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Impacts of bicycle facilities on residential property values in 11 US cities

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ABSTRACT

Bicycle infrastructure has been found to increase nearby residential property values. However, most evidence for this economic impact is limited to a single city. This study investigates the pre- and post-treatment effects of different types of bicycle facilities on the values of single-family and multifamily homes in 11 cities in the United States from 2000 to 2019. We utilize a quasi-experimental approach with matching techniques and hedonic models to track down the changes in the sales price of residential properties over time within an 800-m buffer of bicycle facilities. We found a mixed impact of property value appreciation, depreciation, and no change in the sales price by different types of bicycle infrastructure including on-street and off-street facilities on single-family and multifamily residential properties across the 11 cities. Single-family and multifamily properties near off-street-only facilities experienced appreciation in Los Angeles, Minneapolis, and Cleveland. Meanwhile, single-family homes near on-street-only facilities tended to decrease their values in Columbus, Eugene, Philadelphia, and Tucson, and increase only in Minneapolis. All properties within 800 m of both on-street and off-street facilities saw their values increase in Columbus and Minneapolis. However, we did not find a statistically significant effect of bicycle infrastructure on housing values in Portland, San Francisco, and Seattle. Findings from our study will inform decision-making and planning for bicycle infrastructure while ensuring the equitable distribution of these facilities and affordable housing for disadvantaged populations.

1. Introduction

Empirical research in urban planning, urban economics, and real estate demonstrates the capitalized effect of various transportation facilities on property values. Much of the existing scholarship provides empirical evidence that proximity to transportation systems such as transit and bicycle infrastructure tends to positively influence housing market values (Krizek, 2006; Liu and Shi, 2017; Welch et al., 2016). These studies draw upon a hedonic analysis framework to capture the monetary contribution of property structural characteristics (e.g., the size of the property and number of rooms), neighborhood attributes (e.g., built environment, demographic composition and socio-economics), and other locational attributes such as distance to parks and central business district (CBD) (Conrow et al., 2021; Mohammad et al., 2013; Rosen, 1974), environmental pollution (Kim et al., 2003), and school district performance (Clapp et al., 2008).

Many cities in the United States have been investing in their bicycle infrastructure network to promote bicycle- and pedestrian-friendly urban design and stimulate the local economy (Handy, 2005; Le et al., 2019). Due to this strong focus on bicycle infrastructure investment, several studies have focused on understanding the property value premium effects associated with bicycle facilities (Asabere and Huffman, 2009; Duncan, 2008; Mathur and Ferrell, 2013).

Previous literature shows that the influence of bicycle facility access on housing sales prices in the continental United States is mixed and varies based on the type of bicycle facility and residential property. Liu and Shi (2017) found that the extensiveness of the bicycle network significantly increased the sales price in Portland, OR. Meanwhile, Welch et al. (2016) found that proximity to regional multi-use paths increased property values while on-street bicycle facility was negatively associated with the sales price in the same region. Off-street bicycle facilities were found to increase residential housing values (Asabere and Huffman, 2009; Lindsey et al., 2004; Parent and vom Hofe, 2013). These studies found that properties located closer to greenway trails, greenbelts, and nature trails sold for a premium in Indianapolis, IN, San Antonio, TX, and Cincinnati, OH.

Despite substantial evidence that some bicycle facilities are positively associated with sales prices of residential properties, the existing literature has mainly focused on case studies in a single city, often relying on cross-sectional data that makes it difficult to draw the causal

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link between bicycle infrastructure intervention and changes in housing prices over time across cities characterized by different built environment, socio-economics, and local urban planning policies. In addition, a limitation of prior studies is that while they account for the access to bicycle infrastructure and its density within a short walking distance of residential properties, they did not isolate the impact of each type of bicycle facility (e.g., on-street bike lanes vs. off-street trails) on housing market values.

This study aims to quantify the effects of bicycle facilities on home values in 11 US cities. We hypothesize that the effect of different bicycle facilities on residential property transactions varies across single-family and multifamily residential properties, accounting for neighborhood characteristics. To the best of our knowledge, this study represents the first hedonic pricing analysis to isolate the differential impact of bicycle infrastructure using a quasi-experimental design with data that spans from 2000 through 2019 across different urban contexts. We found mixed impacts of property value appreciation, depreciation, and no change in the sales price of single-family and multifamily homes in the 11 cities. Single-family and multifamily residential properties near off-street-only facilities experienced appreciation in Los Angeles, Minneapolis, and Cleveland. By contrast, single-family properties in closer proximity to on-street-only facilities witnessed a decrease in sales prices in Columbus, Eugene, Philadelphia, and Tucson while gaining value only in Minneapolis. Additionally, all properties near both on-street and off-street facilities sold for significant positive premiums in Columbus and Minneapolis. We did not find a statistically significant effect of bicycle infrastructure on housing values in Portland, San Francisco, and Seattle. The results of this study will inform city planners of the effects of bicycle facilities on housing, local economy, and finance, as well as necessary measures to minimize negative impacts such as potential gentrification in places where housing prices increase due to bicycle infrastructure investments.

2. Background

Many studies investigated the determinants of housing market values in relation to proximity to transportation infrastructure such as train stations, bus stops, and bicycle facilities (Acton et al., 2022; S. Lee and Golub, 2021; Mohammad et al., 2013; Shr et al., 2023). Urban economics literature provides theoretical foundations for hedonic studies on housing market values (Lancaster, 1966; Rosen, 1974). The studies underpinned by urban economic theories suggest that residential properties capitalize on accessibility to transportation infrastructure. For example, the property value might increase with proximity to bicycle facilities due to improved access to activity locations such as jobs (Liu and Shi, 2017).

The existing evidence on the contribution of bicycle infrastructure to residential properties is mixed across the United States, and it varies based on the type of bicycle facility and residential property. For example, Liu and Shi (2017) examined the impact of advanced facilities including cycle tracks, buffered bike lanes, and bike boulevards on single and multifamily residential properties from 2010 through 2013 in Portland, OR. They found that proximity to advanced bicycle facilities and the extensiveness of bicycle networks increase property prices. Another study in Portland by Welch et al. (2016) revealed that closer proximity to off-street trails like multi-use bike paths increases the selling price of single-family and owner-occupied multifamily properties while shorter distances to on-street bicycle facilities negatively influence property values. This study suggests that the decrease in the sales price of residential properties near on-street facilities could be attributed to the nuisance caused by noise, air pollution, or congestion.

Many studies focused on a particular type of bicycle facility, such as off-street trails. In Indianapolis, IN, Lindsey et al. (2004) showed that greenway trails had a significantly positive impact on the sales price of properties located within one-half mile of the trail. A study by Asabere and Huffman (2009) in San Antonio, Bexar County, TX, revealed a similar property value premium by trails and greenbelts as people place a higher value on scenic off-street paths with less noise and pollution from traffic. In addition, Parent and vom Hofe (2013) found that properties located one thousand feet closer to nature trails sold for a premium in Cincinnati, OH. By contrast, Krizek (2006) found that proximity to non-roadside off-street bicycle facilities significantly reduces suburban property values in Minneapolis-St Paul, MN. A more recent study by Conrow et al. (2021) in Tempe, AZ, incorporated a ridership measure into hedonic pricing models to estimate the economic effects of bicycle infrastructure and found that bicycle network density is a more significant draw for homebuyers than the ridership volume. The differential value uplift induced by proximity to bicycle facilities demonstrates how the impact of various types of bicycle facilities such as off-street and on-street facilities varies across single-family and multi-family properties.

Residential property values are also reflective of home buyer's perceived values of school district quality, neighborhood characteristics, and environmental quality. Clapp et al. (2008) used panel data spanning 11 years to examine the impacts of school district quality on property values in Connecticut, finding that student test scores have become more prominent in explaining housing prices in recent years. Lynch and Rasmussen (2001) found that properties in high-crime areas are highly discounted. Other studies have also looked into the impacts of air pollution such as ozone and particulate matter concentrations on housing market values (Chay and Greenstone, 2005). Kim et al. (2003) found that air pollution levels (i.e., sulfur dioxide from factory stacks and coal-burning fireplaces) had a significant impact on housing prices, with willingness to pay for a permanent 4% improvement in air quality estimated at $2333 or 1.43% of mean home values in the Seoul metropolitan area.

Previous studies have mainly employed multivariate hedonic regression (Bartholomew and Ewing, 2011) and spatial econometrics (Acton et al., 2022; Liu and Shi, 2017; Welch et al., 2016) to examine the relationship between real estate valuation and accessibility to transportation facilities. The hedonic regression model is a type of regression model that explains the sales price as a function of property attributes (e.g., age, lot size, and number of bedrooms), locational attributes (e.g., distance to the nearest park and central business district), neighborhood attributes (e.g., density, socioeconomics, and demographics), bicycle facility characteristics, and transaction characteristics. Spatial regression models are often adopted when property sales price exhibits a systematic pattern in their spatial distribution, and therefore, are spatially autocorrelated. These models capture the spatial dependency effect in the association between the sales price of properties and transportation infrastructure (Wilhelmsson, 2002).

The survey of existing literature on the property value premiums associated with bicycle infrastructure demonstrates that most studies rely on cross-sectional research design and transaction records that span short timeframes in a single city (Table 1). Our study attempts to fill this gap by bolstering evidence based on the economic benefits of bicycle infrastructure with a quasi-experimental design to understand the impacts of investments in bicycle infrastructure on residential property values in 11 US cities from 2000 through 2019.

