IMPACT OF BIKE FACILITIES ON RESIDENTIAL PROPERTY PRICES

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Word count: 4,903 words text + 8 tables/figures x 250 words (each) = 6,903 words

Submission Date: August 1, 2016
Revision Date: November 14, 2016

ABSTRACT

As many cities are investing in street improvement or transportation infrastructure upgrade projects to provide better bike access or more complete bike networks, the economic value of bike infrastructure and bike facilities remains an area where many practitioners, planners and policy makers are seeking more conclusive evidence. Using residential property values as indicators of consumer preferences for bicycle infrastructure, many scholars have shown the importance of greenspaces and off-street bike trails as valuable amenities to property owners. However, empirical evidence regarding the relationship of on-street bike facilities and property values remains relatively inconsistent.

This study unique focuses on advanced bike facilities which represent higher levels of bike priority or bike infrastructure investments that have been shown to be more desirable to a larger portion of the population. Estimating ordinary least squares hedonic pricing models and spatial autoregressive hedonic models separately for single and multi-family properties, we find that proximity to advanced bike facilities (measured by distance) has significant and positive effects on all property values, highlighting household preferences for high quality bike infrastructure. Furthermore, we also show that the extensiveness of the bike network (measured by density) is a positive and statistically significant contributor to the property prices for all property types, even after controlling for proximity to bike facilities and other property, neighborhood and transaction characteristics. Finally, estimated coefficients are applied to assess property value impacts of a proposed Portland "Green Loop" signature bike infrastructure concept, illustrating the importance of considering both accessibility and extensiveness of bike facility networks.

Keywords: Bike Facilities, Property Value, Hedonic Model, Spatial Analysis, Economic Impacts

INTRODUCTION

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. The importance of public amenities such as proximity to green spaces, transportation networks (i.e., airports, highways or rail stations, etc.) and school quality in determining property value has been widely discussed in urban economics, planning and real estate research. However, the specific contribution of bike infrastructure and bike facilities to residential property values is relatively undocumented or inconsistent, presenting difficulties in justifying further allocations of resources towards high quality bicycle-related infrastructure.

Relevant research in this area generally focus 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 usage (e.g., walking, biking, running), active transportation-related public health benefits *(3)*, or mode shift-related transportation benefits resulting from new bike lanes or improvements to existing facilities *(4–7)* such as congestion relief, greenhouse gas emissions or noise reductions. 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 extensiveness of the nearby bike facility network should be key determinants of residential property values. In other words, residential property values may serve as indicators of consumer preference for bicycle infrastructure.

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

This study contributes to the existing literature by not only examining the relationship between advanced bike facilities (defined as bike-priority facilities and separated bike lanes) and residential property values, but also by focusing on two major components of bike priority facilities: ease of access (distance) and extensiveness of bike network (density). We begin with a brief summary of the relevant literature and methodologies. Then, we present the results of both a hedonic pricing model and spatial autoregressive models applied in Portland, Oregon. We present an illustration of how the modeling results may be applied to estimate property value impacts of a proposed Portland "Green Loop" concept. Finally, we conclude with a discussion of the policy implications of our research and future research directions.

LITERATURE REVIEW

Although this paper focuses on the property value impacts of bike facilities, it is important to understand the various other determinants of residential home prices to appropriately account for them. Applying Rosen's *(11)* hedonic (or implicit) pricing framework, Mohammad et al. *(12)* categorize three classes of contextual factors that influence property value: economic factors such as supply and demand or economic conditions; internal factors such as size, age or quality of the property; and external factors that may include location, surrounding amenities and transportation network. A large literature of empirical studies investigates how a combination of these factors may impact residential property values *(13, 14)*, and many document 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 *(19)*, where consumers' and businesses' willingness-to-pay for a property is inversely proportional to its distance to destinations such as the central business district (CBD). Researchers such as Ryan *(20)* and Duncan *(21)* illustrate the potential property value impacts of access to transportation facilities, but much of the research emphasis is placed on access to highways, heavy rail, or light rail. Although empirical evidence generally points to positive or neutral property value impacts as the result of proximity to greenspaces or off-street recreational trails *(1, 2, 22)*, we find relatively scant empirical evidence that specifically investigate the property value impacts of on-street bike facilities *(23)*.

