

Is Bike Share an Amenity?: An Exploration of Bike Share's Effect on Single-Family Home Values in Minneapolis

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Abstract

Bicycle sharing systems are rapidly expanding to cities across the globe. Much research has been conducted on transportation and health related benefits purported to occur with bike share implementation, but few studies have sought to understand the economic impacts of bike share. This research builds two hedonic models to estimate changes in single family home prices in Minneapolis, Minnesota based on proximity to the Nice Ride bicycle sharing system. The models suggest that changes in value may be negative in many neighborhoods, though results are not uniform. Other studies have found positive impacts on other types of housing, indicating that further research is necessary to fully understand in what types of circumstances bicycle sharing systems have positive or negative effects on home values.

Introduction

The Nice Ride Minnesota bicycle sharing system opened in 2010 in Minneapolis, Minnesota. Nice Ride opened in 2010 with 700 bicycles available at 65 stations. By 2014, Nice Ride had 170 stations and 1,556 bicycles in the system and was serving the greater Minneapolis-St. Paul 'Twin Cities' area (Nice Ride, 2015). The system originally began in downtown Minneapolis, but quickly expanded into many other neighborhoods throughout the city, as well as St. Paul and the University of Minnesota campus.

The addition of bike share and its expansion fits in with other efforts by the City of Minneapolis to enhance bicycle ridership. The US Census estimates that 4% of Minneapolis residents primarily commuted by bicycle in the 2008-2012 period (McKenzie, 2014). Comparatively, principle cities averaged a 1% bicycle commute rate and the nation as a whole averaged .6% during the same period. This high rate of cycling is reinforced by several efforts undertaken by the city. In the 2011 Bicycle Master Plan, the city identified goals of increasing the mode share of bicycle trips, expanding bike share to "all parts of the city," and setting benchmarks to ensure that all residents have access to bicycle facilities of different kinds by 2020 (Plfaum, 2011). Minneapolis aggressively expanded their bicycle network to achieve these goals. In 2010, the city had 138 lane miles of bicycle facilities and had expanded this network to 213 lane miles by 2014 (City of Minneapolis, 2015).

Nice Ride, like many bicycle sharing systems, received considerable capital funding from public sources. Though operating losses are recovered through sponsorship of the system, Nice Ride had received around \$5 million in public funding through grants, primarily from federal agencies, but also from Hennepin County, Minnesota Department of Transportation, and local

colleges (Nice Ride, 2015). Many bike share systems operate similarly to Nice Ride, covering operating losses with sponsorships, however, there are an increasing number of systems that are receiving annual operating subsidies from local governments. For example, the City of Boulder contributed \$50,000 in 2015 and again in 2016 to Boulder B-Cycle and LA Metro will split any operating losses with the City of Los Angeles for their LA Metro Bike Share (Boulder B-Cycle, 2017; Sotero, 2015). Public investment of funds in this type of infrastructure may be justified if tax revenues are increased based on rising property values.

Many researchers have noted a connection between different types of transportation infrastructure and housing or land values. These effects are seen across many different types of infrastructure from light rail and bus rapid transit, to increased walkability and proximity to bicycle facilities (Yan, Delmelle, and Duncan, 2012; Cervero and Deok, 2011; Pivo and Fisher, 2011; Mogush, Krizek, and Levinson, 2005). Researchers have found both positive and negative relationships between these transportation improvements and property values, as will be noted in the literature review.

To date, only one study has examined the relationship between property values and bicycle sharing systems. El-Geneidy, van Lierop, and Wasfi (2016) modeled the effects of the number of Bixi bike share kiosks in proximity to multifamily housing in Montreal, Canada. They found an approximately 2.7% increase in the sale price of homes with 12 bike share stations within 800 meters. It is unclear if this relationship exists in other areas, and particularly with other housing types, such as single-family dwellings.

This discussion should also consider that increases in property values may be unequally distributed and possibly cause displacement. It may also be the case that bicycle sharing systems lower property values in certain circumstances. If this is the case, this information will help policy makers determine whether other benefits that are provided by bicycle sharing systems are worth the cost to local home owners. Without knowledge of how these impacts are distributed, policy makers cannot adequately weigh the costs and benefits of public investment in bicycle sharing systems. Ultimately the economic impacts of bicycle sharing are one of many possible benefits and should be evaluated holistically with other public objectives.

This paper examines the impact of bicycle sharing systems on single family homes in Minneapolis, Minnesota following the implementation of Nice Ride in 2010. In order to accomplish this, the author developed a hedonic regression model using sales data for the City of Minneapolis from 2006 to 2014. The model is then compared to a fixed effects model.