3. Data and methods

3.1. Study design

Covering 11 cities in the United States, this study evaluates the changes in residential property sales prices from 2000 through 2019 (Fig. 1). The choice of study period was based on the availability of bicycle infrastructure data from local planning agencies and Google Earth imagery. We adopted a quasi-experimental design for the observational data from these 11 cities by splitting housing transaction sales into two groups: a treatment group that includes properties located within an 800 m buffer from the bicycle facilities, and a control group that includes properties that lie outside the 1000 m donut buffer.

Table 1
Summary of hedonic price studies of bicycle facilities.

Study	Location	Bicycle facility	Property	Method	Infrastructure measure and effects on housing values (increase/ + or decrease/− housing values)
Liu and Shi (2017)	Portland, OR	Cycle tracks, buffered bike lanes, bike boulevards	Single-family and multi-family properties (2010−2013)	OLS and SAR	(a) Distance to nearest bicycle facility (−) (b) Bicycle facility density within 0.5 miles of each property (+)
Welch et al. (2016)	Portland, OR	On-street bike lane, local multi-use path and regional multi-use path	Single-family and owner-occupied multifamily properties (2002−2013)	SAR	Distance to the nearest (a) Multi-use path (+) (b) On-street facility (−)
Conrow et al. (2021)	Tempe, AZ	On-street and off-street bike facilities	Single-family properties (2013–2016)	OLS and spatial lag model	Density within 0.5 miles of each property: (a) On-street facility (+) (b) Off-street facility (0) (c) Ridership (0)
Krizek (2006)	Minneapolis- St. Paul, MN	On-street and off-street facilities	Urban and suburban properties (2001)	OLS	Distance to the nearest (a) On-street facility (0) (b) Roadside off-street facility (+) (c) Non-roadside off-street facility (−)
Asabere and Huffman (2009)	San Antonio, TX	Trails, greenbelts and greenways	Residential properties (2001−2002)	OLS	Presence of bicycle facility (+)
Parent and vom Hofe (2013)	Cincinnati, OH	Trail	Single-family properties (2005)	OLS and SAR	Distance between properties and trail (+)
(Lindsey et al., 2004)	Indianapolis, IN	Greenway	Residential properties (1999)	OLS	0.5 miles from bicycle greenways (+)

Notes: (+): positive effect; (−) negative effect; OLS: Ordinary least square regression; SAR: spatial autoregressive regression.

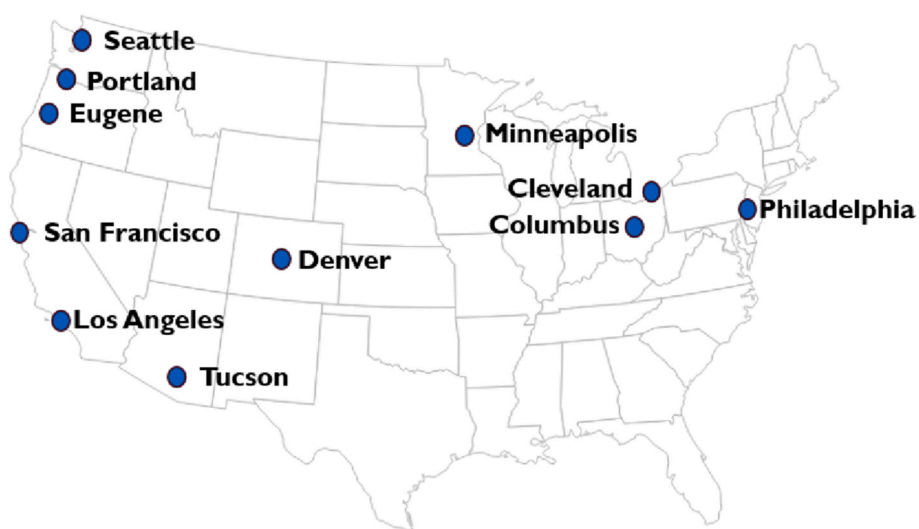

Fig. 1. Eleven US cities included in this study.

The 800 m buffer is the distance a person is willing to travel using non-motorized modes, and it is consistent with previous studies examining the impact of bicycle facilities on residential property prices (Conrow et al., 2021; Lindsey et al., 2004; Liu and Shi, 2017). We also generated datasets of 400 m and 1200 m for sensitivity analysis. We compiled variables of interest including socio-demographic composition, built environment, and locational amenities at the block group level around the properties in the treatment and control groups in the 11 cities.

3.2. Data processing

We constructed a dataset that comprises transaction and physical property characteristics, neighborhood built-environment characteristics, and socioeconomic and demographic indicators. First, we obtained Zillow's assessment and transaction database, which contains information about property characteristics such as building area, lot size, year of construction, number of stories, and total number of rooms from 2000 to 2019 (Zillow, 2023). The transaction database provides information about the sales price and date of the transaction that matches the assessment database's time horizon. The Zillow transaction database did not include short-term sales and foreclosures. In this study, we considered all multifamily properties such as general multifamily residential properties, duplexes (2 units), triplex (3 units), quadruplex (4 units), apartment buildings (5+ units), apartment buildings (100+ units), garden apartments, or court apartments (5+ units), high-rise apartment, boarding house rooming house apartment hotel transient lodging, mobile home park or trailer park, multifamily dwelling (generic any combination 2+), fraternity house or sorority house, apartment (generic), residential dormitory or group quarters, and residential condominium development. Sales price transactions were adjusted for the square footage of transacted properties.

The data was subsequently cleaned to eliminate duplicates and eventually resulted in a unique hedonic dataset for single-family and multifamily properties. The resulting sales price transactions contained repeat sales since each property was observed twice in the housing market.

The bicycle infrastructure database was internally created using different sources for another project (Le et al., 2018, 2019). This dataset was constructed based on the data availability of bicycle traffic count, city size (i.e., small, medium, and large cities), and the availability of shapefile data for bicycle facilities provided by the local planning agencies. We downloaded bicycle infrastructure networks for each city from local agencies' data portals. In cities where the year of construction for the bicycle facilities was unavailable (which is the case in most cities), we relied on Google Earth historical satellite images and Google Street View to get the year of construction. This information was used to create a longitudinal bicycle network by year from 2002 to 2020. Next, we coded the bicycle facilities and aggregated bike lanes, cycle tracks, contraflow bike lanes, and buffered bike lanes into on-street bicycle facilities, and trails and shared-use paths into off-street bicycle facilities.

We created a 3-km buffer around city-wide bicycle networks to extract candidate sales records for each city for the hedonic analysis. Properties located within a 3 km catchment were further split into treatment and control groups based on the type of bicycle infrastructure. The bicycle facilities were categorized into on-street bicycle facilities (bike lanes, cycle tracks, contraflow bike lanes, and buffered bike lanes) and off-street bicycle facilities (trails and shared-use paths). We retained properties that were sold two times over 20 years (2000–2019) by selecting sales transactions that occurred immediately before and after bicycle facility construction.

The distance between the location of each residential property and the nearest park was calculated using the *osmdata* and *sf* packages in R. To calculate the distance to park variable, we identified the parks that are closest to residential properties and then calculated the distance between the nearest park and residential properties.

We used the socioeconomic and core demographic characteristics from the 2000 US Decennial Census as well as the American Community Survey (ACS) 5-year estimates (2009–2013 and 2016–2020) at the block group level. The time horizon was selected to facilitate comparison across non-overlapping values and estimates.

To incorporate built environment indicators into the hedonic dataset, we drew on the Smart Location Database managed by the US Environmental Protection Agency (US EPA, 2023) which provides key built environment indicators for density, land use diversity, built environment, access to destinations, and distance to transit at the census block group-level. Important neighborhood attributes from the Smart Location Database include gross population density, gross employment density, jobs per household, multimodal street network density, distance to the nearest transit stop, jobs within 45-min auto travel time, jobs within 45-min transit commute, and national walkability index value between 1 (lowest walkability) and 20 (highest walkability). We incorporated gross population density and multimodal street network density variables that were highly correlated with the sales price of properties into the final model. Additionally, we derived the distance to the CBD by identifying the census block group with the highest employment density of each city, and then calculated the distance from each residential property to the centroid of this block group.

Finally, each residential property was assigned spatially the built environment features and socioeconomic and demographic characteristics for the block group in which it was located. Two key binary variables were constructed for on-street and off-street facilities to isolate the

Table 2
Variables included in the difference-in-differences hedonic models.

Variable	Description	Year	Source
Transaction characteristics			
Sales price	Natural log of sales price	2000–2019	ZTRAX
After	Dummy for treatment time; 1 if after bicycle facility, 0 otherwise	2000–2019	Derived
Bike	Dummy for bicycle facility; 1 if one type or all bike facilities are present within the 800 m buffer (i.e., treatment group), 0 otherwise.	2000–2020	Derived
After*On-street	DID interaction between the treatment group (for on-street only) and time	2000–2019	Derived
After*Off-street	DID interaction between the treatment group (off-street only) and time	2000–2019	Derived
After*All facilities	DID interaction between the treatment group (for double treatment with on-street and off-street facilities at the same time) and time	2000–2019	Derived
Property attributes			
Building area	Building square footage	2000–2019	ZTRAX
Age	Age in years at time of sale	2000–2019	ZTRAX
Number of stories	Number of stories of property	2000–2019	ZTRAX
Total number of rooms	Total number of rooms per property	2000–2019	ZTRAX
Total number of bedrooms	Total number of bedrooms per property	2000–2019	ZTRAX
Lot size	Square footage area	2000–2019	ZTRAX
Locational attributes			
Distance to CBD	Distance to CBD in km	NA	Derived
Distance to nearest park	Distance to nearest park in m	NA	Derived
Distance to nearest bike facility	Distance to nearest bike facility in m	NA	Derived
Neighborhood attributes			
Population density	People/acre	2017	SLD
Street network density	Multimodal street network density	2017	SLD
National Walkability index	Value between 1 (lowest walkability) and 20 (highest walkability	2017	SLD
Percent Black	Percent population Black in block group	2000–2020	Census, ACS
Percent Hispanic	Percent population Hispanic in block group	2000–2020	Census, ACS
Median household income	Median household income in block group	2000–2020	Census, ACS

Notes: ZTRAX: Zillow Transactions & Assessor; SLD: Smart Location Database; ACS: American Community Survey.