Hedonic pricing analysis, a multivariate regression methodology, is the predominant technique for estimating the marginal implicit prices of property characteristics and amenities. Lindsey et al. *(1)* apply the hedonic price model to three Indianapolis greenway corridors, and find that, in two out of the three modelled corridors, property values show significant and positive impacts when located within a half-mile buffer from the greenways. Utilizing a similar methodological framework in San Antonio, Texas, Asabere and Huffman *(2)* also find that homes near or abutting trails, greenways, and trails with greenbelts are correlated with 2% to 5% price increases. Similar positive property value impacts are found when utilizing street network distance as an alternative measure for proximity and access to greenbelts in Austin, Texas *(24)*. Recent studies expand upon previous hedonic price models by controlling for spatial autocorrelation effects between greenspaces and property values – that is, the correlation between the values of neighboring homes or likelihood of greenspaces. Studies such as Conway et al. *(22)* and Parent and Hofe *(25)* find that proximity to greenspaces or bike trailheads have significant and positive impact on residential property values, even after controlling for spatial autocorrelation effects.

Krizek *(26)* and Welch et al. *(23)* represent examples of the scarce literature that employ hedonic models to examine the differential property value impacts of various types of bike facilities such as off-street trails, on-street facilities, or multi-use paths. While Krizek's *(26)* hedonic pricing models suggest proximity to bike trails and on-street bike facilities in suburban areas negatively impacts home values and no impact from other types of bike facilities in Minneapolis, Welch et al. *(23)* utilize a longitudinal spatial hedonic model in Portland, Oregon to show that shorter distances to off-street trails have positive property value impacts compared to negative impacts stemming from proximity to on-street bike lanes.

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

METHODOLOGY & DATA

Following the existing literature, this study first utilizes a general hedonic price specification in order to characterize the impacts of various factors on residential property values utilizing data from Portland, Oregon. The model is then tested for spatial effects (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 further away. Finally, the coefficient estimates of the models are applied to a proposed bike infrastructure investment in Portland to illustrate the magnitude and distribution of property value impacts in a policy context.

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

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

The dependent variable, P_i, represents property sale price. T_i is a vector that includes transaction characteristics such as year and season of the sale, serving as proxies for general economic factors; H_i is a vector of internal property characteristics such as age, size and property tax liability of the property; R_i is a vector of external neighborhood or regional characteristics such as school quality or crime rate; and B_i represents a vector of bike facility characteristics. This specification exclusively incorporates property tax characteristics due to 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, we incorporate neighborhood fixed-effects into the OLS specifications to capture inherent neighborhood differences that may contribute to property value differences, but are not captured through the existing variables. Each of the estimated coefficients describes the marginal value to the homeowner of amenities in each vector.

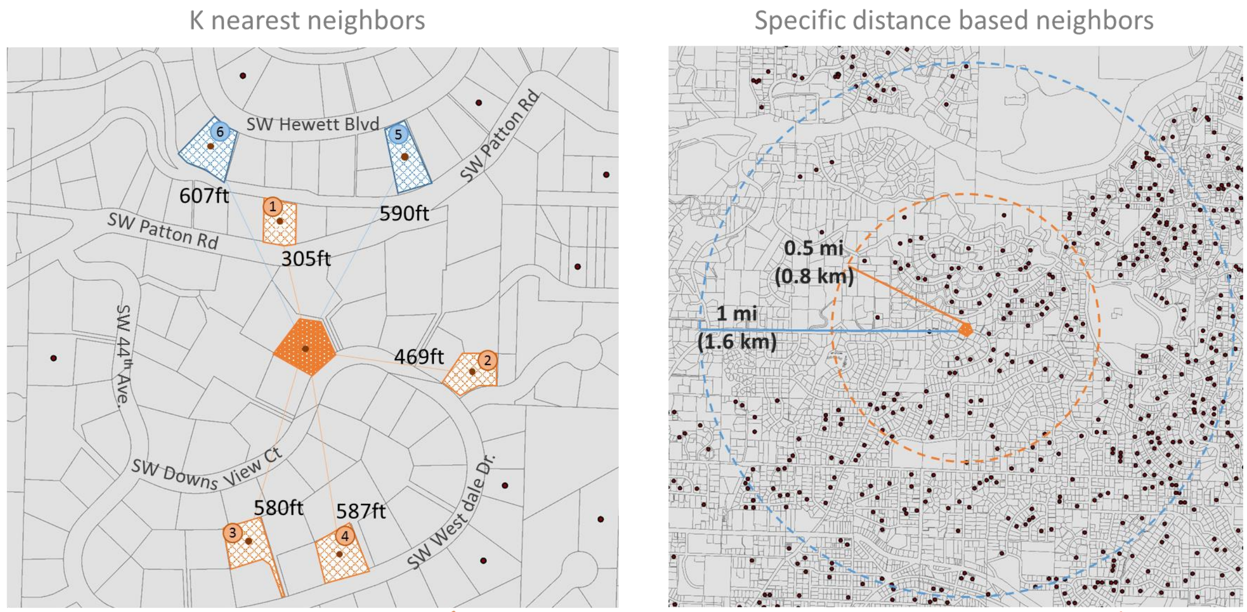
Although many of the variables utilized in residential property value hedonic models are spatial by definition, homebuyers, real estate professionals and many scholars *(22, 29)* have asserted that home values are often heavily influenced and determined by the sale prices of nearby properties. This spatial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

