translated to approximately $4,039 and $4,712 in value for SFHs and MFHs, respectively. These effects were attenuated when neighborhood fixed effects were introduced in Models 3 and 4, which indicated that the neighborhood coefficients were capturing some of the price premiums from bike facilities, because properties within certain neighborhoods might have had homogeneous access to bike facilities. The estimations showed that bike facility network density played a more significant role in determining property values than simple proximity to facilities.

Given the risks of biased or inefficient coefficient estimates in the OLS model described earlier, the Lagrange multiplier test was used to identify spatial autocorrelation effects in the OLS model and to determine the appropriate SAR specifications. The test is commonly used in spatial econometric contexts, because the actual estimation of the spatial (unrestricted) model is not required to test for differences between the restricted OLS model and unrestricted spatial model (*22, 32*). Two spatial weighting matrix methods (i.e., 4-nearest neighbors and 1-mi-distance neighbors) also were tested. The tests showed significant autocorrelation in lag term and error term in both the SFH and MFH models. It was found that spatial lag autocorrelation was stronger for SFHs, while spatial error autocorrelation was stronger for MFHs. As hypothesized, these test results indicated that it was indeed necessary to estimate spatial regression models to avoid overestimation of the coefficients. Models 1 and 2 were augmented with spatial autocorrelation terms. The results from a spatial lag model for SFHs (SFH.SAR or Model 5) and a spatial error model for MFHs (MFH.SAR or Model 6) are shown in Table 3. For both models, statistical tests (i.e., Akaike information criterion; log likelihood ratio) supported employment of the 4-nearest neighbors method to construct the spatial weighting matrix, which meant that the sale prices of the four nearest properties sold tended to have the largest impacts on the property price. The Akaike information criterion and log likelihood ratios shown at the bottom of Table 3 further demonstrate that the spatial models showed better goodness of fit than the OLS models.

Compared with Models 1 to 4, the estimated coefficients of the SAR models in general showed the same signs, although with smaller magnitudes, which reinforced the assertion that OLS specifications tended to overestimate the effects of variables on property value. Again it was found that closer proximity to advanced bike facilities and access to a denser network of these facilities within a ½-mi radius tended to contribute positively to property values. For SFHs, each ¼ mi closer to the nearest advanced bike facility increased the property value by $1,571. An additional ¼ mi of facility density increased values by $1,399. MFHs gained only $211 for each ¼ mi of proximity to advanced bike facilities. However, they experienced a large increase of $3,683 with an additional ¼ mi of facility density within their buffer zone. These coefficient estimates showed that access to advanced bike facilities translated to statistically significant positive price premiums on all residential properties. For MFHs, however, the density of the bike network played a much more significant role in determining property values than proximity to facilities. Through incorporation of spatial autocorrelation, the coefficient estimates appeared to be more robust, with improvements to the overall model fit compared with the OLS models, which the Akaike information criterion and log likelihood ratios (typical goodness-of-fit tests for spatial models) show at the bottom of Table 3.

TABLE 3 SAR Hedonic Model Results

Characteristic	SFH.SAR, Model 5	MFH.SAR, Model 6
Number of observations, *n*	17,163	2,959
Property characteristics		
Age of property (years)	95.64***	−304.45***
	(20.41)	(44.94)
Size of property (ft^2)	117.64***	228.38***
	(0.99)	(2.99)
AV/RMV ratio	−326.87***	104.47
	(48.45)	(119.95)
Regional characteristics		
School quality—out of 100	516.87***	461.06
	(41.64)	(188.41)
Distance to CBD (mi)	−10,393.59***	−25,713.60***
	(438.66)	(2,562.96)
Walk score—out of 100	−10.93	461.06**
	(–)	(188.41)
Crime rate per 1,000 residents	−71.45***	−26.85
	(11.86)	(19.51)
Bicycle facility characteristics		
Distance to nearest bike facility (ft)	−1.19***	−0.16
	(0.17)	(0.99)
Bike facility length (ft)	1.06***	2.79***
	(0.17)	(0.67)
Transaction characteristics		
Sale year (2011)	−13,422.31***	−16,096.37***
	(1,959.80)	(3,143.64)
Sale year (2012)	−4,347.16**	−9,778.45***
	(1,750,70)	(3,330.92)
Sale year (2013)	25,544.81***	14,283.81***
	(1,796.51)	(3,185.97)
Nonrainy season	10,118.49***	7,877.64***
	(1,285.99)	(2,032.32)
Constant	5,375.05***	−9,875.86
	(1,347.15)	(34,235.05)
AIC (AIC for OLS models)	437,438	73,253
	(441,577)	(74,396)
Log likelihood (log likelihood for OLS models)	−218,703	−36,612
	(−220,773)	(−37,181)

NOTE: AIC = Akaike information criterion; dependent variable is property sale price.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

POLICY APPLICATION AND DISCUSSION

To illustrate the policy applicability of this research as a tool in the decision-making and resource-allocation processes, estimated coefficients were applied to a scenario with a proposed 6-mi signature active transportation infrastructure concept, the Portland Green Loop. The Green Loop fits well into the definition of advanced bike facilities, with its high levels of infrastructure investment to provide separated bike lanes and bike paths, and connections through existing or proposed parks and other safety improvements such as traffic signals and lighting.

Multnomah County certified tax rolls were used for all residential properties in 2013 (i.e., 174,453 properties: 156,052 SFHs and 18,401 MFHs). The study found that the Green Loop either decreased the proximity to the nearest advanced bike facility or increased the density of the bike facility network for 12,135 households. Although the additional infrastructure did not translate into large changes in proximity to the nearest bike facility for most properties, it did significantly increase the density of bike facility length within a ½-mi buffer zone of each property. In other words, more potential impacts would be expected to result from the increase in the bike facility network density rather than from ease of access.