Table 3
Mean of the dependent and independent variables.

Variable	Cleveland	Columbus	Denver	Eugene	Los Angeles	Minneapolis	Philadelphia	Portland	San Francisco	Seattle	Tucson
Transaction characteristics											
Sales price	88,570	134, 713	343,436	224,370	667,839	238,469	167,664	321,773	1,155,650	588,535	213,354
Property attributes											
Building area	1650	962	1625	1126	2346	1547	1743	1733	2208	2115	1750
Age	82	52	63	33	72	83	66	67	76	69	26
Number of stories	1.77	1.54	1.35	1.26		1.53	2.12	1	1.63	1.40	1.09
Total number of rooms											7
Total number of bedrooms	3	3	3	3	4	3		3	2	3	
Lot size	6361	12,150	6211	8371	6496	5744	3487	6364	2806	5643	12,890
Locational attributes											
Distance to CBD	8.5	9.14	8	5.1	9.44	5.66	12	8.57	7	7.48	12.75
Distance to nearest park	652	562	481	440	674	398	496	466	339	381	2297
Distance to nearest bike facility	544	491	383	365	626	248	303	195	194	231	295
Neighborhood attributes											
Population density	11.82	9.6	13.11	7.25	26.11	14.45	29.33	13	40	15.74	6
Street network density	3.2	4.2	3.0	2.76	4.58	2.4	11.29	2.03	4	0.73	3.02
Percent Black	28	22.5	10.5	0.9	12.4	15	22	6.2	5.8	5.8	2.7
Percent Hispanic	45	56.7	48.2	62	49.14	42.76	65	44.3	50	46.9	55.4
National walkability index	12.92	11.88	14.26	12.41	14.6	14.4	14.55	15.74	16	15.34	10.58
Median household income	38,937	48,580	65,529	52,046	50,954	62,632	43,121	62,630	91,292	80,276	53,550
Number of observations	25,230	37,588	60,447	16,825	37,810	43,980	21,861	31,353	20,676	41,278	103,061

pathway between treatment (bicycle intervention) and outcome (sales price): (1) before and after the installation of a bicycle facility, (2) the presence or absence of bicycle facility (location). Table 2 and Table 3 present the descriptive statistics of variables included in the hedonic pricing model.

We created a donut buffer that separates the treatment and control groups. Specifically, for the 800 m buffer analysis, we now consider the treatment group any homes within 0-800 m from the bike facilities, and the control group any homes within 1000-3000 m (i.e., discarded homes within the donut buffer). We used the same approach throughout the sensitivity analysis at 400 m, 800 m, and 1200 m buffer distances to spatially isolate the control group from the treatment group at a 200 m distance. We have considered the presence of only on-street facilities, only off-street facilities, or the presence of both on-street and off-street facilities (captured in the "all facilities" variable in the model). This means, the DID values capture the effect of on-street-only facilities on property values relative to off-street-only facilities or the presence of both on-street and off-street facilities.

To account for the overlapping treatment of on-street and off-street facilities, we identified properties that were simultaneously (i.e., during the same time) and sequentially (i.e., either the on-street was constructed first or the off-street facility) double-treated for both on-street and off-street facilities to estimate the effect of double treatment on changes in the sales price of properties.

3.3. Matching and parallel trend analysis

As we employ the quasi-experimental design and DID models, we took extra steps to ensure that the assumptions for these approaches are met. Here we discuss the two most important assumptions: parallel trend assumption and random assignment to the treatment and control groups. *Parallel trend assumption* which requires that in the absence of treatment (i.e., bicycle facility intervention), the difference between the treated group (i.e., properties near bicycle facilities) and the untreated group (i.e., properties that did not receive bicycle infrastructure) stays the same in the post-treatment period as it was in the pre-treatment period (Nick, 2020). The parallel trend assumption prevents unobserved and time-invariant characteristics from confounding the treatment effects. We performed a test of prior trends on the pre-treatment data to ensure the assumption of parallel trends was plausible. The test of prior trends confirms if the treated and untreated properties had differing trends before the treatment. The difference in sales price between treated and control properties should stay the same prior to the bicycle facility construction, implying that had the treatment not occurred, they likely would have followed a similar trend path. A prior trends test for the interaction between treatment time and group ($\beta_2 Time \times Group$ – see SM Section 3) provides information about the trends. If the trends are different and this interaction term is statistically significant, it could mean the parallel trends assumption is violated. However, if the trends are barely different, it could also be attributable to our large sample size (Nick, 2020).

Relatedly, the quasi-experimental approach assumes that assignment to bicycle facility intervention (treatment) is *as if* random since, unlike the gold standard randomized controlled trials, we did not directly assign residential properties to treatment and control groups (Hariton and Locascio, 2018). We therefore used matching techniques to statistically adjust for confounding factors that may affect the results of the quasi-experimental design.

In the matching process, we used nine neighborhood attributes to select observations with similar values of population density, employment density, distance to the nearest park, distance to CBD, multi-modal network density, median household income, core demographic characteristics such as percent Black and percent Hispanic, and walkability index (Acton et al., 2022). We selected these neighborhood attributes to find good counterfactuals since the residential context influences both housing market values and access to bicycle infrastructure. Previous research has shown that homebuyers value these neighborhood attributes and they are often used for propensity score matching (Acton et al., 2022).

We employed the standard nearest neighbor (NN) propensity score method to match properties located within an 800 m buffer of a bicycle facility with the control group that did not receive bicycle infrastructure treatment with replacement (i.e., properties that have been matched already can get another match). To pair up properties near bicycle facilities with similar control properties based on neighborhood attributes, we used the *Matchit* R package (Ho et al., 2011). We chose nearest neighbor matching for two reasons. First, the nearest neighbor matching is preferable for large datasets that cannot be handled by optimal matching. Second, we used nearest neighbor propensity score matching with replacement which is superior to nearest neighbor propensity score matching without replacement (Morgan and Harding, 2006), and this approach allowed us to weight the control properties with nonuniform weights that improved the balancing capabilities of our models (Greifer, 2023).

Only propensity score-matched transactions were included in the final hedonic model. Propensity score statistics such as standardized mean difference (SMD), variance ratio (VR), and empirical cumulative density function (eCDF) were used to identify imbalanced covariates across all study areas. SMD and eCDF close to 0, and values of variance ratios close to 1.0 indicate a good balance (Greifer, 2022). Density, median household, distance to amenities, and demographic covariates were mainly balanced in most cities. The lack of balance for some covariates could be attributed to the larger number of neighborhood attributes selected to characterize each census block group, and the smaller number of observations that resulted from isolating the effect of each bicycle facility intervention (e.g., on-street facility, off-street facility and double treatment across city-wide bicycle network).

3.4. Spatial difference-in-differences hedonic models

We estimated a set of 11 spatial difference-in-differences (DID) models to evaluate the impacts of bicycle infrastructure on property prices for each city. While estimating one single model for all cities would be ideal, we were unable to do so as the sample sizes are very large, which posed a great barrier to estimating spatial models that are computationally intensive.

Our model choice follows several steps. First, we estimated a set of OLS models and performed diagnostic tests on the residuals. We tested for spatial autocorrelation on the residuals using Moran's I (Moran, 1950) for 3 to 6 neighbors to specify the weights matrix (Table S1 in the Supplemental Material - SM). The Moran's I test indicated that there was statistically significant positive spatial autocorrelation in the residuals of the OLS model ($p < 0.0001$). We subsequently conducted Lagrange multiplier tests to select the appropriate spatial models to capture this spatial dependency. The robust Lagrange multiplier test showed that the spatial error model was more appropriate. This model is designed to capture the spatial dependence in the error component of the regression model.

For the final spatial models, we specified the spatial weight matrices using the k-nearest neighbors method (k = 3, as a higher number of neighbors yielded similar results). This means the sales price of the three nearest properties had a bearing on the property values of any particular home. The spatial error DID models control for a category of control variables including neighborhood features and locational attributes, as well as the group differences (treatment vs. control groups) and time differences (pre- vs. post-treatment period) (Card and Krueger, 1994). With the natural log of sales price of residential properties as the dependent variable, the specification of the spatial error DID model is as follows:

$$\begin{aligned} \ln(P_{it}) = {} & \beta_0 + \beta_1 H_{it} + \beta_2 N_i + \beta_3 L_i + \beta_4 Year_{it} + \gamma_1 (On\ street^*After)_{it} \\ & + \gamma_2 (Off\ street^*After)_{it} + \gamma_3 (All\ facilities^*After)_{it} + \lambda W \varepsilon_i + \mu_{it} \end{aligned}$$

Where:

P_{it} = sales price of property *i* at time *t*.

H_{it} = structural characteristics of property *i* at time *t* (e.g., age, size).

N_i = neighborhood attributes of property *i* (e.g., demographics, built environment).

L_i = locational amenities of property *i* (e.g., distance to the CBD, green spaces, etc.)

$Year_{it}$ = indicator variables for the years of property transactions (i.e., from 2000 through 2019).