Literature Review

Bicycle sharing systems, also known as ‘bike share’ or ‘shared use bicycles,’ are rapidly expanding throughout the world. Bike share has been defined as a “short-term bicycle rental available at a network of unattended locations,” or also as “the provision of bikes, which can be picked up and dropped off at self-serving docking stations” (DeMaio and Meddin, 2017; Fishman, 2016, pp. 92). Bike share is characterized by the ability to pick up and drop off bicycles

at unattended and dispersed locations throughout a service area. Bike share systems differ from bike rentals in that they often limit the amount of time a bicycle can be rented. Further, bike rentals "... traditionally target users interested in leisure-oriented mobility..." and require users to return the bike to the same location, while bike share allows users to return bicycles to many locations within the service area (Shaheen, Martin, Cohen, and Finson, 2012b). Bike share is generally considered a type of public transportation.

Bicycle sharing systems have spread rapidly in recent years. In 2014, there were only 13 bicycle sharing programs throughout the world (Fishman, 2016). As of May 2017 there were an estimated 1,286 systems in operation. These systems are estimated to contain approximately 3,415,750 bicycles (Meddin and DeMaio, 2017). Bicycle sharing systems continue to spread rapidly based on a myriad of purported benefits. These benefits typically include improvements to the local transportation system, public health benefits, and, to a lesser extent, economic benefits for users and the community.

Evolution of Bicycle Sharing Systems

Bike share systems have evolved through three distinct generations of technology, and many scholars believe that current systems are moving into a fourth generation (Shaheen, et al. 2012b; DeMaio, 2009; Midgely 2011). The first generation of bike share was launched with the White Bikes of Amsterdam in 1965. Other European cities adopted similar free bike sharing programs, but vandalism and theft shuttered most programs (DeMaio 2009). Portland, Oregon, Boulder, Colorado, and several other United States cities attempted first generation bike share programs in the 1990s (Shaheen, et al. 2012b).

Second generation bike share featured coin operated kiosks to help address issues of theft and damage. Typically coin operated, these systems still faced issues of theft and damage due to user anonymity. The third generation of bike share attempted to solve these issues by using technology to track bicycles and identify users. Third generation bike share featured magnetic card readers, credit card readers, key fobs, electronically locking stations, and other features that would help keep track of bicycles and who was renting them (DeMaio, 2009; Midgely, 2011).

Fourth generation bike share is being currently discussed. Features include dockless stations, mobile phone applications, solar powered stations and bicycles, pedal assist bikes or electronic bicycles, and potentially transit smartcard integration (Fishman, 2016; Midgely, 2011). Systems with these features are beginning to appear around the United States with operators like Social Bikes and Motivate using smart bikes rather than kiosks. These systems integrate GPS, locking, and payment into the bicycles in conjunction with mobile phone applications to allow users to lock to any bicycle rack, rather than just at kiosk stations (Motivate, 2017).

Benefits of Bike Share

Bike share feasibility studies and planning documents often tout many benefits that will accrue with installation of a system. Proponents often extol bike sharing for improving the local transportation system, improving public health, and, to a lesser degree, providing economic benefits for users and the community.

The Institute for Transportation and Development Policy's *The Bike Sharing Planning Guide* (2013) lists benefits that include congestion reduction, increased accessibility, and increased access to transit (first mile/last mile). Researchers in a variety of studies have confirmed many of these benefits, as well as several others. Shaheen, Guzman, and Zhang (2012a) noted that benefits include improving access to bicycles by removing barriers such as maintenance and storage, solving the 'first mile/last mile' problem of connecting to transit, and mode shift leading to lowered traffic congestion.

Other scholars have found that bike share can reduce greenhouse gas emissions, increase the share of trips by bicycle, and increase transit usage (DeMaio, 2009; Shaheen et al., 2012b). The speed of deployment of bike sharing systems has also been noted as a benefit. This rapidity allows bike share to quickly fill in gaps in the transportation system (Midgely, 2011). Some bike share operators publish data on estimated CO₂ reduction by estimating emissions based on the number of miles traveled by their bicycles (CitiBike, 2017; Denver Bike Sharing, 2017; Boulder B-Cycle, 2017). Other operators allow users to see in real time the number of miles ridden and estimated carbon reduction their personal trips have made (Social Bikes, 2017).

Health benefits, both public and private are noted as benefits and justifications in bike share feasibility studies and planning documents (ITDP, 2013; Toole Design Group, 2014; Dosset, et al., 2008). Scholars have also noted the health benefits of shifting from passive modes of transportation, like an automobile, to active modes. One study of the bicycle sharing system in London found significant health benefits for users related to increased physical activity, which was not offset by the increased risk of collision with automobiles or contact with air pollution (Woodcock, Tainio, Cheshire, O'Brien, and Goodman, 2014). The authors of that study noted the relatively lower risk of a collision with an automobile compared to cyclists more generally. Many bike share operators publish data about calories burned by users of their systems or allow users to track this themselves (Social Bikes, 2017; CitiBike, 2017; Denver Bike Sharing, 2017).