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

where ρWY is the spatially lagged dependent variable that represents the omitted variable in the regression model, p is the spatial lag parameter, and W is the spatial weighting matrix that represents the interaction between different locations *(22)*. 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 ($\varepsilon = \lambda W\varepsilon + v$). λ represents the spatial error parameter, $W\varepsilon$ is the spatial error, interpreted as the mean error from neighboring locations, and v is the independent model error *(22, 29)*. Lagrange multiplier (LM) tests are conducted to identify the appropriate SAR models. Another key consideration is 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 are utilized to construct matrices for each residential property, k-nearest neighbors (i.e., 4-nearest neighbors) and specific distance based neighbors (i.e., within 1 mile buffer zone). Figure 1 illustrates these two methods for a sample property sold in southwest Portland, where the left sub-figure shows that the sale price of the subject property is most heavily influenced by the nearest four or six properties sold in the specified timeframe, and the right sub-figure shows the influence of all properties within a one-mile or half-mile buffer zone around the subject property. Again, statistical tests are performed to determine the spatial weighting methodology.



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

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

• Properties sold between 2010-2013

FIGURE 1. Spatial Weighting Matrix Diagrams for Two Neighboring Methods

In order to construct the dataset for our estimations, Multnomah County (where Portland, Oregon is located) residential property tax roll data from 2010-2013 was collected. This study focuses on the impact of bike facilities on residential properties, including both single-family homes and multi-family homes (condominiums), so other property types were excluded in our study. Distressed transaction such as foreclosures, short sales, or other types of non-"arm's length" transactions were also excluded since they do not accurately reflect the actual property values. The distribution of property sale transactions and sale prices are shown in Figure 2. Single-family home (SFH) transactions occurred relatively evenly throughout the City of Portland, whereas multi-family home (MFH) transactions are much more concentrated in the city center with relatively higher sale prices.

Using the geo-location of each property, other regional and bike facility characteristics are spatially joined. In order to capture school quality, each property is assigned an elementary school catchment area where the average of state-published reading and math scores (measured by the percentage of students exceeding state standards in the catchment area) is adjoined. Safety, represented by crime rates (number of crimes per 1000 residents in 2012), is incorporated from a neighborhood incidence of crime dataset from the Portland Police Bureau. The distance to CBD, representing access to jobs and other central city amenities and measured as the distance from each neighborhood centroid to Portland downtown, and Walk Score®, representing access to walking-distance neighborhood amenities from a proprietary source, are both spatially matched to each property. Additionally, because residential property sales are affected by overall economic and market conditions as well as seasonality *(30)*, a sale year and a season of sale variable (non-rainy season is defined as June to September) are incorporated to capture these trends in the market.

In additional to property characteristics such as square-footage and building age, we calculated a property tax measure, an assessed value to real market value ratio (AV/RMV ratio) that describes the percentage of a property's real market value on which property taxes are assessed. For example, a property with a 0.60 AV/RMV ratio will only be assessed property taxes on 60% of its real market value, which represents a significant tax advantage compared to a similar property with an AV/RMV ratio of 0.90. Liu and Renfro *(28)* showed that the AV/RMV ratio is a significant determinant of property sale prices, even after controlling for all other characteristics.

In general, there are two broad categories of bike facilities: off-street paths, which include exclusively off-road bicycle facilities and multi-use paths jointly utilized by all non-motorized modes; and on-street facilities, which may include simple striped bike lanes, separated bike lanes, bike boulevards, etc. Studies showed that cyclists preferred 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 these facilities *(7, 27, 31)*. This study will focus on the property value impacts of "advanced bike facilities". In the context of Portland, advanced bike facilities include cycle tracks (also known as separated bike lanes), buffered bike lanes and bike boulevards (Figure 3).

Two key variables are constructed to represent advanced bike facilities characteristics at each property: distance to nearest advanced bicycle facility and advanced bike facility density within a half-mile radius (half-mile is a commonly used buffer zone distance for measuring bike facility accessibility in bike/greenways studies *(1)*). The first variable represents the availability and ease of access to advanced bike facilities from each property, and the second variable represents the extent of the advanced bike facility network around the property. Figure 4 shows the geographic distribution of advanced bike facilities in Portland (both distance to nearest facility and density of bike facilities). Although properties are, on average, only 0.68 miles (3,602 feet) away from the nearest advanced bike facility and have more than 0.74 miles (3,896 feet) of facilities within a half-mile radius, the spatial distribution of the bike amenities are not equally spread within the city boundaries, and drop off significantly along the edges of the city.