On $street_i$ = a binary variable with a value of 1 if property *i* is within 800 m from on-street bicycle facilities and 0 otherwise.

Off $street_i$ = a binary variable with a value of 1 if property *i* is within 800 m from off-street bicycle facilities and 0 otherwise.

All $facilities_i$ = a binary variable with a value of 1 if property *i* is within 800 m and treated for both on-street and off-street bicycle facilities at the same time and 0 otherwise.

$After_i$ = a binary variable with a value of 1 if the transaction of property *i* occurred after the bicycle facility was built and 0 if before.

λ = spatial error parameter.

W_ε = spatially lagged error term.

μ = error terms.

The coefficients for γ from the DID terms indicate how much bigger the sales price gap between treatment and control properties has grown after bicycle facilities were built. In each city, we separately estimated two DID hedonic models for single-family and multifamily properties accounting for three types of bicycle-facility interventions: on-street facilities (i.e., presence of only on-street facility), off-street facilities (presence of only off-street facility) and all facilities (i.e., double treatment where a home is close to both types of facilities at the same time). As a result, we estimated three DID terms (i.e., on-street, off-street, and all facilities) for three types of bicycle infrastructure intervention across single-family and multifamily properties in 11 cities.

We estimated two models: one with all transactions for each house so houses being transacted twice during the study period will be entered twice in the model and another model with houses being transacted once during the study period (i.e., removing any transactions in between). We kept the former model as the main model and used the other one for robustness checks.

Additionally, we tested models with normalized sales price of both single-family and multifamily properties to the base year 2000 to account for inflationary and deflationary periods. We also ran a separate set of models to estimate the impacts of bicycle facilities on the sales price per square foot for selected cities where we found that bicycle infrastructure had significant impacts on housing market values. To further probe the spatial heterogeneous treatment effect of bicycle facility interventions, we carried out a sensitivity analysis at 400 m and 1200 m buffer distances in addition to the 800 m buffer distance in the main models. Our hedonic models accounted for the changes in the sales price for the same property between the two sale times before and after bicycle facility construction and therefore similar to repeat-sales models which are common in real estate economics and urban economics (Harding et al., 2007; Lee et al., 2018).

3.5. Estimated tax revenue changes with infrastructure investment

We also calculated changes in annual property tax revenues per home as a result of bicycle facility construction. We used the mean sales price of property transactions from the Zillow transactions database, changes in home values from our DID models, and the average property tax rate from the Zillow Property Tax Calculator in 2021 (Zillow, 2021). We specified the changes in property tax revenue in city i as follows:

$$\begin{aligned} Change\ in\ tax\ revenues_i = {} & mean\ sales\ price_i \times change\ in\ home\ value_i \\ & \times average\ property\ tax\ rate_i \end{aligned}$$

Where:

mean sales price$_i$ represents the mean sales price of single-family or multifamily properties in city i.

change in home value$_i$ represents the effect size of each type of facility. The effect size is γ_1 for on-street-only facilities; the effect size is γ_2 for off-street only facility; and the effect size is γ_3 for both on- and off-street facilities (double treatment), with γ from the hedonic model in Section 3.4.

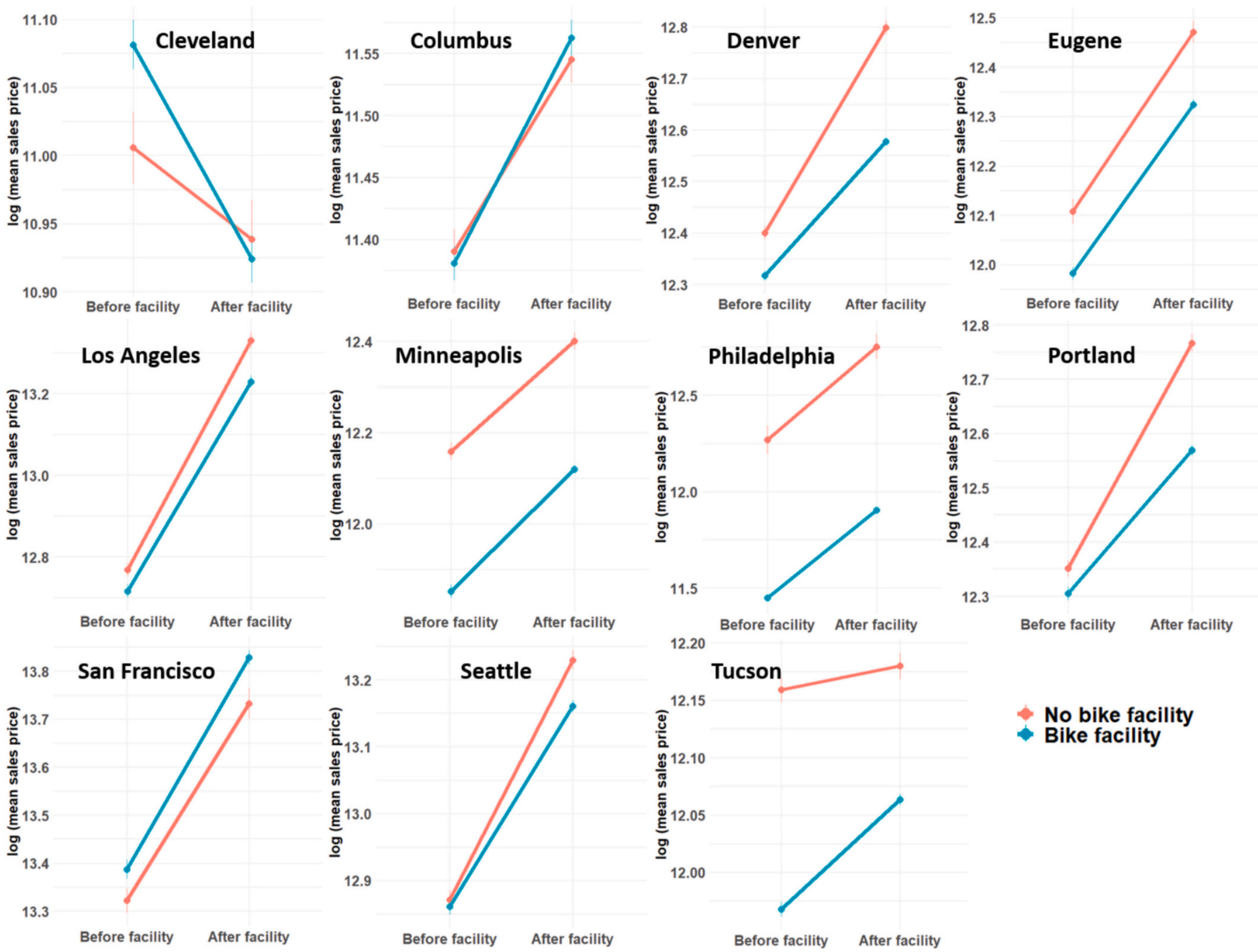

Fig. 2. Mean sales price (unscaled) of properties before and after installing bike facilities.

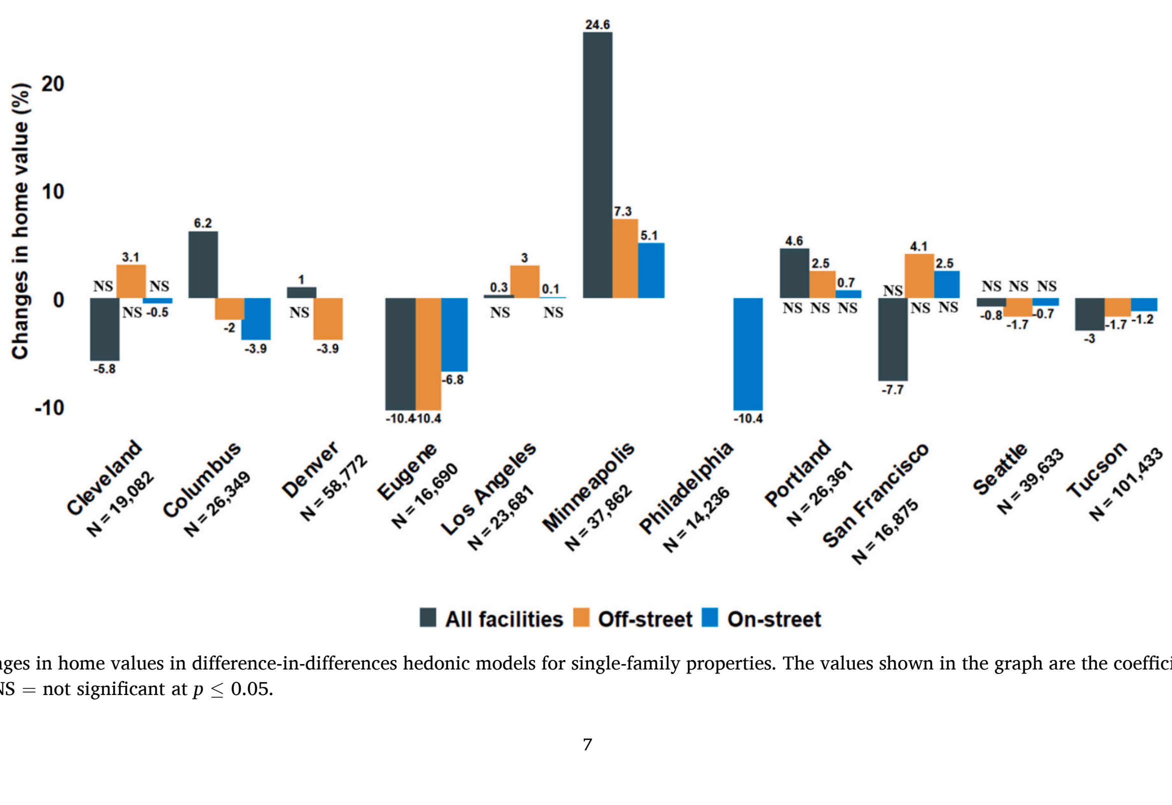

Fig. 3. Changes in home values in difference-in-differences hedonic models for single-family properties. The values shown in the graph are the coefficients of the 3 DID terms. NS = not significant at $p \leq 0.05$.

property tax rate$_i$ represents the average property tax rate in County areas for city i.

