Article

An In-Depth Understanding of the Residential Property Value Premium of a Bikesharing Service in Portland, Oregon

Sangwan Lee

Department of Urban Planning and Engineering, Hanyang University, Seoul 04763, Korea; esangwan@hanyang.ac.kr

Abstract: Bikesharing (BSS) is an emerging alternative mode of transportation with various benefits, such as reducing reliance on single-occupancy automobiles, boosting public health, lowering pollution levels, and enhancing accessibility. Accordingly, proximity to BSS stations can be factored into residential property values. Thus, this research attempts to explore whether (1) proximity to BSS was positively associated with residential property prices in Portland, Oregon, (2) proximity to BSS and public transportation modes showed synergistic effects on the values, and (3) the magnitude of the BSS premium intensified over time. The findings of spatial hedonic models indicate (1) a premium for proximity to BSS in both single-family and multi-family housing markets with varying magnitudes, (2) synergetic effects between BSS and public transportation modes, including light rail transit, streetcar, and bus, and (3) an unchanged premium for BSS between 2016 and 2019 with a few exceptions. The findings expand discussions around transportation-induced property value premium and offer policy implications.

Keywords: bikesharing service; real estate; premium; economic impact; spatial analysis

1. Introduction

Bikesharing services (BSS) are a relatively new entrant into the shared-use mobility business [1]. Travel time saving, reduced pollution, increased accessibility, and enhanced public health are just a few advantages BSS may provide [2–4]. Accordingly, positive externalities might be converted into higher property values within a reasonable distance of BSS stations. Nonetheless, empirical research has not only remained limited in its estimations of capitalized influence on property prices in the surrounding area, but has also left some research concerns unaddressed.

Thus, this study aims to answer the following research questions. First, was proximity to BSS positively associated with residential property value in Portland, Oregon? Second, did proximity to BSS and public transportation modes, including light rail transit, synergistically affect residential property values? Third, did the magnitude of the property value premium produced by BSS intensify over time? This paper contributes to (1) assisting policymakers, transportation authorities, and the public in better understanding the property value premium of BSS, (2) broadening discussions surrounding transportation-induced property value premium, and (3) presenting policy implications.

The rest of the paper is organized as follows. The second section summarizes and synthesizes previous research. Section 3 discusses the research design, including the methodological approaches used in this study. Finally, Sections 4 and 5 present and discuss the findings, and Section 6 concludes this study.

2. Literature Review

Theoretically and empirically, many types of so-called macro transportation infrastructures, such as heavy rail, light rail, highway, bus rapid transit, and airports, generally induce property value premiums for decades due to their accessibility benefits [5–13]. On
the other hand, empirical research on the economic impact has shown that homes near transit stations sell for less, due to unfavorable externalities such as noise and traffic, which outweigh the accessibility benefits to properties near transit stations [14–16]. According to Pan [17], however, while the considerable negative effects on residential property values were evident within a quarter mile of a stop, the effects turned positive and significant between one and three miles.

The uplifting of property value due to infrastructure interventions can be applied to bikesharing services (BSS). Specifically, since being close to a BSS has the potential to deliver significant socio-economic benefits to users of alternate modes of transportation (e.g., increased accessibility to nearby public transportation and employment), the benefits can be transferred into higher property prices within a reasonable distance of BSS stations. For instance, Qiao et al. [18] found a significant relationship between accessibility to dockless BSS and housing rental prices in Beijing, China; specifically, a one-unit increase in the accessibility generated a premium of 28.02 CNY in the housing rental. In addition, Zhou et al. [19] found a positive premium (4.6%) of BSS use intensity in Shanghai, China. Additionally, the intensity of BSS uses raised apartment sale prices, particularly in neighborhoods far from metro stations. In contrast, the empirical analysis of Zhao and Ke [20] revealed an increase in home values near metro stations, showing a complementary effect of BSS and subway networks in Beijing, China. In addition, within a one-kilometer radius of a metro station, the introduction of dockless BSS increased housing values by 2.51%.

In the North American context, Lee and Golub [21] examined the residential value uplift induced by proximity to BSS in New York City. They discovered that, all other factors being equal, both single-family and multi-family homes near BSS (CitiBike) stations sold for higher values in New York City. Moreover, the multilevel longitudinal model of El-Geneidy et al. [22] demonstrated that in Montreal, Canada, the price of multi-family housing increased by $709 for each additionally available station; in other words, when there were 12 stations within an 800-m distance, the price of multi-family housing was predicted to rise by roughly 2.7%.

In sum, the literature review identified several research gaps. First, while much study has examined the premium of macro modes of transportation, little attention has been paid to the relationship between property prices and BSS [23]. Second, many issues about the economic impact of emerging modes of transportation in the U.S. context remain unresolved. Third, the understanding of BSS impact on property values remains limited. This study aims to fill these gaps by answering the three research questions.