Similar results were found in other studies of bike share and public health (Fishman and Schepers, 2016; Fishman, 2016). In a review of bike sharing safety in a number of cities, researchers concluded that despite several behaviors and characteristics of bike share users that would suggest an increased rate of injury, there was actually a lower risk of injury while using bike share compared to the use of personal bicycles (Martin, Cohen, Botha, and Shaheen, 2016). Martin, et al. (2016) partially attributed this to user behavior on bike share bikes, noting

that bicycles in sharing systems “...are designed to be larger, slower, and sturdier than personal bicycles, they are not ridden as aggressively as personal bicycles” (pp. 58).

Researchers looking at economic benefits of bike share have found both public and private benefits. Shaheen, et al. (2012a) note that users can save money by reducing automobile related expenses. Other researchers have noted that much of the benefit to private individuals results from time savings both resulting from the ability to use bike share for short trips or link bike share with public transportation for longer trips, though they concede that “... the benefit of these time savings has not been estimated in economic terms,” (Bullock, Brereton, and Bailey, 2017, pp. 77).

Bullock, et al. (2017) also noted that time savings extended to create public benefits through increased productivity, but that many of the public benefits are related to increased public health, an outcome noted in various other studies. Schoner, Harrison, and Wang (2012) analyzed economic activity around Nice Ride stations in Minneapolis and found a positive association between station activity and the number of food-related destinations around the station. Further investigation through surveys of Nice Ride members revealed that they often substituted Nice Ride for trips they would have previously made by automobile, leading the authors to conclude that businesses around Nice Ride stations benefited from users changing where they would have spent money as a result of using their desired choice of transportation. The authors also pointed out that spending by Nice Ride users was generally moderate, and did not generally induce additional trips that would not have otherwise occurred. Research on economic activity by bicyclists as a broad category generally agrees with these findings (Clifton, Muhs, Morrissey, Morrissey, Currans, and Ritter, 2013).

As demonstrated in the Bullock, Brereton, and Bailey (2017) study, many of the benefits of bicycle sharing in all categories – sustainable mobility, health, and economic – largely depend on mode share shift away from private automobiles. The convenience of bicycle sharing combined with bike share creating a “...hip, modern image ...” that can “...help transform the cycling culture in a city...” is supposed to induce motorists to make trips by bicycle (ITDP, 2013, pp. 14). Studies on mode shift have produced mixed results.

A 2016 survey of Capital Bike Share users in Washington, D.C. found that more than half of users reported reduction in nearly all other modes including driving an automobile, taking a taxi, using ride-hailing services (Uber and Lyft), Metrorail, and bus. More than one third of respondents reported walking less (LDA Consulting, 2017). Ma, Liu, and Erdogan (2015) found that Capital Bike Share stations may increase transit ridership. Shaheen, et al. (2012b) analyzed surveys conducted by three bike share operators and found that 41% of users had made some trips by bike share and transit that they previously would have made by automobile. The degree to which users of each system agreed that they had replaced auto trips with bike share trips varied considerably between the cities. DeMaio (2009) noted increases in the bicycle mode share of commutes in Barcelona and Paris after the introduction of bicycle share systems.

Not all research suggests that large mode shift away from automobiles is taking place. In a review of bike share systems in the United States, the United Kingdom, and Australia,

Fishman, Washington, and Haworth (2014), found large differences between cities in the reduction of vehicle kilometers traveled as a result of bike share and the percentage of trips that bike share substituted for auto use. Results ranged from 3% to 21% of users reporting their most recent trip substituted bike share for a private automobile. A much greater proportion of users in all cases replaced trips that would have otherwise been taken by transit or walking. A review of bike share literature by Fishman (2016) included other studies that confirmed his prior findings. In summary he noted, "... a central motive for the development of bikeshare is sustainable transport outcomes, yet no standard methodology has been established to enable operators and researchers to accurately and consistently measure the impact BSPs have on car use, climate change, congestion or public health," (Fishman, 2016, pp. 93).

Land Value Impacts

One of the only sets of impacts from bicycle share that is not dependent on mode shift are changes in property values due to proximity to the system. Transportation infrastructure is well known to have impacts on land use values due to changes in levels of accessibility. These impacts have the ability to shape land use patterns at the regional level if the infrastructure is large, such as heavy rail (Knight and Trygg, 1977). Other large investments such as light rail have been found to have substantial positive impacts on the value of homes near them (Yan, et al., 2012). Several studies on bus rapid transit have shown that these improvements also increase home and commercial property values around stations (Cervero and Deok, 2011; Perk and Catala, 2009).