Descriptive statistics are shown in Table 1, including transaction characteristics, property characteristics, regional characteristics as well as bicycle facilities characteristics. During the 2010-2013 time period, a total of 20,122 residential properties were transacted in Portland, at an average price of $303,834. Single-family homes tend to garner higher prices, and are larger, older and have lower AV/RMV ratios when compared to multi-family homes. Multi-family homes sold tend 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 due to the concentration of multi-family homes in central locations with higher density, multi-family homes tend to also have better access to advanced bike facilities (shorter distance) and a denser network of facilities.

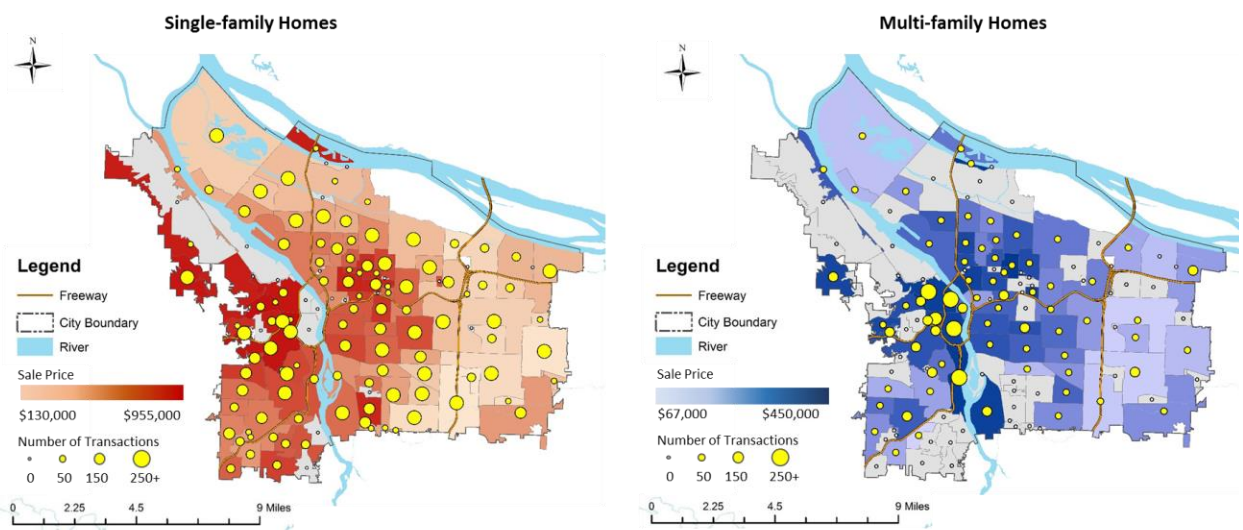


FIGURE 2. Distribution and Values of Property Transactions by Neighborhoods (2010-2013)

FIGURE 3. Types of Advanced Bike Facilities in Portland

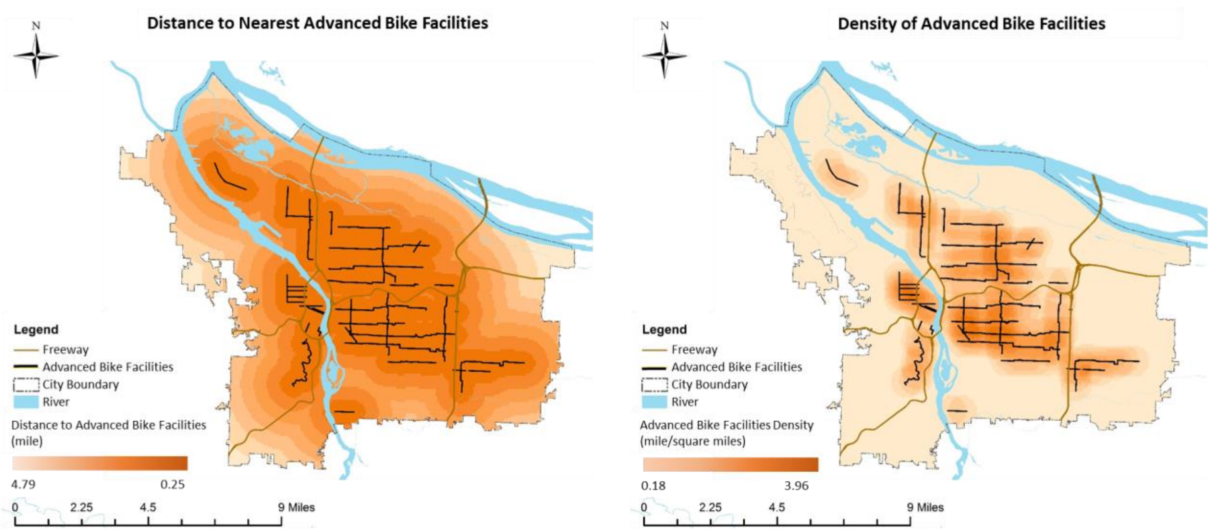


FIGURE 4. Distribution (distance to nearest and density) of Advanced Bike Facilities in Portland

TABLE 1. Descriptive Statistics

Variables	Overall Average (n=20122)	Single-Family Home (n=17163)	Multi-Family Home (n=2959)
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 (Percent of transactions between June to 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 (sqft)	1636 (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 1000 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: Values in parentheses represent the minimum and maximum values of each variable.