3. Research Design

3.1. Study Area

3.1.1. Study Area Selection

This study chose Portland, Oregon, as a case study area to investigate bikesharing service (BSS) premium for the following reasons. First, the city has been the top-tier city in bike usage in the United States [24,25]. Specifically, Portland has built a denser network to make it easier for many Portland residents to access routes, a cohesive network to provide people with direct routes to their destinations, and an appealing network that incorporates the best design standards worldwide [26]. For instance, the number of miles of buffered bike lanes increased from 3.6 in 2010 to 29.9 in 2019 [27]. Moreover, Figure 1 demonstrates that, between 2000 and 2019, the majority of census block groups saw a considerable rise in bike use for commuting trips. On average, the proportion was around 1.8% in 2000 and grew to 6.3% in 2019. Second, Biketown, a docked BSS system in the study area, has run for approximately six years. Third, the city offers a variety of public transportation options, such as light rail transit and streetcar (see Figure 2). Fourth, since the Case–Shiller index, which is a widely used housing price index, reveals a general upward tendency in the housing market price without substantial fluctuations over the research period, there may be nothing that substantially drives or manipulates the real estate market. Therefore, the selection of the study region was
appropriate since the important characteristics of the area can assist in providing answers to the three research questions.

Figure 1. Use of bicycles for commuting for workers aged 16 years and over. Prepared by Social Explorer (accessed on 10 June 2022).

Figure 2. Descriptions of the study area (Data source: Regional Land Information System and Bureau of Transportation Statistics) (accessed on 15 April 2022).

3.1.2. Bikesharing Service: Biketown

Biketown, the BSS system in the study area, debuted in July 2016 with roughly 1,000 bikes and 100 stations across the city [27,28]. It is supported by a collaboration between Nike, the Portland Bureau of Transportation (PBOT), and other BSS providers [29].
Since its introduction to the market, Figure 2 shows that it has expanded its service areas and stations [30,31]. For instance, the service area has been pushed to the northern and eastern parts of Portland [32]. The number of BSS stations has also increased (see Figure 2).

Additionally, Figure 3 shows details on the ridership of BSS. Ridership has been concentrated in the downtown region. Riders have used the mode mainly during rush hour, weekends, and summer, which is consistent with past research [33–37].

**1) Ridership by stations**

**2) Ridership by days and time**

**3) Ridership by dates**

![Ridership of Biketown during the study period](https://www.biketownpdx.com/system-data/historical) (accessed on 10 June 2022).

### 3.2. Variables

Table 1 illustrates the final set of variables in detail, and Table 2 presents their descriptive statistics. This study selected the variables because previous studies have demonstrated their significance in determining property values [38,39]. The following subsections describe dependent and independent variables in further detail.

| Name | Description | Source |
|------|-------------|--------|
| In(Adjusted Price) | Log-transformed inflation-adjusted sale price (adjusted to 2019) [40] | RLIS |
| **Independent variable** | | |
| In(Dist BSS) | Log-transformed distance in miles between each observation and the nearest bikesharing service (Biketown in Portland, Oregon) station [21] | BTS |
| In(Dist LRT) | Log-transformed distance in miles between each observation and the nearest light rail transit station (MAX in Portland, Oregon) RLIS |
| In(Dist SC) | Log-transformed distance in miles between each observation and the nearest streetcar station RLIS |
| In(Dist FWY) | Log-transformed distance in miles between each observation and the nearest freeway RLIS |
| In(Dist RAMP) | Log-transformed distance in miles between each observation and the nearest on-ramp RLIS |
| In(Dist ABF) | Distance in miles between each observation and active advanced bike facilities, including a buffered bike lane, a protected bike lane, an off-street path/trail, and a separated in-roadway [41,42] RLIS |
| In(Lot Area) | Log-transformed land area in square footage of the property at sale year RLIS |
| In(Bldg Area) | Log-transformed building area in square footage of the property at sale year RLIS |
### Table 1. Cont.

| Name               | Description                                                                 | Source        |
|--------------------|-----------------------------------------------------------------------------|---------------|
| Built Year         | Year when the property was built                                            | RLIS          |
| Neighborhood       | characteristics                                                            |               |
| Land Mix Index     | The evenness in the spatial footprint of three land uses at the census      | RLIS          |
|                    | block group level: residential, commercial/industrial, and others at sale   |               |
|                    | year                                                                          |               |
|                    | Land Mix Index = 1 - \( \frac{|r - \frac{1}{3}| + |c - \frac{1}{3}| + |o - \frac{1}{3}|}{4/3} \) |               |
|                    | Where \( r \) is acres in residential use, \( c \) is commercial/industrial |               |
|                    | use, \( o \) is acres in other land uses, and \( T = r + c + o \) [43].      |               |
| Net Den            | Total length of networks in feet per acre at the census block group level  | SLD           |
| ln(Pop Den)        | Log-transformed total population per square mile at the census block group   | ACS           |
|                    | level at sale year                                                            |               |
| White              | Percentage of the residents who are non-White at the census block group     | ACS           |
|                    | level at sale year                                                             |               |
| ln(HH Income)      | Log-transformed median household income at the census block group level at    | ACS           |
|                    | sale year                                                                     |               |
| Low Education      | Percentage of the residents who attained less than college and associate     | ACS           |
|                    | degrees at the census block group level at sale year                          |               |
|                    | Sales Year Dummy                                                              |               |
| SoldYear2016       | 1 if the sale transaction occurred in 2016, otherwise 0                       | RLIS          |
| SoldYear2017       | 1 if the sale transaction occurred in 2017, otherwise 0                       | RLIS          |
| SoldYear2018       | 1 if the sale transaction occurred in 2018, otherwise 0                       | RLIS          |
| SoldYear2019       | 1 if the sale transaction occurred in 2019, otherwise 0                       | RLIS          |

Sources: Regional Land Information System 2016, 2017, 2018, 2019, 2020 (RLIS), American Community Survey 2016, 2017, 2018, and 2019 (5-year estimates) (ACS), Smart Location Database (SLD), and Bureau of Transportation Statistics (BTS).