Active transportation infrastructure has also been shown to have impacts on land values, though in many cases these have smaller positive impacts and occasionally negative impacts in certain circumstances. Pivo and Fisher (2011) found a positive association between Walkscore, a composite measure of walkability based on infrastructure and nearness to local amenities, and commercial real estate values. Mogush, et al. (2005) investigated the connection of bicycle facilities of several types to home values in Minneapolis, Minnesota. They separated homes into classifications of urban and suburban and then analyzed on-street bike lanes, on street trails, and off-street trails. Their results suggested that in some instances, bicycle facilities are considered an amenity and have a positive association with home values, while in other contexts, particularly more suburban ones, bicycle facilities have a negative association with home values. Analyzing Portland, Oregon, Liu and Shi found that proximity to bicycle facilities was positively associated with home value. These studies indicate that the land use impacts of smaller-scale infrastructure, particularly related to active transportation is not as direct as for other types of transportation access and may have different effects in different areas.

As previously stated, only one study has attempted to quantify the impacts of bicycle sharing systems on home values. El-Geneidy, et al. (2015) found increased home values given proximity to bicycle sharing stations. However, that study was limited to multifamily housing. Single family housing is the dominant housing type for many areas in the United States, including Minneapolis, where 44.6% of households live in single family detached dwellings (United States Census Bureau, 2012). This study fits within the larger literature of how

transportation infrastructure influences the value of homes, expanding upon other work looking at smaller-scale and active transportation related infrastructure. As noted by El-Geneidy, et al., study of the economic impacts of bicycle sharing systems is limited at the present. This work fills a portion of that gap by investigating how small scale, active transportation infrastructure – bike share in this case – can influence single family home values.

Methodology

Property transactions involve non-homogenous markets with many attributes. In order to assess the relative value of a property, many studies, including this one, employ hedonic price regressions. Rosen (1974) described a methodology by which non-homogenous goods could be priced by defining their value as “... the implicit prices of attributes ...” that “... are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them,” (pp. 35). Much of the literature previously cited employs this methodology (El-Geneidy, et al., 2015; Mogush, et al., 2005; Liu and Shi, 2016; Pivo and Fisher, 2011; Cervero and Deok, 2011; Yan, et al., 2012). Using this approach, the dependent variable, gross sale price of a home (P_h), is derived from the sum of price of the attributes of the home. These attributes are categorized as structural (P_s), neighborhood characteristics (P_n), and locational accessibility (P_l). Thus, the price of any individual property can be expressed as the equation: $P_h = P_s + P_n + P_l$.

Housing characteristics present in the model include number of bedrooms, number of bathrooms, above ground area in square feet, below ground area in square feet, size of the lot in square feet, number of fire places, and the age of the house at the time of sale in years. The Minneapolis Assessors Office provided data for all property transactions from 2006 to 2014 as well as structural characteristics for each year from 2010 to 2014. At the time of the study data was unavailable for structural characteristics for years 2006 to 2009. Sales that took place during this period are modeled using 2010 attributes.

Using the statistical programming language R, a panel data set was assembled by filtering all sales down to only those with the type “Single Family Dwlg.” This filtered out non-comparable sales, which included multifamily, commercial, and single family attached housing, among others. The housing and land characteristics were joined to the sales records by the tax assessment PIN number assigned to each property. The age of the house at time of sale was created by subtracting the year the structure was built from the sale date. A dummy variable was created for the year of sale to control for fixed effects of the sale years. Comparing properties only with other sales in the same year helps to control for large changes in housing prices during the study period caused by the Great Recession.

Figure 1: Number of Sales each year of the study

Year	Num. of Sales
2006	4,681
2007	3,917
2008	3,735
2009	4,271
2010	3,280
2011	3,122
2012	3,888
2013	4,320
2014	4,081
Total	35,295

Data was cleaned to remove outliers and non-representative units. First, sales under \$30,000 were dropped because they are unlikely to be 'arms length' transactions. Sales over \$500,000 were removed as they are not likely to be representative of the market. Next, all units with zero bathrooms, more than five bedrooms, and more than three bathrooms were deleted. This approach is found in the literature as a way to enhance model accuracy (El-Geneidy, et al., 2016). After cleaning the data, 35,295 sales remained in the panel.