The tax rates for property in each city were estimated by Zillow and contained state, school district, and city taxes.

4. Results

4.1. Parallel trend analysis

Fig. 2 illustrates a varying difference between the average sales prices of residential properties in the treatment and control groups depending on the type of bicycle facility across all 11 cities. Parallel trends show that properties in the treatment and control groups are comparable except for those in Cleveland and Columbus, suggesting that these cities are likely to violate the parallel trend assumption of DID. This means the DID results for these should be interpreted with caution.

We found that the control and treatment properties trend in the same direction and at the same rate years before the treatment went into effect in most cities except Cleveland, Denver, and Tucson, suggesting that a parallel trend is unlikely to hold in these cities and the only reason we would see the divergence of the trends is not because of the treatment itself (see Table S3 in the SM). Similarly, changes in the sales price of properties in Columbus should be interpreted with caution due to the presence of unparalleled trends. In cities where the parallel trend assumption holds, we have a plausible causal effect because control and treated properties would have followed parallel trends without bike facility intervention. However, it is also important to consider the context in those cities and account for the other developments that might have happened during the study period.

4.2. Impacts of bicycle facilities on sales price

From our DID model results, the impact of bicycle infrastructure varied by type of facility, property, and across cities, with on-street, off-street, and the presence of both on-street and off-street facilities having varying degrees of influence in terms of the magnitude and direction of the impact. Fig. 3 and Table 4 provide the impact of bicycle facilities on single-family properties.

The effect of bicycle facilities on single-family properties was mixed in the 11 cities (Fig. 4). Proximity to *on-street facilities* was associated with single-family property appreciation only in Minneapolis (5.1%), depreciation in Columbus (4%), Eugene (7%), Philadelphia (10%), and Tucson (1%). We found no statistically significant impacts in Cleveland, Denver, Los Angeles, Portland, San Francisco, and Seattle.

Closer proximity to *off-street facilities* led to single-family home value appreciation in Los Angeles (3%) and Minneapolis (7%), whereas it led to depreciation in Columbus (2%), Denver (4%), Eugene (10%), and Tucson (2%). We found no statistically significant impacts of off-street facilities on single-family properties in Cleveland, Portland, San Francisco, and Seattle.

With respect to single-family properties *near both types of facilities*, we found that the sales price of properties increased by approximately 6% in Columbus and 25% in Minneapolis. However, single-family properties near both on-street and off-street facilities decreased by approximately 10% in Eugene and 3% in Tucson, and there was no effect for the rest of the cities.

As for multifamily properties, Fig. 5 and Table 5 depict mixed impacts of property value appreciation, depreciation, and no change in sales price. Properties within 800 m of *on-street facilities* experienced an increase in sales price in Cleveland (9%), and a decrease in Los Angeles (4%) and Philadelphia (17%) while we found no statistically significant impacts of on-street facilities in Columbus, Denver, Minneapolis, Portland, San Francisco, Seattle, and Tucson.

Regarding multifamily properties near *off-street facilities*, only properties in Cleveland witnessed an increase of 14% in sales price while properties in Los Angeles experienced a decline of 12%. Additionally, off-street facilities in Columbus, Denver, Minneapolis, Portland, San Francisco, Seattle, and Tucson exhibited no statistically significant effect on multifamily properties. Moreover, Fig. 6 illustrates that multifamily properties with both *on-street and off-street facilities* appreciated nearly 22% in Columbus and 20% in Minneapolis while properties in Los Angeles depreciated approximately 21%. We found no statistically significant effect for multifamily properties with both on-street and off-street facilities for the rest of the cities.

4.3. Impacts of property and neighborhood attributes on sales price

The coefficients of most property attributes and neighborhood features were statistically significant, albeit varied in magnitude and impact. As expected, most estimates for property structural characteristics were positively and significantly associated with the housing sales price. For instance, the sales price increases with the building's square footage, number of stories, and number of bedrooms, and decreases with the age of the property. However, in multifamily property models, the sales price was negatively associated with lot size in Minneapolis, Portland, and Los Angeles. Multifamily property values also declined as the total number of bedrooms increased in Columbus, Cleveland, and Portland. With respect to neighborhood attributes, the model estimates revealed that homebuyers paid a premium for properties in walkable neighborhoods with closer proximity to amenities in the central business district in most cities. By contrast, for each additional kilometer a single-family property was located away from the CBD, the house sold for a significant premium in Columbus, Minneapolis, Cleveland, Portland, and Los Angeles. Multifamily properties located farther away from the CBD also sold for a significant premium only in Columbus and Minneapolis.

When it comes to accessibility to bicycle facilities, the sales price of single-family properties increased with distance from bicycle facilities in Eugene, Seattle, Portland, and Los Angeles. By contrast, the closer the multifamily properties were to bicycle facilities, the larger the price premium in Columbus and Cleveland. In terms of the socio-demographic composition of neighborhoods in which properties were located, results suggest that an increase in the percentage of Blacks and Hispanics was negatively associated with the sales price of properties in all cities except Eugene and Denver respectively.

4.4. Robustness check and sensitivity analysis

Regarding robustness checks for properties treated for both on-street and off-street facilities, we compared the first model of properties being transacted twice (i.e., the main model in Section 4.3) with the second model with only most recent transactions per property. The comparison model was similar to our core model in terms of the direction of effect except Denver where bicycle facility interventions resulted in positively significant effects on single-family properties (see Figs. S2-S3 in the SM). However, the magnitude of the effects was slightly lower in the comparison models. Most bicycle facilities had no impact on housing market values in the comparison model for multifamily properties. While this approach does not entirely address the double treatment issue (e.g., when a home is in a neighborhood with fast growth in cycling facilities), it gave us more confidence in the results of the main models.

With respect to the normalized sales price, while the results are quite similar to the main model results, modest decreases and increases in the sales price of single-family properties in Columbus, Minneapolis, and Eugene were very close to our estimates in the core models (See Fig. S8 and Fig. S9 in the Supplemental Material). We also found that multifamily housing market values slightly declined. However, there is no significant gap in the magnitude of the effect between normalized and non-normalized property values.

Regarding sales price per square foot, we found no major differences in the effects of bicycle values on sales price per building area square foot compared to the main models (i.e., with home sales price as the

Table 4
Single-family Difference-in-differences hedonic model results*

Variable	Cleveland	Columbus	Denver	Eugene	Los Angeles	Minneapolis	Philadelphia	Portland	San Francisco	Seattle	Tucson
Transaction characteristics											
After*on-street	−0.005	−0.04**	0.00007	−0.07***	0.0012	0.05***	−0.11*	0.007	0.025	−0.007	−0.012**
After*off-street	0.03	−0.02*	−0.04***	−0.11***	0.03*	0.07***		0.025	0.04	−0.017	−0.017***
After*all facilities	−0.06	0.06*	0.01	−0.11***	0.003	0.22***		0.045	−0.08	−0.008	−0.03*
After	0.02	0.13***	−0.002	0.08***	0.011	−0.05***	0.14*	−0.04***	−0.0005	0.03***	0.006
On-street	0.03*	0.02*	−0.01*	0.02*	0.006	−0.03*	−0.47***	−0.006	0.002	−0.0003	0.003
Off-street	0.03*	0.02*	0.014*	0.02	−0.008	−0.05***		−0.033*	0.02	−0.0001	0.004
All facilities	−0.07	0.14**	0.11***	−0.003	−0.2***	−0.23***		−0.14*	0.25	0.08**	−0.1***
Property attributes											
Building area	0.0003***	0.0006***	0.0004***	0.0001***	0.0004***	0.0004***	0.0003***	0.0003***	0.0002***	0.0003***	0.0005***
Age	−0.009***	−0.001***	0.000004	−0.003***	0.0004	−0.002***	−0.002***	0.0011***	0.0003***	−0.0002***	−0.002***
Number of stories	0.2***	0.38***	0.014*	0.13***		0.06***	−0.011	0.10***	0.04**	0.13***	−0.09***
Total number of rooms											−0.013***
Total number of bedrooms	0.008	0.025***	−0.03***	0.09***	−0.04***	0.02**		0.01*	0.0002	−0.032**	
Lot size	0.000003**	-1E-10	0.000001	0.00002***	0.00001***	0.00002***		0.000001	0.00005***	0.00001***	0.000002***
Locational attributes											
Distance to CBD	0.014***	0.02***	−0.026***	−0.04***	0.02***	0.08***	0.005*	−0.009***	−0.09***	−0.031***	−0.002***
Distance to nearest park	−0.00004**	−0.00006*	0.00014***	−0.00008**	0.00001	−0.00002	0.00004	0.00005**	−0.00003	−0.00013***	0.000008***
Distance to nearest bike facility	−0.000005	−0.00001	−0.00003*	0.0002***	0.00005**	0.00003	0.00003	0.00006*	−0.00004	0.00008***	−0.00008***
Neighborhood attributes											
Population density	−0.005***	0.006***	−0.002**	0.009***	−0.008***	0.003***	−0.00007	−0.0032**	−0.001*	0.003***	−0.014***
Street network density	−0.0007	−0.03***	0.007***	−0.013***	−0.0065*	0.002	−0.013***	−0.02***	−0.003*	−0.02***	−0.002*
National walkability index	0.02***	0.03***	0.03***	−0.009***	0.02***	0.035***	−0.006	0.02***	0.005	0.03***	−0.002*
Percent Black	−0.7***	−0.78***	−0.3***	0.52**	−0.88***	−0.85***	−0.73***	−0.36***	−1***	−0.73***	−0.43***
Percent Hispanic	−0.03	−0.32***	0.02**	−0.2***	−0.065***	−0.08**	−0.0006	−0.15***	−0.1**	−0.10**	−0.12***
Median household income	8E-06***	0.00001***	3E-06***	0.000001***	3.2E-06***	3.4E-06***	0.00001***	0.000003***	2.6E-06***	1.4E-06***	1.5E-06***
(Intercept)	10.5***	9.76***	11.28***	11.6***	11.36***	10***	11.4***	10.97**	13.17***	11.6***	11.3***
Lambda	0.46***	0.52***	0.58***	0.48***	0.58***	0.45***	0.37***	0.45***	0.44***	0.5***	0.57***
n	19,082	26,349	58,772	16,690	23,681	37,862	14,236	26,361	16,875	39,633	101,433