### Table 2. Descriptive statistics of variables.

| Variables          | Unit | Single-Family Homes (n = 19,482) | Multi-Family Homes (n = 3666) |
|--------------------|------|----------------------------------|------------------------------|
|                    |      | Mean | Median | Std. Dev | Mean | Median | Std. Dev |
| Price              | $    | 452,048 | 400,000 | 215,778 | 437,785 | 345,000 | 310,355 |
| Adjusted Price     | $    | 518,882 | 461,439 | 248,000 | 506,472 | 394,925 | 365,533 |
| ln(Adjusted Price) | -    | 13.06 | 13.04 | 0.44 | 12.94 | 12.89 | 0.59 |
| Dist BSS           | Mile | 2.20 | 1.95 | 1.66 | 1.29 | 0.21 | 1.68 |
| ln(Dist BSS)       | -    | 0.33 | 0.67 | 1.15 | -1.01 | -1.57 | 1.76 |
| Dist LRT           | Mile | 1.33 | 1.13 | 0.92 | 0.87 | 0.49 | 0.89 |
| ln(Dist LRT)       | -    | 0.04 | 0.12 | 0.74 | -0.59 | -0.72 | 0.96 |
| Dist SC            | Mile | 3.78 | 3.55 | 1.96 | 2.00 | 0.54 | 2.40 |
| ln(Dist SC)        | -    | 1.16 | 1.27 | 0.65 | -0.46 | -0.62 | 1.77 |
| Dist FWY           | Mile | 1.19 | 1.03 | 0.85 | 0.65 | 0.30 | 0.81 |
| ln(Dist FWY)       | -    | -0.17 | 0.03 | 0.96 | -1.04 | -1.19 | 1.12 |
| Dist RAMP          | Mile | 2.36 | 2.30 | 1.22 | 1.36 | 0.72 | 1.40 |
| ln(Dist RAMP)      | -    | 0.67 | 0.83 | 0.72 | -0.30 | -0.33 | 1.17 |
| Dist ABF           | Mile | 0.52 | 0.44 | 0.36 | 0.28 | 0.17 | 0.30 |
| ln(Dist ABF)       | -    | -0.94 | -0.81 | 0.86 | -1.83 | -1.79 | 1.15 |
| Lot Area           | ft²  | 7060 | 5207 | 7838 | 735 | 262 | 2869 |
| ln(Lot Area)       | -    | 8.69 | 8.56 | 0.54 | 5.36 | 5.57 | 1.41 |
| Bldg Area          | ft²  | 1598 | 1409 | 779 | 1278 | 1007 | 2346 |
| ln(Bldg Area)      | -    | 7.28 | 7.25 | 0.44 | 6.95 | 6.91 | 0.51 |
| Built Year         | Year | 1952 | 1950 | 32 | 1982 | 1990 | 30 |
| Land Mix Index     | -    | 0.37 | 0.36 | 0.21 | 0.56 | 0.57 | 0.21 |
Table 2. Cont.

| Variables       | Unit     | Single-Family Homes (n = 19,482) | Multi-Family Homes (n = 3666) |
|-----------------|----------|----------------------------------|-------------------------------|
|                 | Mean     | Median  | Std. Dev | Mean     | Median  | Std. Dev |
| Net Den         | ft/acre  | 25.79   | 26.45    | 7.32     | 31.94   | 10.50    | 30.67    |
| Pop Den         | Person/mi² | 7373  | 7418    | 3281    | 11,674  | 9601    | 8221    |
| ln(Pop Den)     | -        | 8.76   | 7.91    | 0.65    | 9.12    | 9.17    | 0.77    |
| White           | %        | 78     | 81      | 0.12    | 80      | 83      | 0.12    |
| HH Income       | $        | 74,396 | 65,469  | 33,848  | 69,533  | 68,449  | 28,965  |
| ln(HH Income)   | -        | 11.13  | 11.09   | 0.42    | 11.05   | 11.13   | 0.46    |
| Low Education   | %        | 25     | 23      | 0.16    | 17      | 11      | 0.15    |
| SoldYear2016    | Dummy    | 0.22   | 0.41    | -       | 0.23    | 0.42    | -       |
| SoldYear2017    | Dummy    | 0.43   | 0.50    | -       | 0.44    | 0.50    | -       |
| SoldYear2018    | Dummy    | 0.18   | 0.38    | -       | 0.17    | 0.38    | -       |
| SoldYear2019    | Dummy    | 0.17   | 0.37    | -       | 0.16    | 0.37    | -       |

3.2.1. Dependent Variable

The dependent variable was log-transformed inflation-adjusted sales prices. There are some essential details on the dependent variable. First, the prices were adjusted to 2019 constant U.S. dollars, using the housing price index specific to the Portland Metropolitan area provided by Federal Housing Finance Agency to reduce heteroscedasticity that may exist in an untransformed sales price [40,45]. Second, this study used a logarithmic transformation to manage a highly skewed variable and convert it into one with a distribution that was more nearly normal. Third, this study explored single-family and multi-family housing markets because of the expected disparities in capitalized effects on properties with different types of land use [46]. Fourth, the study period was between July 2016 and December 2019 for the following reasons. Specifically, BSS in Portland was offered to start in July 2016. Additionally, because BSS ridership declined by 72.7 % on average during the COVID-19 period [47], its premium on property values may shift [48]. Thus, this study used sales data until December 2019. Fifth, regarding data pre-processing, this study excluded records with missing transaction price information or sale prices equal to zero. Additionally, it excluded sales transactions with prices lower than $50,000 or higher than $2 million that were unrepresentative of market values in the study area, like the process Dong [49] employed.