Figure 2: Location of sales included in the model



ESRI's ArcMap software was used to generate spatial data for several variables. This data includes distance to the centroid of the central business district, distance to the frequent transit network, and the presence of bike share. Distance to the central business district and

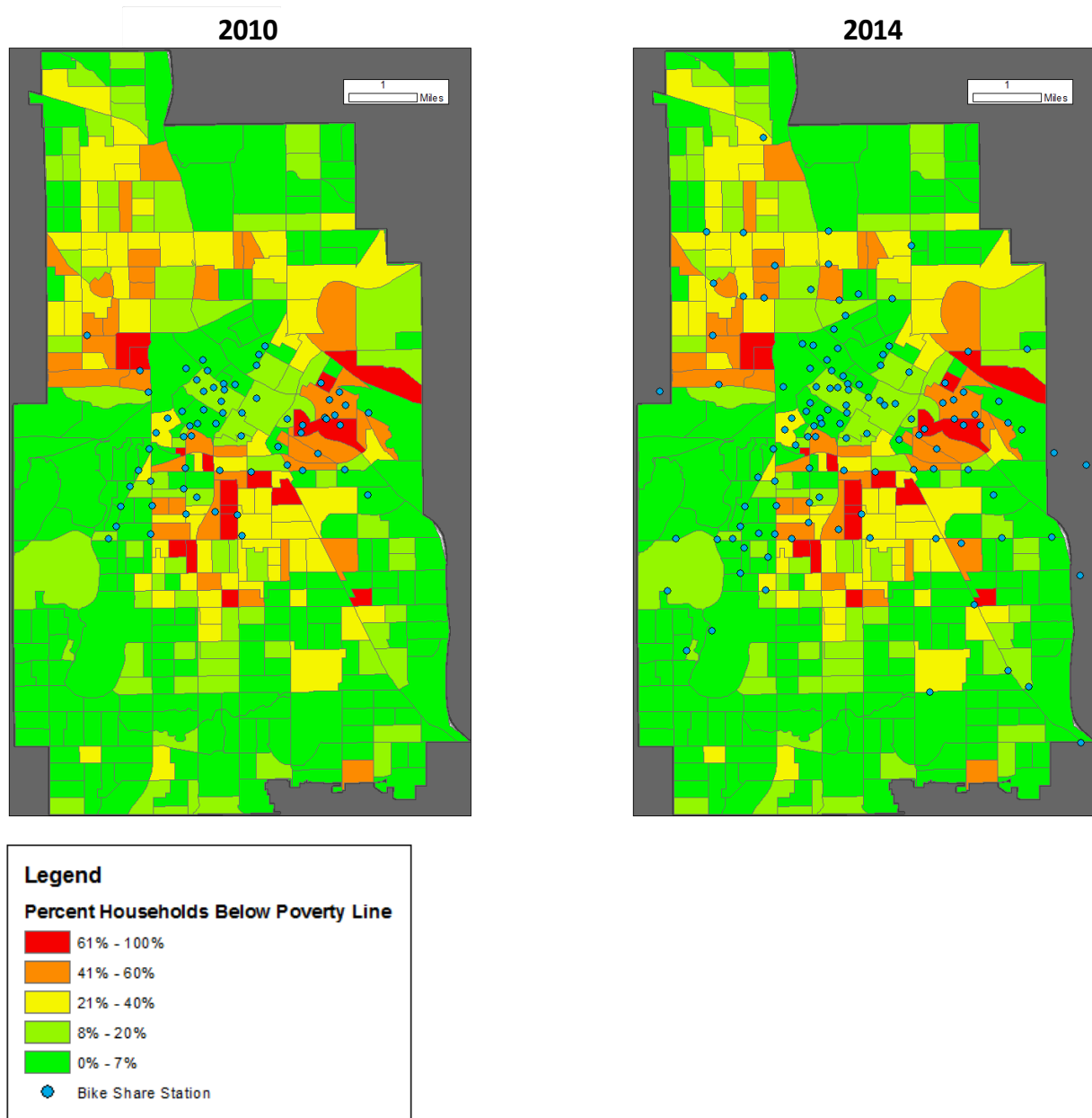
proximity to the frequent transit network were both found in similar studies as ways to compare accessibility in a hedonic model (Liu and Shi, 2016; El-Geneidy, et al., 2016). After testing, however, distance to the CBD was not significant in the model and was dropped as a variable.

The Nice Ride system expanded rapidly during the period of between 2010 and 2014. Initially Minneapolis featured 65 stations within the study area, but the system had grown to 114 stations within the city limits. Figure 3 shows the growth of area within Minneapolis within .25 miles of bike share stations. Parcels in the study panel were assigned a variable for each year for whether or not they were within .25 miles of a bike share station. In total, 1,703 sales occurred with the presence of bike share.