All models control for the year dummies. Significance codes: ***p ≤ 0.0001, **p ≤ 0.001, *p ≤ 0.05.

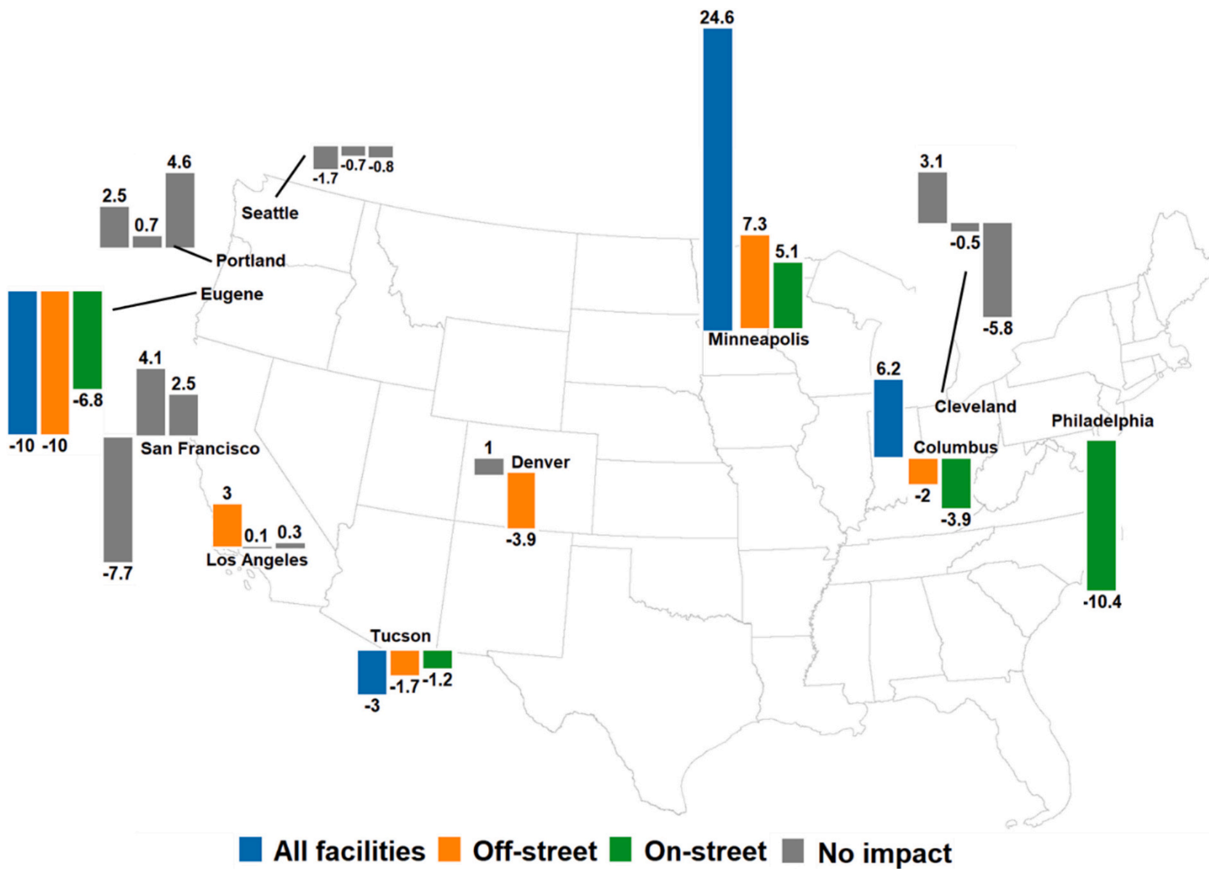

Fig. 4. Effect size of the individual and combined impacts of on-street and off-street facilities for single-family properties.

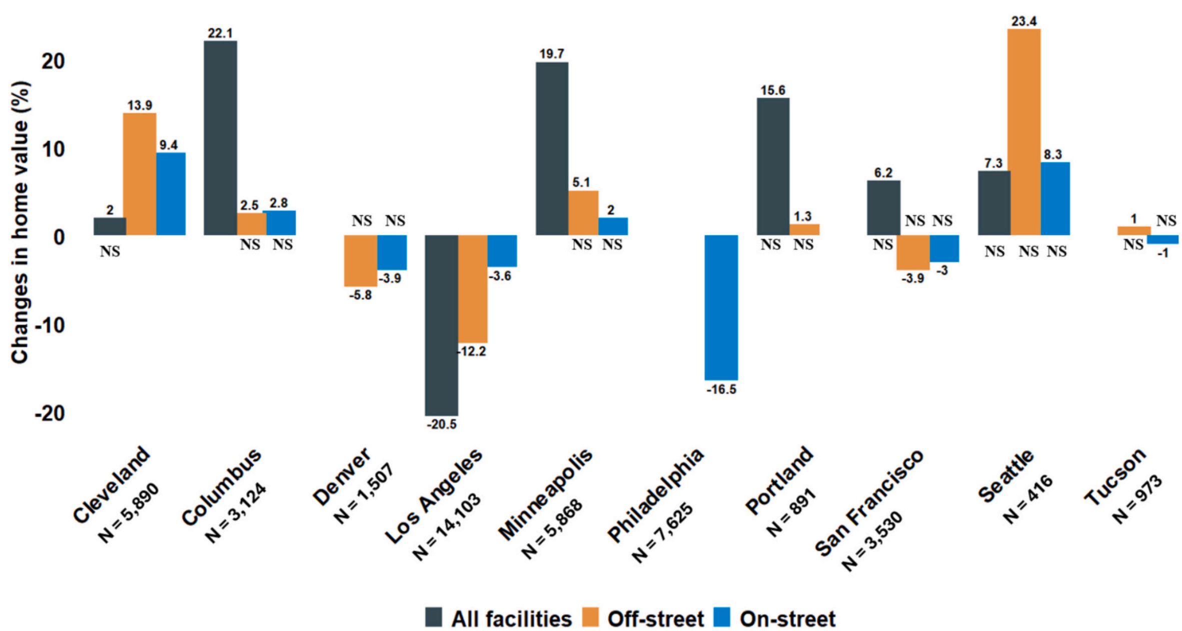

Fig. 5. Changes in home values in difference-in-differences hedonic models for multifamily properties. The values shown in the graph are the coefficients of the 3 DID terms. NS = not significant at $p \leq 0.05$.

dependent variable) (See Fig. S10 and Fig. S11 in the Supplemental Material). Similar to the core models of the study, the results show that multifamily properties that were treated for both on-street and off-street facilities appreciated more than single-family properties in Columbus while the effect was slightly higher for single-family properties in Minneapolis.

We performed a sensitivity analysis to check if the effects of bicycle facilities on home values persist on a smaller or larger scale than the 800 m buffer size tested in the main models. Therefore, we estimated models using the 400 m and 1200 m buffers as the cut-off for treatment groups

Table 5
Multifamily Difference-in-differences hedonic model results.