The application of coefficient estimates from the OLS and SAR model specifications for SFHs and MFHs (i.e., Models 1, 2, 5, and 6) showed that the introduction of the Green Loop in general would increase property values. The OLS models predicted average increases of approximately 1.77% for SFHs and 8.22% for MFHs, while SAR models predicted attenuated increases of 1.02% and 6.42% for the two property types, respectively. Because the Green Loop is designed as a city center infrastructure investment, the geographic distribution of the residential property value impacts tended to be more concentrated in the city center (Figure 4). In addition, only very limited numbers of SFHs were located in these neighborhoods. By contrast, more than half of all MFHs in the city were located within the range of impact of the Green Loop, which accentuated

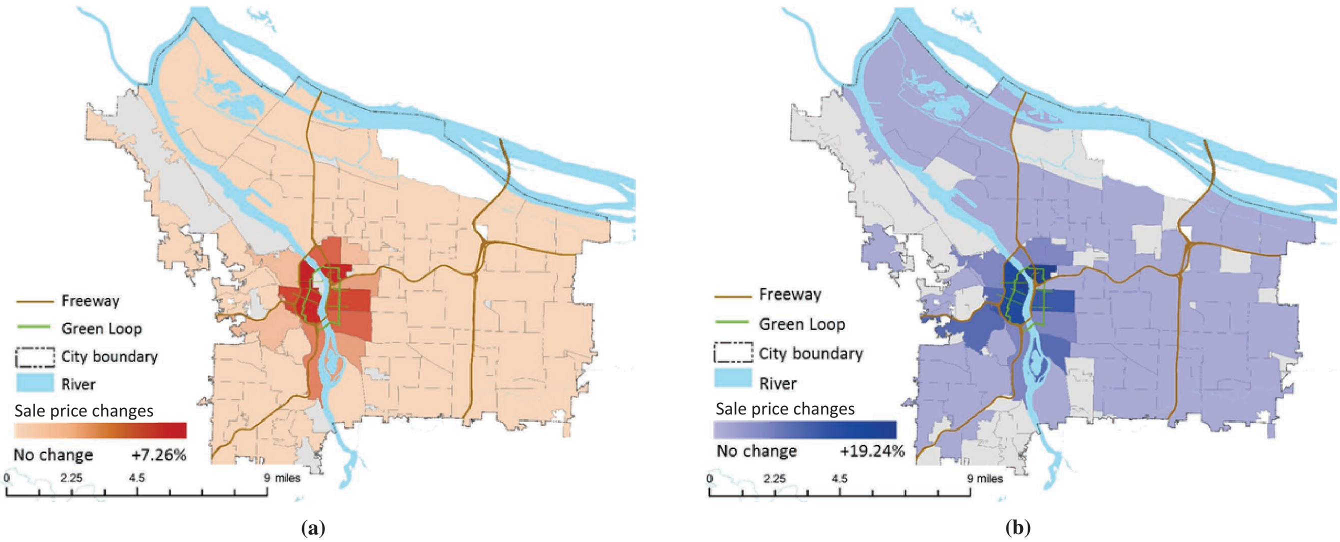

FIGURE 4 Geographic distribution of estimated property value impacts of proposed Portland Green Loop concept: (*a*) SFHs and (*b*) MFHs.

further the potential real estate market impact of such a large-scale project.

CONCLUSION

Many cities are investing in street improvement and infrastructure upgrade projects to provide better bike access and more complete bike networks. Still, consumer preferences and the economic value of bike infrastructure and bike facilities remain lingering questions, which many practitioners, planners, and policy makers are struggling to answer. The importance of public amenities (e.g., proximity to green space, transportation networks, school quality) in the determination of property value is well documented. However, fewer studies have delved into understanding how households value access to urban greenways or on-street bike facilities through the impact on property values. The present study focused on examining the relationship between advanced bike facilities, which tend to attract larger numbers of users, and the impact on residential property values. The study further contributed to the research literature through the use of two measures of these facilities that may affect property values: ease of access (distance) and extensiveness of bike network (density).

After it was found that the determinants of SFH and MFH property values were structurally different, the study proceeded to estimate separate OLS hedonic pricing models in Portland, Oregon, and to control for property, regional, transaction, and bike facility characteristics, including distance and density measures. It was found that proximity to advanced bike facilities had significant and positive effects on SFH and MFH property values, which was consistent with earlier research. The results also showed that the extensiveness of the bike network was a positive and statistically significant contributor to the property prices for all property types, even after controlling for proximity to bike facilities and other internal and external variables. The model specifications then were enhanced with spatial autocorrelation effects to prevent overestimation. They yielded similar but slightly tempered positive and statistically significant impacts of proximity and density of advanced bike facilities on residential property values.

It is hoped that these study results will provide essential information to aid those who seek to make policy or resource allocation decisions. However, caution is urged against the inference of causal relationships from these findings. Further research is necessary to establish the pre- and posttreatment effects from different types of bike facility investments. The study was able to define advanced bike facilities within the context of Portland, Oregon. However, a precise and comprehensive definition of what constitutes different levels of infrastructure investment or bike facility desirability is likely to be necessary to further validate the research methodology across multiple urban areas. Finally, the incorporation of additional bike facility types (i.e., on-street and off-street trails) into sensitivity analysis of different buffer zone distances will further contribute to a better understanding of how these infrastructure improvements provide value to urban residents.

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