For the first model, an ordinary least squares regression, data was added to the panel to account for neighborhood characteristics. Census data for the American Community Survey 2008-2012 was obtained from Social Explorer and joined to the panel using the Census tract FIPS code. Census tract level data was selected because of the larger standard errors found in block group level data. Variables for the model were chosen based on their significance in other hedonic models found in the literature and attempt to control for neighborhood characteristics and local accessibility. These variables include population density, percent of residents that identify racially as non-Hispanic white, median income, median age, and average commute.

In addition to the distance to transit variable generated in the GIS analysis, Walkscore is included in the model to better account for variations in locational accessibility because both have been found to influence property values (Cervero and Deok, 2011; Yan, et al. 2012; Pivo and Fisher, 2011; Liu and Shi, 2016). Walk Score was generated by using the latitude and longitude for each parcel to query the Walk Score API using a script in R. Proximity to bicycle facilities has been shown to have an effect on property values and may have a greater effect combined with bike share, however this was not included due to data unavailability (Liu and Shi, 2016; Mogush, et al. 2005). Inclusion may not have been desirable, as in at least one study, variables that measured the local bicycle network were highly correlated with Walk Score (El-Geneidy, et al., 2016).

Figure 3: Growth of Nice Ride stations and percentage of residents in block group in poverty in 2010 and 2014



In the fixed-effects model, the Census block group of the parcel was modeled as a set of dummy variables. Block groups were used because they have been found to better approximate heterogeneous neighborhoods compared to Census tracts (Goodman, 1977). American Community Survey data has greater standard errors at the block group level compared to the tract level, however, there are no estimates of data about residents associated with a fixed-effects model, so this issue does not present the same challenge as it did in the OLS model. Appendix A contains a full listing of the sources of data for each variable in the models.

Figure 4: Descriptive statistics for sales without bike share at the time of sale

	Min	Max	Mean	Median
Bedrooms	0	5	2.84	3
Bathrooms	1	4	1.55	1
Fireplaces	0	5	0.41	0
Age (years)	0	195	79.06	84
Sale Price	\$30,010	\$499,900	\$183,175	\$177,000
Above Ground Area (sq. ft.)	376	3,850	1,219	1,176
Below Ground Area (sq. ft.)	0	2,467	824.20	828
Lot Size (sq. ft.)	1,053	33,020	5,668	5,208
Walk Score	0	195	79.06	84
Distance from CBD (ft.)	3,492	33,539	20,844	20,504
Distance from Transit (ft.)	40	17,416	4,133	3,108
Population Density (pop./sq. mi.)	1,685	24,440	6,908	6,599
Median Age	19	46	35.25	35.90
Median Income	\$13,511	\$121,364	\$61,621	\$54,946
Percent Renters	2%	95%	29.09%	24%
Percent White	6%	97%	70.49%	77%
Average Commute (minutes)	17	36	22.80	23

Figure 5: Descriptive statistics for properties with bike share at the time of sale

	Min	Max	Mean	Median
Bedrooms	0	5	2.94	3
Bathrooms	1	4	1.55	1
Fireplaces	0	5	0.26	0
Age (years)	1	131	89.58	97
Sale Price	\$30,111	\$498,650	\$148,132	\$126,000
Above Ground Area (sq. ft.)	392	3,788	1,317	1,268
Below Ground Area (sq. ft.)	0	2,104	791.10	804
Lot Size (sq. ft.)	1,023	20,253	5,593	5,265
Walk Score	19	97	68.12	68
Distance from CBD (ft.)	4,463	31,563	14,727	14,344
Distance from Transit (ft.)	63	12,238	2,883	2,197
Population Density (pop./sq. mi.)	1,685	27,442	8,541	7,642
Median Age	19	46	31.64	30.00
Median Income	\$13,511	\$112,264	\$45,310	\$42,917
Percent Renters	4%	92%	47.66%	50%
Percent White	6%	93%	57.25%	69%
Average Commute (minutes)	17	36	22.80	23

Results and Discussion

Figure 6 shows the results of both regression models. Several trends emerge when looking at the models in comparison, however, it is useful to first look at the models separately. In the OLS model all independent variables were significant when adding them sequentially into the model, however, the age of the house and distance from the central business district became insignificant in the full model. As expected, increases number of bedrooms, number of bathrooms, size of the house above and below ground, size of the lot, fireplaces, and Walk Score were associated with higher property values holding other variables constant. The age of the home is negatively associated with property values. Neighborhood characteristics positively associated with home values include percentage of neighborhood residents that identify as non-Hispanic white, population density, and median income. Average commute time and median age were both negatively associated with property values.