Variable	Cleveland	Columbus	Denver	Los Angeles	Minneapolis	Philadelphia	Portland	San Francisco	Seattle	Tucson
Transaction characteristics										
After*on-street	0.09*	0.028	−0.04	−0.037*	0.02	−0.18*	0.0003	−0.03	0.08	−0.01
After*off-street	0.13**	0.025	−0.06	−0.13***	0.05		0.013	−0.04	0.21	0.01
After*all facilities	0.02	0.2*		−0.23*	0.18**		0.145	0.06	0.07	
After	−0.09*	0.07	0.02	0.05**	−0.02	0.2*	0.05	0.10	0.002	0.03
On-street	−0.009	0.008	0.02	0.035**	0.05	−0.2*	−0.032	0.003	−0.06	0.007
Off-street	−0.037	0.032	0.024	0.11***	0.02		−0.05	0.02	−0.21*	−0.015
All facilities	−0.04	0.25*		−0.16	−0.06		−0.44	0.16	−0.07	
Property attributes										
Building area	0.00012***	0.00005***	0.00004***	0.00005***	0.0002***	0.27***	0.00008***	0.00003***	0.00009	0.00008***
Age	−0.005***	−0.002	−0.0034*	−0.003***	−0.003***	−0.003***	0.0009	−0.003**	−0.0001	−0.004*
Number of stories	0.11*	0.08	0.4***		0.15***	0.17***	0.24***	0.07*	0.06	0.11
Total number of rooms										−0.05
Total number of bedrooms	−0.03***	−0.05***		0.03***	0.014		−0.0007	0.02***	0.008	
Lot size	6.7E-07	6.3E-06***		−0.000012***	−0.000002		−0.00001**	0.00002	0.00005	0.000012***
Locational attributes										
Distance to CBD	0.007	0.02*	−0.06**	0.002	0.04**	−0.008*	0.011	−0.068***	−0.04*	−0.07*
Distance to nearest park	−0.0002**	0.0002*	0.00003	−0.00006*	−0.00002	0.00003	−0.0001	−0.000006	−0.0003	0.0002
Distance to nearest bike facility	−0.00011*	−0.0002*	−0.00003	0.00004	−0.00006	0.001	−0.0003	−0.00009	−0.0002	0.0005
Neighborhood attributes										
Population density	−0.00014	0.01***	0.004	0.004***	0.005***	0.0003	0.007	0.0005	0.001	0.03*
Street network density	0.006	−0.012**	0.04***	0.005*	0.0045	−0.007***	0.002	0.0009	−0.013	0.13***
National walkability index	0.023**	0.025*	0.05**	0.012**	0.02*	0.01	−0.008	−0.014	0.05*	−0.07*
Percent Black	−0.55***	−0.97***	−0.34*	−0.34***	−1.1***	−0.98***	−0.2	−1.2***	−0.62*	−0.11
Percent Hispanic	0.06	−0.4	−0.24***	−0.11***	−0.08	0.08	0.09	0.056	0.06	−0.04
Median household income	0.00001***	4.3E-06**	1.1E-06	4.5E-06***	1.4E-06*	5.2E-06***	9.3E-07	0.000002**	3E-07***	4E-06*
(Intercept)	10.6***	11.15***	11.31***	11.68***	10.6***	10.52******	11.5***	13.7***	11.7***	11.97***
Lambda	0.43***	0.46***	0.6***	0.47***	0.42***	0.44***	0.52***	0.43***	0.52***	0.81***
n	5890	3124	1507	14,103	5868	7625	891	3530	416	973

All models control for the year dummies. Significance codes: ***p ≤ 0.0001, **p ≤ 0.001, *p ≤ 0.05.

(see Figs. S4-S7 in the SM). We found that the effect of bicycle facilities on property transactions at a 400 m buffer distance did not persist on the same significance and magnitude level as the 800 m buffer distance for core models. The closer the single-family property was to the bicycle facility the smaller the magnitude of the effect was regardless of its direction. Additionally, bicycle facilities had a significant impact on property values in fewer cities compared to 800 m and 1200 m buffers. The significant impacts of bicycle facilities disappeared for single-family and multifamily properties in Columbus and Philadelphia within 400 m distance. With respect to properties within 1200 m of bicycle facilities, the positive effect of bicycle facilities on single-family and multifamily properties increased with distance. For example, as the distance to bicycle facilities increased (i.e., 1200 m buffer distance), properties in Columbus and Minneapolis sold for a larger premium.

4.5. *Estimating city tax revenue changes due to investment in bicycle infrastructure*

Results in Table 6 show substantial variations in the changes in revenues from sales price transactions of single-family and multifamily properties. The construction of bicycle facilities around single-family properties boosted revenues from property taxes, leading to a $646 increase in tax revenues in Minneapolis due to the presence of both on-street and off-street facilities and $218 from the construction of off-street facilities in Los Angeles. There was also a rise in tax revenues from multifamily properties, with the lowest revenues being generated by on-street facilities ($139) in Cleveland and the highest by the presence of both on-street and off-street facilities ($554) in Columbus. The estimates revealed that, in Columbus, revenues from property taxes received a boost only when on-street and off-street facilities were built near single-family and multifamily properties at the same time while the presence of either only on-street or off-street facilities decreased single-family property tax revenues. Bicycle facility interventions in closer proximity to single-family properties decreased property tax revenues in Denver, Eugene, Philadelphia, and Tucson.

5. Discussion and conclusions

5.1. *Summary of the results*

This study investigated the differential impact of different types of bicycle infrastructure such as on-street, off-street, and the presence of both on-street and off-street bicycle facilities on single-family and multifamily residential property values across 11 cities in the US from 2000 to 2019 using a quasi-experimental design with propensity score matching and spatial hedonic pricing models. The findings from our study were mixed. *Single-family homes* near *on-street-only facilities* saw a positive change in prices only in Minneapolis; and negative changes in

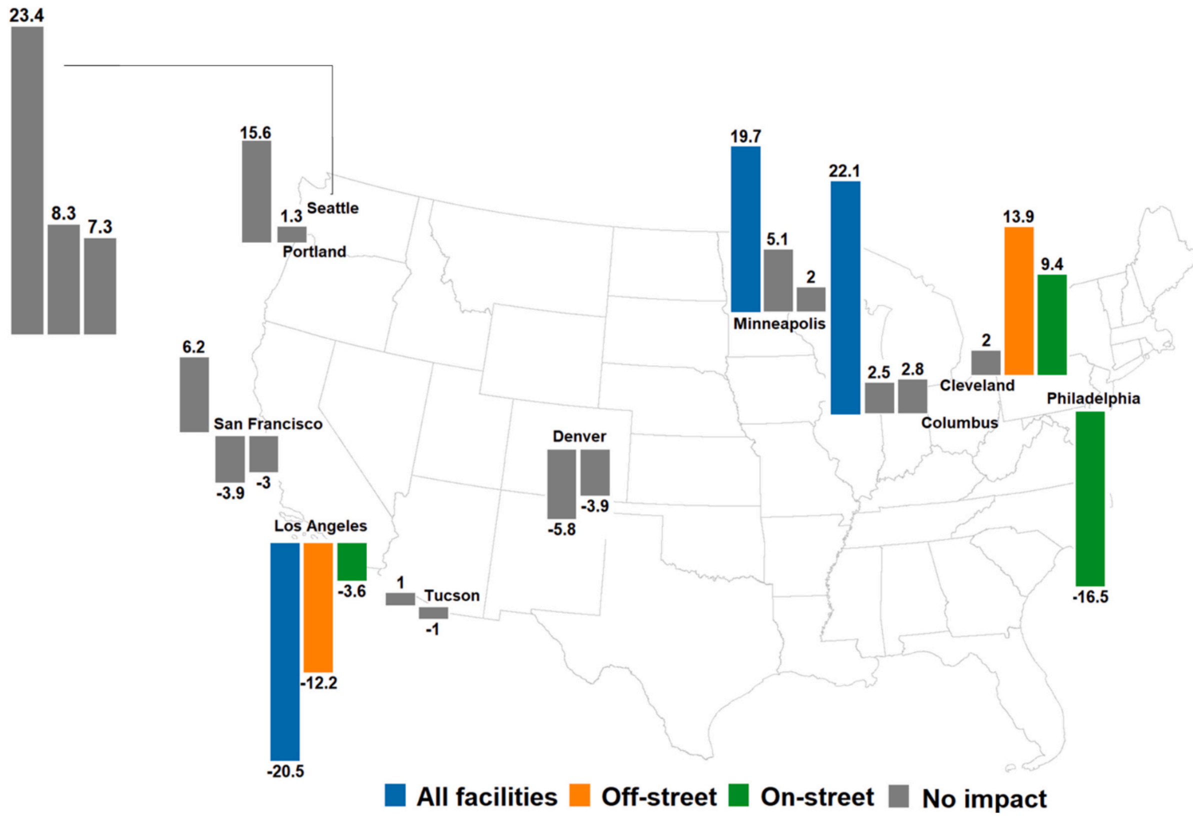

Fig. 6. Effect size of individual and combined impacts of on-street and off-street facilities on multifamily properties (some bars were scaled to map).

Table 6
Change in property tax revenues due to investment in bicycle infrastructure.

City	Treatment type	Tax rate (%)	Change in home value (%)		Mean sales price ($)		Change in property tax revenues per home ($)	
			Single-fam	Multi-fam	Single-fam	Multi-fam	Single-fam	Multi-fam
Cleveland	On-street only			9.42				139
	Off-street only			13.8				205
	On- and off-street	2	N/A	N/A	93,090	73,760	N/A	N/A
Columbus	On-street only		−3.92	N/A			−73	N/A
	Off-street only	1.43	−1.98	N/A	130,730	174,952	−37	N/A
	On- and off-street		6.18	22.14			116	554
Denver	On-street only		N/A	N/A			N/A	N/A
	Off-street only	0.42	−3.92	N/A	330,141	863,401	−54	N/A
	On- and off-street		N/A	N/A			N/A	N/A
Eugene	On-street only		−6.76	N/A			−117	N/A
	Off-street only	0.77	−10.42	N/A	224,370	N/A	−180	N/A
	On- and off-street		−10.42	N/A			−180	N/A
Los Angeles	On-street only		0	−3.63			N/A	−318
	Off-street only	1.16	3.05	−12.2	616,320	754,304	218	−1067
	On- and off-street		N/A	−20.6			N/A	−1798
Minneapolis	On-street only		5.13	N/A			135	N/A
	Off-street only	1.09	7.25	N/A	240,729	224,022	190	N/A
	On- and off-street		24.61	19.72			646	482
Philadelphia	On-street only	0.74	−10.42	−16.47	168,113	166,826	−130	−203
Portland	On-street only							
	Off-street only	0.94	N/A	N/A	313,738	526,697	N/A	N/A
	On- and off-street							
San Francisco	On-street only							
	Off-street only	1.18	N/A	N/A	1,037,726	1,707,931	N/A	N/A
	On- and off-street							
Seattle	On-street only							
	Off-street only	0.77	N/A	N/A	546,114	1,649,491	N/A	N/A
	On- and off-street							
Tucson	On-street only		−1.19				−16	
	Off-street only	0.65	−1.69	N/A	206,107	732,852	−23	N/A
	On- and off-street		−2.96				−40	

N/A: not available; bicycle facilities had no statistically significant impacts on property value.