After data processing, the total number of single-family and multi-family homes was 19,482 and 3,666. Figure 4 depicts the distribution of observations and their inflation-adjusted house prices. The properties with higher adjusted prices are represented by the dark blue dots, while the light blue dots show the homes with lower prices.

3.2.2. Independent Variables of Interest

To answer the three research questions, this study used the following three types of key variables: (1) the distance to the nearest BSS, (2) interaction terms between the distance to BSS and public transportation modes, including light rail transit, streetcar, and bus, and (3) interaction terms between the distance to BSS and sales year dummy variables. The first variable was utilized in the base and interaction models 1 and 2, whereas the second and third variables were only included in interaction model 1 and interaction model 2. The distance variables were measured using the Euclidean distance.
which is an ordinary least squares model (OLS), and spatial autoregressive models (SAR) (1) structural qualities, (2) locational factors, (3) neighborhood characteristics, and (4) sales property characteristics did not significantly change the estimated size of the property value year dummy variables were included in interaction model 2. This study developed three year. In terms of structural qualities, there were three criteria to consider, including building size. However, this study did not control for additional essential factors such as the number of bedrooms because of the data limitations. Given that the inclusion of property characteristics did not significantly change the estimated size of the property value premium of transportation modes in a meta-analysis study [39], the inability to control for additional variables in this analysis may not significantly influence the estimated premium of BSS and validity of the final models. Another vital set of control variables is locational factors [38], such as distance to transportation infrastructures. Furthermore, the final models controlled for six factors, since neighborhood characteristics such as household income, racial composition, and population density can influence property values [14,55]. For additional detail, this study omitted some factors with variance inflation factors (VIFs) greater than 10 in linear regression models, such as distance to the Central Business District and employment accessibility by car and transit, due to multicollinearity issues. Lastly, final models included sales year dummy variables for addressing seasonality issues to single out the BSS premium.

3.2.3. Control Variables

As the hedonic framework suggested [50–52], the property value premium generated by proximity to BSS cannot be singled out without controlling for other aspects because housing is a bundle of attributes [53,54]. This study used the following four sets of variables: (1) structural qualities, (2) locational factors, (3) neighborhood characteristics, and (4) sales price. In terms of structural qualities, there were three criteria to consider, including building size. However, this study did not control for additional essential factors such as the number of bedrooms because of the data limitations. Given that the inclusion of property characteristics did not significantly change the estimated size of the property value premium of transportation modes in a meta-analysis study [39], the inability to control for additional variables in this analysis may not significantly influence the estimated premium of BSS and validity of the final models. Another vital set of control variables is locational factors [38], such as distance to transportation infrastructures. Furthermore, the final models controlled for six factors, since neighborhood characteristics such as household income, racial composition, and population density can influence property values [14,55]. For additional detail, this study omitted some factors with variance inflation factors (VIFs) greater than 10 in linear regression models, such as distance to the Central Business District and employment accessibility by car and transit, due to multicollinearity issues. Lastly, final models included sales year dummy variables for addressing seasonality issues to single out the BSS premium.

3.3. Spatial Error Model

This study developed six spatial error models (SEM) with the uniform kernel weight matrix [56,57]. The distance to the nearest BSS station was included in the base model. Interaction model 1 added either interaction terms between BSS proximity and three public transportation modes, while interaction terms between BSS proximity and sales year dummy variables were included in interaction model 2. This study developed three models, each for single-family and multi-family homes.

This study chose SEM over other models, including the a-spatial hedonic model, which is an ordinary least squares model (OLS), and spatial autoregressive models (SAR) for the following reasons. First, when it came to the selection of spatial econometrics, this study observed that the residuals from the OLS models showed spatial dependency, as shown in the results of the Moran’s I [58] and Lagrange multiplier (LM) tests [59] in Table 3. Therefore, this study used a spatial econometrics model since the inability to account for spatial characteristics in an a-spatial method can lead to biased and inconsistent results [60–62]. Furthermore, this study tested whether SEM outperformed SAR based on LM tests for spatial lag (LMlag), the Hausman test [63], Akaike Information Criterion

---

**Figure 4.** Distribution of observations and their inflation-adjusted house prices (Data Source: Regional Land Information System).
(AIC), and log-likelihood (LL). SEM is appropriate in this analysis, according to the results in Tables 3 and 4. Specifically, SEM shows a lower AIC and higher LL compared to SAR and OLS, with statistical significance in all Hausman tests. Thus, this study developed and presented the six SEM models.