Unexpectedly, increased distance to the frequent transit network is positively associated with property values. As noted in the literature review other studies have generally found high frequency transit to increase property values (Cervero and Deok, 2011; Yan, et al., 2012). Minneapolis' high frequency network during this period contained one light rail line, but was otherwise frequent, albeit 'regular' bus service. It is unknown if the disamenity of frequent transit is related to most of the network consisting of bus service, as some types of bus service – specifically bus rapid transit – have been shown to increase home values (Perk and Catala,

2009; Cervero and Deok, 2011). Perk and Catala (2009) cite many studies where home values were found to contextually increase and decrease in relation to transit services based on a variety of factors specific to those locations. Much greater exploration than the scope of this research allows would be necessary to fully understand the impact of this variable on property values in the study area.

One of the primary variables of interest, presence of bike share within .25 miles, was positively associated with home values. The other, presence of bike share within .5 miles, but not within .25 miles was not significant. Holding all other values constant, the model predicts proximity to bicycle sharing within .25 miles increases the sale price of a home \$11,212.57 or approximately 6.6% of the mean home value in the study. The r^2 value of .615 indicates that the model has fairly large predictive power, though also that there are clearly many factors that are contributing to the price of properties that are not explained by this model.

Looking at the fixed-effects model produces slightly different results. Coefficients for nearly all variables were the same. Three major differences arise: first, age of the home becomes significant and increased age is associated with decreasing home values. Second, almost all coefficients are smaller in magnitude compared to the OLS model. Given the slightly different approach to this model and the higher r^2 value of .697, this model suggests that the OLS model is overestimating coefficients, likely as a result of omitted variable bias.

Figure 6: Model coefficients

	OLS		Fixed-Effects	
	Coefficients	Significance	Coefficients	Significance
Housing Characteristics				
(Intercept)	-110,295.44	***	28,991.23	***
Bedrooms	1,226.94	*	2,911.36	***
Bathrooms	16,036.37	***	13,579.58	***
Above Ground Area	70.90	***	59.05	***
Below Ground Area	14.62	***	14.35	***
Lot Size	2.84	***	2.98	***
Fireplaces	19,872.81	***	12,437.50	***
Age	-21.10		-103.42	***
Transportation Characteristics				
Walkscore	511.74	***	-	
Presence of Bike Share 1/4 mi.	11,212.57	***	-5,943.09	***
Presence of Bike Share 1/2 mi.	-916.94		-3,167.43	**
Dist. to CBD	0.07		-	
Dist. to High Freq. Transit	1.08	***	-	
Neighborhood Characteristics				
Percent White	1,358.54	***	-	
Population Density	0.70	***	-	
Median Age	-497.52	***	-	
Median Income	1.29	***	-	
Average Commute	-554.85	***	-	
Block Group Dummy Variables	-		1	
Time Variables				
Sale Date 2007	-14,785.50	***	-15,688.94	***
Sale Date 2008	-52,915.99	***	-51,023.16	***
Sale Date 2009	-61,867.45	***	-59,911.77	***
Sale Date 2010	-57,043.94	***	-56,341.76	***
Sale Date 2011	-75,065.23	***	-73,395.04	***
Sale Date 2012	-65,270.83	***	-64,059.40	***
Sale Date 2013	-43,470.19	***	-40,582.39	***
Sale Date 2014	-33,679.73	***	-30,310.01	***
r^2	0.615		0.697	

¹ Block Group Dummy Variables are omitted from the table for space reasons

Significance levels * <math>P < 0.05</math> ** <math>P < 0.01</math> *** <math>P < 0.001</math>

Mogush, et al. (2005), noted that in complicated real estate markets, such as in Minneapolis, controlling for fixed effects helps to eliminate some omitted variable bias. This bias in the OLS model stems from endogenous placement of infrastructure and other amenities, particularly infrastructure such as bicycle lanes or bicycle sharing stations. Put another way, the infrastructure studied in this research and in others are not randomly distributed, but rather strategically built and thus are highly correlated to other variables. Leaving these variables out of the model contributes to lower explanatory power and less accurate model predictions. Fixed effects models eliminate some of this bias by effectively comparing house sales *within* a neighborhood rather than *between* neighborhoods based on a set of defined variables.

The final difference in model coefficients is likely the most interesting: the coefficient for proximity to bike share within .25 miles switches signs, indicating that bicycle share stations are considered a disamenity holding housing characteristics constant. In the model, presence of bike sharing within .25 miles of a home is associated with a -\$5,943.09 reduction in value. This represents 3.5% of the mean home value. Houses located more than .25 miles but within .5 miles of bicycle sharing stations are estimated to have a -\$3,167.43 reduction in value, or 1.9% reduction. The smaller effect on properties in the farther band is consistent with other studies that have attempted to model the effect of infrastructure on properties – that is, the effect is typically stronger as distance to the infrastructure decreases.