FINDINGS

A pooled OLS hedonic price regression was first conducted on all residential property sales. However, the Chow test (F = 53.05, $p<0.01$) indicated the existence of structural change between the determinants of single- and multi-family home values, and supported separate SFH and MFH property type restricted models. In Models 1 and 2 (SFH.I and MFH.I), the model specifications include transaction characteristics (sale year and seasonality fixed effects), property characteristics, regional characteristics and bicycle facility characteristics. In Models 3 and 4 (SFH.II and MFH.II), neighborhood fixed effects are introduced in order to control for any unobserved heterogeneity across neighborhoods as an alternative to the regional variables that are calculated at the neighborhood scale (e.g., crime rate, Walk Score and distance to CBD). R-squared values range from 0.728 to 0.821 for these estimated models, indicating that the specifications describe approximately between 72.8% and 82.1% of the property sale price variation.

As expected, residential property values are positively and statistically significantly impacted by its size, proximity to CBD and better school districts. Each additional square foot contributes between $128 and $231 of additional value, depending on the property type and model specification. Age contributes positively to property values in single family homes, but shows negative impacts on multi-family homes, potentially due to the inherent value of historical building structures, and also because older homes may be associated with larger lot sizes. The estimated coefficient for the AV/RMV ratio is statistically significant and negative for single family homes, indicating that consumers are willing to pay higher prices for properties that have relatively lower property tax liabilities (as a percentage of the real market value). The property tax effect does not appear to be significant for multi-family homes, possibly due to the much smaller range of AV/RMV ratios that exists in this property type (which tend to be newer and less subject to large variations in property tax liabilities). Higher crime rates is negatively associated with property values, indicating a clear preference for neighborhood safety. Higher Walk Scores, on the other hand, are negatively correlated with single family property values while positively correlated with multi-family property values. This represents 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 differences in the transportation patterns (e.g., SFH owners may drive more) between buyers of the two property types. Sale year fixed effect coefficients show that the real estate market dipping down in year 2011 compared to 2010 (base year), but indicate recovery in property prices starting in 2012 and 2013. Homes sold between June and September (considered to be the non-rainy season in Portland) tend to garner a price premium of $9,959 to $11,920 compared to those sold during the rainy season.

Being closer to advanced bike facilities and having access to a denser network of these facilities within a half-mile radius tend to contribute positively to property values. Each quarter mile closer to the nearest advanced bike facility represents a $686 premium for single family homes and $66 for multi-family homes (although the MFH effect is not statistically significant in this specification). In addition, increasing the density of advanced bike facilities by a quarter mile within a half-mile radius of a property translates to approximately $4,039 and $4,712 of value for SFHs and MFHs respectively. These effects are attenuated when neighborhood fixed effects are introduced in Models 3 and 4, indicating that the neighborhood coefficients are capturing some of the price premiums from bike facilities as properties within certain neighborhoods may have homogeneous access to bike facilities. The estimations show that bike facility network density plays a more significant role in determining property values than simple proximity to facilities.

TABLE 2. Ordinary Least Squares (OLS) Hedonic Regression Model Results (Dependent variable – property sale price)

	SFH.I (Model 1)	MFH.I (Model 2)	SFH.II (Model 3)	MFH.II (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 (sqft)	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 1000 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)
Non-rainy 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	0.728	0.767	0.788	0.821
Adjusted R^2	0.728	0.766	0.786	0.816

*** significant at 1% level; ** significant at 5% level; * significant at 10% level.

- Neighborhood fixed effect coefficients are omitted for space in Models 3 and 4.
- The Chow test is an econometric test that determines whether the coefficients in two linear regressions have differential impacts on different subgroups of the population. In our case, the 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.