Table 3. Results of spatial dependency tests.

| Models        | Moran’s I | Lagrange Multiplier (LM) Tests |
|---------------|-----------|---------------------------------|
|               |           | LMlag | LMerr |
| **Single-family housing** |           |       |       |
| Base model    | 0.034 *** | 0.13  | 5699 *** |
| Interaction model 1 | 0.033 *** | 8.63 *** | 5565 *** |
| Interaction model 2 | 0.035 *** | 0.09  | 5658 *** |
| **Multi-family housing** |           |       |       |
| Base model    | 0.022 *** | 71.32 *** | 395 *** |
| Interaction model 1 | 0.027 *** | 127.06 *** | 615 *** |
| Interaction model 2 | 0.021 *** | 68.82 *** | 406 *** |

Note: LM tests for spatial lag (LMlag) and LM tests for spatial error (LMerr). *** Significant at \( p < 0.01 \).

Table 4. Results of final model performance.

| Models        | Akaike Information Criterion (AIC) | Log-Likelihood (LL) | Hausman Test |
|---------------|------------------------------------|---------------------|--------------|
|               | SEM      | SAR    | OLS    | SEM    | SAR    |                  |
| **Single-family housing** |           |       |       |        |       |                  |
| Base model    | 3520.764 | 4282.983 | 4281.100 | −1738.382 | −2119.492 | 233.01 *** |
| Interaction model 1 | 3442.156 | 4135.736 | 4142.400 | −1696.078 | −2042.868 | 215.47 *** |
| Interaction model 2 | 3496.662 | 4256.886 | 4255.000 | −1723.331 | −2103.443 | 255.44 *** |
| **Multi-family housing** |           |       |       |        |       |                  |
| Base model    | 1351.477 | 1364.205 | 1433.400 | −653.738 | −660.102 | 141.14 *** |
| Interaction model 1 | 1269.095 | 1277.661 | 1403.300 | −609.547 | −613.830 | 119.47 *** |
| Interaction model 2 | 1277.185 | 1291.649 | 1358.400 | −613.593 | −620.824 | 153.03 *** |

Note: Spatial autoregressive model (SAR), spatial error model (SEM), and a-spatial hedonic model (OLS). *** Significant at \( p < 0.01 \).

The question of SEM is as follows [64]:

\[
y = \beta_0 + \beta_i X_i + \delta W \epsilon + u \tag{1}
\]

where \( y \) denotes log-transformed inflation-adjusted housing prices, \( X_i \) contains explanatory variables used in this study (see Table 1), \( \beta_i \) are their associated parameters, and \( u \) is the error term. \( \delta \) denotes lambda, which is spatial error coefficient, \( W \) indicates the uniform kernel weight matrix, \( \epsilon \) is the error term in the a-spatial model.

4. Results

This section presents and interprets the results of the final spatial error models (SEM) in Tables 5 and 6 to answer the three research questions. This study developed the following three models each for single-family and multi-family homes: (1) base model, (2) interaction model 1 by adding interaction terms between the proximity to BSS and public transportation modes to the base model, and (3) interaction model 2 by including interaction terms between the proximity to BSS and sales year dummy variables in the base model. Tables 5 and 6 demonstrate that the spatial error coefficients (lambda) in all six models were positive and significant, corroborating the findings in Tables 3 and 4 that nearby housing units showed significant spatial autocorrelation, and spatial models outperformed a-spatial models.
Table 5. Results of spatial error models in the single-family housing market.

| Variables                                      | Base Model         | Interaction Model 1 | Interaction Model 2 |
|------------------------------------------------|--------------------|---------------------|---------------------|
|                                                | Independent Variables of Interest |                     |                     |
| ln(Dist BSS)                                   | −0.020 *** (0.005)  | −0.028 *** (0.010)  | −0.030 *** (0.006)  |
| ln(Dist BSS) * ln(Dist LRT)                    | 0.013 *** (0.004)  |                     |                     |
| ln(Dist BSS) * ln(Dist SC)                     | −0.041 *** (0.004) |                     |                     |
| ln(Dist BSS) * ln(Dist BUS)                    | 0.006 ** (0.003)   |                     |                     |
| ln(Dist BSS) * SoldYear2017                    |                    | 0.012 *** (0.004)  |                     |
| ln(Dist BSS) * SoldYear2018                    |                    | 0.024 *** (0.005)  |                     |
| ln(Dist BSS) * SoldYear2019                    | 0.003 (0.005)      |                     |                     |
| Control Variables                              |                     |                     |                     |
| Constant                                       | 5.601 *** (0.191)  | 5.743 *** (0.192)  | 5.600 *** (0.191)  |
| ln(Dist LRT)                                   | −0.004 (0.005)     | −0.008 (0.006)     | −0.004 (0.005)     |
| ln(Dist SC)                                    | −0.224 *** (0.009) | −0.238 *** (0.009) | −0.223 *** (0.009) |
| ln(Dist BUS)                                   | 0.020 *** (0.003)  | 0.018 *** (0.003)  | 0.020 *** (0.003)  |
| ln(Dist FWY)                                   | 0.046 *** (0.004)  | 0.048 *** (0.004)  | 0.047 *** (0.004)  |
| ln(Dist RAMP)                                  | 0.010 (0.007)      | 0.004 (0.007)      | 0.010 (0.007)      |
| ln(Dist ABF)                                   | 0.017 *** (0.003)  | 0.018 *** (0.003)  | 0.017 *** (0.003)  |
| ln(Lot Area)                                   | 0.117 *** (0.005)  | 0.115 *** (0.005)  | 0.117 *** (0.005)  |
| ln(Bldg Area)                                  | 0.399 *** (0.005)  | 0.400 *** (0.005)  | 0.400 *** (0.005)  |
| Built Year                                     | 0.001 *** (0.0001) | 0.001 *** (0.0001) | 0.001 *** (0.0001) |
| Land Mix Index                                 | −0.009 (0.012)     | −0.005 (0.012)     | −0.009 (0.012)     |
| Net Den                                        | 0.004 *** (0.0005) | 0.004 *** (0.0005) | 0.004 *** (0.0005) |
| ln(Pop Den)                                    | 0.002 (0.004)      | 0.004 (0.004)      | 0.002 (0.004)      |
| White                                          | 0.001 *** (0.0002) | 0.001 *** (0.0002) | 0.001 *** (0.0002) |
| ln(HH Income)                                  | 0.081 *** (0.008)  | 0.074 *** (0.008)  | 0.082 *** (0.008)  |
| Low Education                                  | −0.004 *** (0.0003) | −0.003 *** (0.0003) | −0.004 *** (0.0003) |
| SoldYear2017                                   | −0.027 *** (0.005) | −0.029 *** (0.005) | −0.033 *** (0.006) |
| SoldYear2018                                   | −0.069 *** (0.006) | −0.071 *** (0.006) | −0.078 *** (0.007) |
| SoldYear2019                                   | 0.012 * (0.007)    | 0.012 * (0.007)    | 0.010 (0.007)      |