This effect, however, is *on average* at the city scale. These conflicting results are not entirely unexpected. Looked at in the context of other work, particularly, Mogush, et al. (2005), the results suggest that bike share may be an amenity that raises property values in some places but not in others. The average effect when looking at all block groups is negative, though the OLS model suggests that bike share adds value to homes. It may be that some areas are strongly negatively affected and this changes the average, though that hypothesis warrants further investigation.

In order to further explore this relationship, an interaction variable between presence of bicycle sharing and each block group dummy was added into the model. Few of the interaction variables were significant. The ones that were had large standard errors and coefficients that approached the mean sale price, indicating that the data did not support such a granular look at the effects of bicycle sharing on home values. In order to broaden the scope, and potentially make the interaction more understandable, the same technique was applied using the neighborhood name for each sale. The results proved similar. Exploring this level of data may be possible in the near future. The model included only 1,703 homes sold with the presence of bike share within .25 miles. As additional years of data become available, especially given the rapid expansion of the Nice Ride system, the model may be able to more accurately assess the impacts of bicycle share on single family home prices.

Conclusion

These models prove that bicycle sharing infrastructure has an effect on single family homes in Minneapolis. The conflicting signs in the models for whether bike share is considered

an amenity indicate that the effects are not universal. Bicycle sharing may not be considered an amenity for single family homes in the way that other studies have found that it has a positive impact on multifamily housing.

From a policy stand point this has several implications. First, bike sharing appears to decrease single family home values in at least some circumstances. While further investigation is necessary to fully understand the relationship, in neighborhoods that may be negatively affected the goals of bike sharing should be weighed against any negative impacts on home values. Second, policy makers need to justify public investment of funds into bike share systems based on other beneficial aspects of bike sharing at the city scale. Research indicates that bike share has a positive impact in some circumstances, and investment in those areas may be made up for by increased tax revenues, but this does not appear to be the case in many neighborhoods in Minneapolis.

Finally, this data appears to demonstrate that bicycle sharing does not appear to have gentrifying effects on most neighborhoods. Again, it is possible that the impacts are disproportionately felt in different areas or by different types of housing. This relationship needs to be further explored before any conclusions can be drawn, but at present, bike share does not appear to be increasing home values in single family neighborhoods.

This provides several areas for further research. As more data becomes available, it may be possible to explore changes in value at the neighborhood level. Understanding where bicycle sharing is an amenity can help contribute to exploring what aspects of those neighborhoods makes bicycle sharing valuable to those residents. There may be connections between the built environment, other local amenities, job or housing densities, or some other aspects of these neighborhoods that contribute to increasing home values. Additionally, understanding what about these neighborhoods leads to increasing values when bike share is implemented can lead to pro-active approaches to mitigating displacement and gentrification issues in the face of rising values.

This can also help to understand where bicycle sharing is viewed negatively, indicating that these neighborhoods may not be good candidates for bicycle share or that clearly articulated alternative reasons should provide justification for implementation there. While actual ridership data is outside of the scope of this work, lowered transaction prices indicate that residents see bicycle share as a negative. In those circumstances, bike share may not be well used and resources might better be deployed elsewhere.

Finally, because these models suggest changes in value are not uniform across the board, further investigation into the effects on different categories of homes may provide helpful information for planners. It may be possible that lower-valued homes see greater increases in prices, or that a greater share of the value is added to higher income homes. Understanding who benefits most from investments in infrastructure can lead to more informed conversation about potentially capturing the value these systems create, who should pay for them, and whether they're right for all neighborhoods within a city.

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Appendix A: Sources of data for model variables

Model Variable	Source
Bedrooms	Minneapolis Assessor's Office
Bathrooms	Minneapolis Assessor's Office
Fireplaces	Minneapolis Assessor's Office
Age	Minneapolis Assessor's Office
Sale Price	Minneapolis Assessor's Office
Above Ground Area	Minneapolis Assessor's Office
Below Ground Area	Minneapolis Assessor's Office
Lot Size	Minneapolis Assessor's Office
Walk Score	Walkscore API
Distance from CBD	Generated in ArcMap
Distance from Transit	Generated in ArcMap
Population Density	ACS 2008-2012
Median Age	ACS 2008-2012
Median Income	ACS 2008-2012
Percent Rent	ACS 2008-2012
Percent White	ACS 2008-2012
Average Commute	ACS 2008-2012
Block Groups	US Census/TIGER