Given the risks of biased or inefficient coefficient estimates in the OLS model described previously, we use the Lagrange Multiplier (LM) test to identify spatial autocorrelation effects in OLS model, and to determine the appropriate spatial autoregressive specifications. It is commonly used in spatial econometric contexts, since 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, 4-nearest neighbors and 1-mile distance neighbors, are also tested. The tests show significant autocorrelation in both lag term and error term in both single family and multi-family models, and we find that spatial lag autocorrelation was stronger for single family homes while spatial error autocorrelation was stronger for multi-family homes. As hypothesized, these test results indicate that it is indeed necessary to estimate spatial regression models to avoid overestimating the coefficients. Models 1 and 2 are augmented with spatial autocorrelation terms, and the results from a spatial lag model for single-family homes (SFH.SAR or Model 5) and a spatial error model for multi-family homes (MFH.SAR or Model 6) are shown in Table 3. For both models, statistical tests (Akaike information criterion and log-likelihood ratio) support employing the 4-nearest neighbors method to construct the spatial weighting matrix, which means that the sale prices of the four nearest properties sold tend to have the largest impacts on the property price. Akaike information criterion and log-likelihood ratios shown at the bottom of Table 3 further demonstrate that the spatial models show better goodness-of-fit when compared to the OLS models.

Compared with Models 1 to 4, the estimated coefficients of the spatial autoregressive models generally have the same signs although with smaller magnitudes, reinforcing the previous assertion that OLS specifications tend to overestimate the effects of variables on property value. We again find that being closer to advanced bike facilities and having access to a denser network of these facilities within a half-mile radius tend to contribute positively to property values. For single family homes, each quarter mile closer to the nearest advanced bike facility increases the property value by $1,571 and an additional quarter mile of facility density increases values by $1,399. On the other hand, multi-family homes gain only $211 for each quarter mile of proximity to advanced bike facilities, but experience a large increase of $3,683 with an additional quarter mile of facility density within its buffer zone. These coefficient estimates show that access to advanced bike facilities translate to statistically significant positive price premiums on all residential properties, but the density of the bike network plays a much more significant role in determining property values than proximity to facilities for multi-family homes. By incorporating spatial autocorrelation, the coefficient estimates appear to be more robust with improvements to the overall model fit when compared to the OLS models, as demonstrated by the Akaike information criterion and log-likelihood ratios (typical goodness-of-fit tests for spatial models) shown at the bottom of Table 3.

TABLE 3. Spatial Autoregressive (SAR) Hedonic Model Results
(Dependent variable – property sale price)

	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 (sqft)	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 1000 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)
Non-rainy 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	437438	73253
(AIC for OLS models)	(441577)	(74396)
Log-likelihood	-218703	-36612
(Log-likelihood for OLS models)	(-220773)	(-37181)

*** significant at 1% level; ** significant at 5% level; * significant at 10% level.

POLICY APPLICATION & DISCUSSION

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

Using Multnomah County certified tax rolls for all residential properties in 2013 (a total of 174,453 properties – 156,052 SFHs and 18,401 MFHs), we find that the Green Loop either decreases the proximity to nearest advanced bike facility or increases the density of the bike facility network for 12,135 households. Although the additional infrastructure does not translate to large changes in proximity to nearest advanced bike facility for most properties, it does significantly increase the density of bike facility length within a half-mile buffer zone of each property. In other words, we would expect more potential impacts to result from the increase in bike facility network density rather than from ease of access.

Applying coefficient estimates from both the OLS and SAR model specifications for both SFHs and MFHs (Models 1, 2, 5 and 6), we find that the introduction of the Green Loop generally increases property values. The OLS models predict average increases of approximately 1.77% for SFHs and 8.22% for MFHs, while SAR models predict 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 tends to be more concentrated in the city center as shown in Figure 5. In addition, only very limited numbers of single family homes are located in these neighborhoods, while more than half of all multi-family units in the city are located within the range of impact of the Green Loop, further accentuating the potential real estate market impacts of such large scale projects.