Model statistics

| Observations                                    | 19,482 | 19,482 | 19,482 |
| Lambda                                         | 0.003 *** | 0.003 *** | 0.003 *** |
| Wald Statistics                                | 184,554,000 *** | 114,393,700 *** | 184,459,200 *** |
| Log−likelihood                                 | −1738.382 | −1696.078 | −1723.331 |
| AIC                                            | 3520.764 | 3442.156 | 3496.662 |

* Significant at p < 0.10; ** Significant at p < 0.05; *** Significant at p < 0.01. Dependent variable: Log-transformed inflation-adjusted sale price.

4.1. Research Question 1: Premium of the Proximity to Bikesharing Service in the Base Model

The base model indicates that distance to BSS stations showed a significant and negative coefficient, indicating that single-family and multi-family residences closer to BSS stations kept their value better after its introduction. Specifically, in the single-family housing market, the estimated premium of BSS in a natural log was around −0.020, and it was around −0.114 in the multi-family housing market. In other words, when single-family homes moved 1% closer to a BSS station, the home value increased by 2% on average, holding all other factors in the model constant. The estimated magnitude of BSS in this study was between 2 and 5%, which was within the elasticity range of the premium in previous studies [22]. The effect size of proximity to BSS, on the other hand, was considerable; for example, a 1% decrease in distance to the BSS station was associated with an 11.4% increase in its worth.
Table 6. Results of spatial error models in the multi-family housing market.

| Variables                              | Base Model                  | Interaction Model 1                  | Interaction Model 2                  |
|----------------------------------------|-----------------------------|--------------------------------------|--------------------------------------|
|                                        | Estimates (St. Err)         | Estimates (St. Err)                   | Estimates (St. Err)                   |
| Independent Variables of Interest      |                             |                                      |                                      |
| ln(Dist BSS)                           | −0.114 *** (0.007)          | −0.142 *** (0.016)                   | −0.140 *** (0.009)                   |
| ln(Dist BSS) × ln(Dist LRT)            | −0.024 *** (0.004)          |                                      |                                      |
| ln(Dist BSS) × ln(Dist SC)             | −0.015 *** (0.004)          |                                      |                                      |
| ln(Dist BSS) × ln(Dist BUS)            | −0.011 ** (0.005)           |                                      |                                      |
| ln(Dist BSS) × SoldYear2017            |                            |                                      | 0.018 *** (0.007)                   |
| ln(Dist BSS) × SoldYear2018            |                            |                                      | 0.031 *** (0.009)                   |
| ln(Dist BSS) × SoldYear2019            |                            |                                      | 0.076 *** (0.009)                   |
| Control Variables                      |                             |                                      |                                      |
| Constant                               | 2.693 *** (0.432)           | 2.582 *** (0.432)                    | 2.775 *** (0.428)                    |
| ln(Dist LRT)                           | 0.005 (0.008)               | −0.007 (0.008)                       | 0.005 (0.008)                       |
| ln(Dist SC)                            | −0.0151 *** (0.008)         | −0.096 *** (0.012)                   | −0.054 *** (0.008)                  |
| ln(Dist BUS)                           | 0.081 *** (0.008)           | 0.074 *** (0.009)                    | 0.078 *** (0.008)                   |
| ln(Dist FWY)                           | 0.052 *** (0.007)           | 0.052 *** (0.007)                    | 0.053 *** (0.007)                   |
| ln(Dist RAMP)                          | −0.005 (0.010)              | 0.033 *** (0.011)                    | −0.003 (0.010)                      |
| ln(Dist ABF)                           | −0.009 * (0.005)            | −0.005 (0.005)                       | −0.011 ** (0.005)                   |
| ln(Lot Area)                           | 0.011 * (0.006)             | 0.004 (0.006)                        | 0.013 ** (0.006)                    |
| ln(Bldg Area)                          | 0.735 *** (0.011)           | 0.738 *** (0.011)                    | 0.741 *** (0.011)                   |
| Built Year                             | 0.002 *** (0.0002)          | 0.003 *** (0.0002)                   | 0.002 *** (0.0002)                  |
| Land Mix Index                         | −0.050 (0.032)              | −0.019 (0.032)                       | −0.053 * (0.032)                    |
| Net Den                                | 0.002 *** (0.001)           | 0.002 *** (0.001)                    | 0.003 *** (0.001)                   |
| ln(Pop Den)                            | −0.014 (0.009)              | −0.017 * (0.009)                     | −0.017 * (0.009)                    |
| White                                  | 0.003 *** (0.001)           | 0.002 *** (0.001)                    | 0.003 *** (0.001)                   |
| ln(HH Income)                          | 0.055 *** (0.016)           | 0.038 ** (0.016)                     | 0.055 *** (0.016)                   |
| Low Education                          | −0.006 *** (0.001)          | −0.005 *** (0.001)                   | −0.005 *** (0.001)                  |
| SoldYear2017                           | −0.051 *** (0.012)          | −0.051 *** (0.012)                   | −0.029 ** (0.014)                   |
| SoldYear2018                           | −0.085 *** (0.016)          | −0.087 *** (0.015)                   | −0.051 *** (0.018)                  |
| SoldYear2019                           | −0.047 *** (0.016)          | −0.042 *** (0.016)                   | 0.032 * (0.019)                     |