Columbus, Eugene, Philadelphia, and Tucson, consistent with a past study (Welch et al., 2016). We found a null effect in Cleveland, Denver, Los Angeles, Portland, San Francisco, and Seattle.

The closer a *single-family or multifamily property* was to an *off-street only bicycle facility* in Los Angeles and Cleveland, the higher the selling price of the structure. These results are consistent with findings from past studies (Asabere and Huffman, 2009; Conrow et al., 2021; Lindsey et al., 2004) in San Antonio, TX, Tempe, AZ, and Indianapolis, IN where proximity to off-street bicycle facilities like trail and shared use path had a significant and positive impact on property values. As for *single-family and multi-family* properties with *both on-street and off-street facilities*, Columbus, Los Angeles, Cleveland, and Minneapolis experienced an appreciation whereas Eugene, Denver, and Tucson witnessed a decline in the sales price for properties in closer proximity to both facilities. In Los Angeles, however, multifamily properties with both on-street and off-street facilities depreciated, unlike single-family properties.

Overall, while we found evidence that bicycle facilities have significant positive impacts on housing market values within an 800 m buffer distance, the sensitivity analysis shows that being very close (e.g., at 400 m distance) from the bike facilities does not guarantee the highest gain in housing value as compared to being 800 m or 1200 m away. It could be the case that we have fewer homes within the 400 m buffer distance and this low number of observations affected the model results. In addition, there may be a potential local nuisance that may diminish property values, suggesting that the nuisance effect could be relevant for properties near bicycle facilities. It is also noteworthy to mention that a larger sample of properties within a 1200 m buffer distance could be driving the higher price premium associated with the presence of bicycle facilities. Therefore, it is important to account for contextual factors such as the presence of other amenities, traffic volume, speed limit, and urban design that may influence the impacts of bicycle facilities on property values at 400 m distance.

Overall, the effects of cycling infrastructure on home values varied by infrastructure type and city, perhaps due to the cities' different cycling culture and investment, as well as other potential land use and economic changes over the year. As for infrastructure, access to off-street bicycle facilities acts as a signal of the quality of the built environment and locational attributes, such as the quietness and accompanied green space and water near the trails. On the other hand, on-street facilities are abundant on major streets, which encourages buyers who like cycling or value walkability and accessibility, but also discourages buyers who are concerned about noise, traffic, and other nuisance effects.

As for the city characteristics, major investment in infrastructure in certain cities translated to increased home values. For example, the City of Minneapolis added 76 miles of bike lanes between 2007 and 2013 (Fields et al., 2022) and bicycling increased by 58% between 2000 and 2010 (Levinson, 2015), resulting in a positive gain in home values in places near bicycle facilities. Columbus and Cleveland also have made significant investments in bicycle facilities (MORPC, 2024) and witnessed an increase in bike commuting in recent years (Bike *Bike Cleveland—working for safe streets,* 2024). Meanwhile, cities with high housing shortages and housing costs such as Portland and San Francisco did not see increases in home values near certain types of bicycle facilities despite having a strong cycling culture.

Overall, the presence of bicycle facilities was associated with property value appreciation, depreciation, and no impact in our study areas over time. Yet it is unknown how long the effects will last, and whether the negative effects will be reversed in the future with changes in cycling infrastructure, investment, cycling activities, and attitudes. Most importantly, the effect of bicycle facilities on property values in Cleveland, Tucson, and Denver should be interpreted with caution since the test of prior trends on the pre-treatment data suggests that any deviations from the trend are not because of bicycle facility intervention per se. Similarly, findings from Columbus should be interpreted with caution due to the presence of unparallel trends. In the case of Philadelphia, we did not have the off-street facility data and we did not weigh the presence of on-street facilities against off-street facilities because we did not have data for off-street facilities in Philadelphia. Additionally, there was a significant imbalance between the treatment and control groups and this could be attributed to the strong negative result.

The results of this study highlighted the importance of equitably distributing bicycle facilities as exemplified by the negative association of certain demographics, especially Blacks and Hispanics, with housing market values. Previous research (Braun, 2021; Braun et al., 2019, 2023) showed that there is a disparity in access to bicycle paths and the health benefits of cycling, with disadvantaged neighborhoods with higher proportions of Black and Hispanic residents, and lower income and educational attainment having disproportionately lower accessibility to bicycle facilities.

Our property tax analysis shows that from a tax revenue standpoint, cities will have financial gain by investing in bicycle facilities. Other studies have shown that cycling is good for the local economy through other channels such as boosting local sales (Blondiau et al., 2016; Volker and Handy, 2021). Overall, our analysis lends support to existing findings that cycling infrastructure can generate positive returns on investment for cities, and these tax revenues can be used to build new bicycle facilities and maintain the old bicycle infrastructure. Of course, this comes with a cost of potential gentrification effects, hence cities should prepare for potential interventions such as tax assistance or affordable housing for existing residents with low income.

5.2. Limitations and directions for future research

This study has some limitations. First, we did not cover many other US cities of different sizes, which limits the generalizability of our findings. Second, due to the lack of data, we did not control for school district performance and traffic conditions which were found to have a significant influence on the sales prices of residential properties. Third, the DID approach did not allow an investigation of long-term trends across multiple transactions – we only incorporated transactions that were closest to the time the nearest bicycle facility was constructed. Future studies could address the above issues and extend the analysis to understand multiple bicycle infrastructure benefits such as safety, health, home value, and local retail. Even though our study used a quasi-experimental design that accounts for the presence of bicycle facilities within a certain distance, it did not account for the city-wide bicycle network connectivity and access to destinations. For example, the connectivity and access to destinations in bike infrastructure networks of 1 mile will differ from the 20-mile system. Therefore, future research could further explore the extent to which system connectivity influences the relationship between housing transactions and the presence of bicycle facilities within a certain distance.

We acknowledge the possibility of heterogeneous treatment effects across space and time. It is noteworthy that the estimated effects of bicycle facilities on home values were the averages taken over space and time. For example, the effect of a new bicycle facility does not suddenly drop to zero at a specific buffer (e.g., 400 m, 800 m, or 1200 m in our case) or suddenly change at a specific time (e.g., 2018 or 2020). We also did not consider local variables that could vary over time in a way that is spatially correlated with bicycle facilities due to data limitations. More specifically, the variables that might influence both bicycle facilities and the housing market such as population density and street network density were time-invariant in our model.

Our study did not consider the potential anticipation effect during the project announcement phase (i.e., home values change in response to a future project). While this announcement effect may be less common in bicycle infrastructure than it is in larger projects such as transit, a future study could explore the role of the announcement effect in the impacts of bicycle facilities on property values. Moreover, research shows that proximity to greenspaces and parks commands housing value premiums (Piaggio, 2021). Future studies should consider quantifying multiple (simultaneous) treatments such as greenspaces and bicycle infrastructure on housing market values.

Our study area reflects some potential self-selection effects. We chose these 11 cities in part because local planning agencies made the data available, suggesting that these cities value cycling investment more than average American cities. More representation from other cities, especially in the Southeast, West, and North Central is desirable for future research. In addition, decision-making on the investment and construction of bicycle facilities often occurs at different levels of the government beyond cities. Therefore, future studies could investigate the impacts of bicycle facilities on property values at the county or metropolitan statistical area level.

We also did not record the full date of bicycle facility construction and therefore, we cannot infer the temporal impact within the same year in our model. In addition, census geographies may change shape over time throughout the 20-year study period. This issue may affect the aggregation of results at the blog group level (i.e., the modifiable areal unit problem) and thus may also affect the model estimates.

5.3. Policy implications

This study fills a gap by distinguishing itself with a quasi-experimental design with data over a period of 20 years across multiple urban contexts in the United States. Isolating the pre- and post-treatment effects of different types of bicycle facility investment contributes to understanding home buyers' perceived value of nearby on-street and off-street facilities which have a bearing on local tax revenues through their influence on property prices.

Findings from this study have significant policy implications for the local economy, equity, sustainability, safety, and health. First, the increased property value associated with closer proximity to bicycle facilities could help policymakers prioritize investment in certain types of bicycle infrastructure that could lead to higher property tax revenues via an increase in the sales price of residential properties. Second, policymakers need to ensure that bicycle infrastructure is equitably distributed by prioritizing marginalized neighborhoods. At the same time, investment in bicycle facilities in disadvantaged neighborhoods should be coupled with affordable housing policies to avoid unintended gentrification in the future since infrastructure provision in those communities might appeal to those on the upper-end of the socioeconomic scale. Investing in bicycle facilities in disadvantaged neighborhoods also has the potential to advance health equity as cycling enhances cardiorespiratory fitness through physical activities and improves air quality. Third, the higher premium associated with bicycle facility interventions around multifamily residential properties implies that investing in bicycle infrastructure near multi-family housing has the potential to encourage cyclists to move into these areas. Finally, findings from this study could be transferable to other urban housing markets, and they could be used as a tool to prioritize locations and types of facilities in urban areas.

CRediT authorship contribution statement

Abdirashid Dahir: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Huyen T.K. Le:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2025.104146.

Data availability

The authors do not have permission to share data.

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