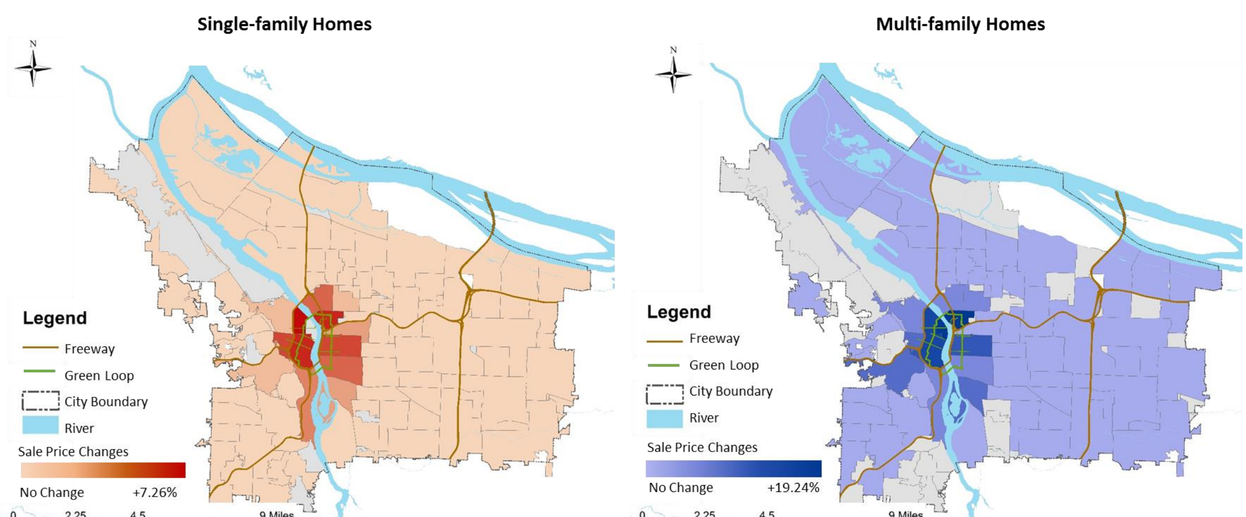


FIGURE 5. Geographic Distribution of Estimated Property Value Impacts of Proposed Portland "Green Loop" Concept

CONCLUSION

As many cities are investing in street improvement or transportation infrastructure upgrade projects to provide better bike access or more complete bike networks, the consumer preference and economic value of bike infrastructure and bike facilities remain as lingering questions that many practitioners, planners and policy makers are struggling to answer. Although the importance of other public amenities such as distance to green spaces, transportation networks and school quality in determining property value is well documented, fewer people have delved into understanding how households value access to urban greenways or on-street bike facilities via impacts on property values. In this study, we focus on examining the relationship between advanced bike facilities that tend to attract larger numbers of users and residential property values. We further contribute to the research literature by utilizing two measures of these bike priority facilities that may impact property values: ease of access (distance) and extensiveness of bike network (density).

After determining that the determinants of single family and multi-family property values are structurally different, we proceed with estimating separate ordinary least squares hedonic pricing models in Portland, Oregon, and control for property, regional, transaction and bike facility characteristics, including both distance and density advanced bike facility variables. We find that proximity to advanced bike facilities has significant and positive effects on both single family and multi-family property values, which is consistent with previous research. Our results also show that the extensiveness of the bike network is 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. Enhancing the model specifications with spatial autocorrelation effects to prevent overestimation yields similar but slightly tempered positive and statistically significant impacts of both proximity and density of advanced bike facilities on residential property values.

It is our hope that these study results will provide essential information to aid those seeking to make policy or resource allocation decisions. However, we caution against implying causal relationships from these findings because further research utilizing time series data will be necessary to establish the pre- and post-treatment effects from different types of bike facility investments. Although the authors have been able to define advanced bike facilities in the Portland context, a precise and comprehensive definition of what constitutes different levels of infrastructure investment or bike facility desirability is likely necessary to further validate the research methodology consistently across multiple urban areas. Finally, incorporating additional bike facility types (both on-street and off-street trails) with sensitivity analysis of different buffer zone distances will further contribute to a better understanding of how these infrastructure improvements provide value for urban residents.

ACKNOWLEDGEMENTS

This research is funded as part of the Portland Climate Action Collaborative, a research partnership between Portland State University's Institute for Sustainable Solutions (ISS) and Portland Bureau of Portland Sustainability (BPS). Many thanks to Joseph Broach, who provided us with bicycle infrastructure data. Our views do not necessarily reflect those of our sponsors and collaborators.