**Model statistics**

| Observations | 3666 | 3666 | 3666 |
|--------------|------|------|------|
| Lambda       | 0.002 *** | 0.002 *** | 0.002 *** |
| Wald Statistics | 748.471 *** | 1462.266 *** | 786.665 *** |
| Log – likelihood | −653.738 | −609.547 | −613.593 |
| AIC           | 1351.477 | 1269.095 | 1277.185 |

*Significant at p < 0.10; ** Significant at p < 0.05; *** Significant at p < 0.01. Dependent variable: Log−transformed inflation—adjusted sale price.

4.2. Research Question 2: Synergistic Effects between the Proximity to Bikesharing Service and Public Transportation Modes in Interaction Model 1

This study developed interaction model 1 to investigate whether there were any synergic impacts between being close to BSS and using three different types of public transportation: light rail transit (LRT), streetcar (SC), and bus. The three interaction terms were found to be significant, as shown in Tables 5 and 6, confirming the synergic effects. In addition, the results demonstrate that single-family residences located closer to both the BSS station and bus stops had higher values, while the remaining two interaction components had positive parameter estimates. However, the interaction terms between proximity to BSS and SC showed a negative coefficient. In the multi-family housing market, however, findings suggest that proximity to BSS stations and all three modes of public transit had a synergic effect. For example, the estimate of the interaction term between distance to BSS and LRT was −0.024, the greatest of the three interaction terms.
4.3. Research Question 3: Intensifying Premium of the Proximity to Bikesharing Service over Time in Interaction Model 2

This study developed interaction model 2 to investigate whether the premium of BSS changed between 2016 and 2019. First, the differences in coefficients from interaction model 2 were looked at directly [65]. At a glance, in both housing markets, the influence of proximity to BSS on property value intensified, according to the estimation results. In particular, the effect size in multi-family homes increased from 0.018 to 0.076 between 2016 and 2019, while it only increased in single-family homes between 2016 and 2018.

Additionally, this study used the z-test [66–68] to examine whether the parameter estimations of the interaction terms were statistically different in a model. Table 7 shows that the coefficients in the single-family housing market between 2016 and 2018 were significantly different. However, even at the marginally significant level, the impacts of proximity to BSS on multi-family property values between 2016 and 2018 were not significantly different. Only after 2018, the effect magnitude grew dramatically.

Table 7. Z-tests for coefficients in interaction models 2.

|                      | Single-Family Housing |                      | Multi-Family Housing |                      |
|----------------------|-----------------------|----------------------|----------------------|----------------------|
|                      | Z-Test 1   | Z-Test 2   | Z-Test 3   | Z-Test 1   | Z-Test 2   | Z-Test 3   |
| z                    | −1.874 ** | −         | −         | −1.140     | −5.086 *** | −3.535 *** |

Note: Z-test 1 is between coefficients of ln(Dist BSS)* Year2017 and ln(Dist BSS)* Year2018. Z-test 2 is between coefficients of ln(Dist BSS)* Year2017 and ln(Dist BSS)* Year2019. Z-test 3 is between coefficients of ln(Dist BSS)* Year2018 and ln(Dist BSS)* Year2019. ** Significant at p < 0.05; *** Significant at p < 0.01.