REFERENCES

1. Lindsey, G., J. Man, S. Payton, and K. Dickson. Property values, recreation values, and urban greenways. *Journal of Park and Recreation Administration*, Vol. 22, No. 3, 2004, pp. 69–90.
2. Asabere, P. K., and F. E. Huffman. The Relative Impacts of Trails and Greenbelts on Home Price. *The Journal of Real Estate Finance and Economics*, Vol. 38, No. 4, 2009, pp. 408–419.
3. Krizek, K. J. *Guidelines for analysis of investments in bicycle facilities (No. 522)*. Transportation Research Board, Washington, D.C, 2006.
4. Barnes, G., K. Thompson, and K. Krizek. A longitudinal analysis of the effect of bicycle facilities on commute mode share. Presented at the 85th Annual Meeting of the Transportation Research Board. Transportation Research Board, Washington, DC, 2006.
5. Dill, J., and T. Carr. Bicycle commuting and facilities in major US cities: if you build them, commuters will use them. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1828, 2003, pp. 116–123.
6. Nelson, A., and D. Allen. If you build them, commuters will use them: association between bicycle facilities and bicycle commuting. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1578, 1997, pp. 79–83.
7. Tilahun, N. Y., D. M. Levinson, and K. J. Krizek. Trails, lanes, or traffic: Valuing bicycle facilities with an adaptive stated preference survey. *Transportation Research Part A: Policy and Practice*, Vol. 41, No. 4, 2007, pp. 287–301.
8. Drennen, E. *Economic Effects of Traffic Calming on Urban Small Businesses*. Department of Public Administration San Francisco State University, 2003.
9. Flusche, D. *Bicycling Means Business: The Economic Benefits of Bicycle Infrastructure*. League of American Bicyclists, 2012.
10. Clifton, K., C. Muhs, S. Morrissey, T. Morrissey, K. Currans, and C. Ritter. *Customer Behavior and Travel Mode Choice*. 2012.
11. Rosen, S. Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy*, Vol. 82, No. 1, 1974, pp. 34–55.
12. Mohammad, S. I., D. J. Graham, P. C. Melo, and R. J. Anderson. A meta-analysis of the impact of rail projects on land and property values. *Transportation Research Part A: Policy and Practice*, Vol. 50, 2013, pp. 158–170.
13. Sirmans, S., D. Macpherson, and E. Zietz. The Composition of Hedonic Pricing Models. *Journal of Real Estate Literature*, Vol. 13, No. 1, 2005, pp. 1–44.
14. Harrison, D. J., and D. Rubinfeld. Hedonic Housing Prices and the Demand for Clean Air. *Journal of Environmental Economics and Management*, Vol. 5, No. 1, 1978, pp. 81–102.
15. Clapp, J. M., A. Nanda, and S. L. Ross. Which school attributes matter? The influence of school district performance and demographic composition on property values. *Journal of Urban Economics*, Vol. 63, No. 2, 2008, pp. 451–466.
16. Lynch, A. K., and D. W. Rasmussen. Measuring the impact of crime on house prices. *Applied Economics*, Vol. 33, No. 15, 2001, pp. 1981–1989.
17. Smith, K., and J.-C. Huang. Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models. *Journal of Political Economy*, Vol. 103, No. 1, 1995, pp. 209–227.
18. Crompton, J. L. The Impact of Parks on Property Value: A Review of the Empirical Evidences. *Journal of Leisure Research*, Vol. 33, No. 1, 2001, pp. 1–31.
19. O'sullivan, A. *Urban Economics*. McGraw-Hill/Irwin, New York, 2011.
20. Ryan, S. Property value and transportation facilities: Finding the Transportation-Land Use Connection. *Journal of Planning Literature*, Vol. 13, No. 4, 1999, pp. 412–427.
21. Duncan, M. Comparing Rail Transit Capitalization Benefits for Single-Family and Condominium Units in San Diego, California. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2067, 2008, pp. 120–130.
22. Conway, D., C. Q. Li, J. Wolch, C. Kahle, and M. Jerrett. A Spatial Autocorrelation Approach for Examining the Effects of Urban Greenspace on Residential Property Values. *The Journal of Real*

Estate Finance and Economics, Vol. 41, No. 2, 2010, pp. 150–169.

23. Welch, T. F., S. R. Gehrke, and F. Wang. Long-term impact of network access to bike facilities and public transit stations on housing sales prices in Portland, Oregon. *Journal of Transport Geography*, Vol. 54, 2016, pp. 264–272.
24. Nicholls, S., J. L. Crompton, and others. The impact of greenways on property values: Evidence from Austin, Texas. *Journal of Leisure Research*, Vol. 37, No. 3, 2005, pp. 321–341.
25. Parent, O., and R. vom Hofe. Understanding the impact of trails on residential property values in the presence of spatial dependence. *The Annals of Regional Science*, Vol. 51, No. 2, 2013, pp. 355–375.
26. Krizek, K. J. Two Approaches to Valuing Some of Bicycle Facilities' Presumed Benefits: Propose a session for the 2007 National Planning Conference in the City of Brotherly Love. *Journal of the American Planning Association*, Vol. 72, No. 3, 2006, pp. 309–320.
27. Broach, J., J. Dill, and J. Gliebe. Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, Vol. 46, No. 10, 2012, pp. 1730–1740.
28. Liu, J. H., and J. Renfro. *Oregon Property Tax Capitalization: Evidence from Portland*. Northwest Economic Research Center, 2014.
29. Cellmer, R. Use of Spatial Autocorrelation to Build Regression Models of Transaction Prices. *Real Estate Management and Valuation*, Vol. 21, No. 4, 2013, pp. 65–74.
30. Waddell, P., B. J. Berry, and I. Hoch. Residential property values in a multinodal urban area: New evidence on the implicit price of location. *The Journal of Real Estate Finance and Economics*, Vol. 7, No. 2, 1993, pp. 117–141.
31. Krizek, K. J., A. El-Geneidy, and K. Thompson. A detailed analysis of how an urban trail system affects cyclists' travel. *Transportation*, Vol. 34, No. 5, 2007, pp. 611–624.
32. Anselin, L. *Spatial Econometrics: Methods and Models*. Kluwer Aceademic, Dordrecht, Netherlands, 1988.