4.4. Additional Key Findings on the Relationship between Residential Property Values and Control Variables

A couple of findings deserve further attention. First, Tables 5 and 6 show estimation results for control variables such as findings from previous studies. For instance, distance to a streetcar (SC) was negatively associated with residential property values in Portland, Oregon. As expected, housing characteristics, such as building and lot areas, had a significant and positive impact on home values. Second, single-family home values were positively associated with distance to advanced biking facilities (ABF), but multi-family home prices were significantly and negatively associated with proximity to ABF (elasticity of 0.9%). Some academics have suggested that properties near bicycle infrastructure may be subject to negative externalities such as privacy concerns, criminal activity, and loud noise [69], translating into decreased property values of single-family homes. However, in the multi-family housing market, positive externalities such as the improved aesthetic value of areas and increased access to social infrastructures (Lindsey et al., 2004; Parent & vom Hofe, 2013) may outweigh negative ones. Third, model results reveal that distance to LRT was insignificantly associated with single-family and multi-family home values. The dissipated effect on property value premium when transit starts to operate in previous literature [62,70] may explain the results.

5. Discussion

5.1. Discussions of Key Findings

Key findings deserve to be discussed. Specifically, as more homes benefit from the proximity to bikesharing services (BSS), perceived usefulness as a location for residential activity grows, increasing demand for the land and its value. As a result, people are willing to pay for the proximity to BSS, which is reflected in the price. Moreover, since residents in multi-family homes may prefer to use active transportation modes, the premium in multi-family homes (11.4%) was significantly greater than that in single-family homes (2.0%).

Moreover, two factors could account for the significant synergetic effects between BSS and public transportation modes. First, Bike Plan [71] aims to create a future in which more individuals have multi-modal transportation options to fulfill their daily needs by combining BSS with public transportation modes such as MAX light rail transit, WES com-
muter rail, and bus. For instance, the transportation agency (TriMet) in Portland has been locating appropriate BSS stations and linking fare systems for the transit systems to integrate BSS into the fixed-route network. In addition, BSS is regarded as a first-and-last-mile mode of transportation, providing good access and connection to public transportation options [72–74]. In other words, the emerging mode of transportation offers commuters “BSS-public transportation” that provides better flexibility, convenience, and access to current infrastructure. The use of public transportation, such as transit, has increased because of BSS, according to academic studies [75–77]. In sum, government efforts to integrate BSS and public transportation modes and first-and-last-mile connectivity may be reflected in the significant synergetic impacts found in this study.

Lastly, this study hypothesized that the effect size of the premium might intensify over time, especially in areas with considerable infrastructure and service expansions (see Figures 1–3). Specifically, Biketown in Portland, Oregon, has expanded to serve a greater range of population groups in previously unreachable regions, such as east side Portland communities along the 50s Bikeway [31]. Furthermore, the public becomes more aware of the sharing service as time passes. However, findings indicate that the BSS premium did not change nor intensify over time in the single-family and multi-family housing markets, with a few exceptions. The steady ridership seen in Figure 5 from 2016 to 2019 may explain the result. For example, the graph shows only minor changes in BSS system ridership in Portland, Oregon, with a few significant increases in May 2018 (79,400) and February 2019 (26,329). The consistent ridership trend may indicate that individual perceptions of BSS benefits may not change over time, reflecting a statistically insignificant change in the BSS premium over time in the study area. Nonetheless, it is essential to note that the BSS in the study has been in operation for around six years. This suggests that the findings may only investigate the economic impact in the intermediate term, a time when the BSS system has not yet reached its mature state.

Figure 5. Biketown ridership by months and years (Data source: https://www.biketownpdx.com/system-data) (accessed on 10 June 2022).

5.2. Expanded Discussions on Bikesharing-Induced Gentrification

The findings suggest a discussion of BSS-induced gentrification in the broader policy context. Creating and enhancing macro transportation infrastructure, such as a heavy rail system, may foster gentrification by directing public and private capital in ways that benefit some areas and disadvantage others [78,79]. Residents in this situation may no longer easily access economic possibilities, public services, or amenities, and they can also no longer live within reasonable commuting distance of their workplace [80].

In a similar vein, although the analysis of this study did not offer empirical evidence to support this, theoretical discussions and the findings may raise concerns around BSS-induced

| Time | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 2016 | 26,201 | 51,673 | 39,115 | 19,229 | 15,984 | 7858 |
| 2017 | 6573 | 8610 | 13,401 | 20,294 | 37,280 | 40,207 | 54,471 | 47,104 | 33,268 | 24,883 | 14,099 | 11,028 |
| 2018 | 12,649 | 13,008 | 22,585 | 22,648 | 21,390 | 50,904 | 39,103 | 40,681 | 39,508 | 26,723 | 23,283 | 17,680 | 12,690 |
| 2019 | 16,691 | 26,329 | 11,964 | 28,645 | 40,904 | 39,103 | 40,681 | 39,508 | 26,723 | 23,283 | 17,680 | 12,690 |
gentrification. Specifically, consumption-side theories [81] suggest that BSS may attract middle- and high-income people because of the improved accessibility and multi-modal alternatives they can bring to the communities. Moreover, production-side theories [82] argue that landlords can transform their properties for more lucrative uses or sell them to private developers at a higher price with infrastructure development and improvements. As a result, BSS may expose some people to risks, while providing economic, environmental, and social benefits to others. In addition, the problem may be significant for those who rely heavily on BSS as their primary mode of transportation, such as low-income people.

Of course, whether the magnitude of the BSS-induced premium is significant enough to price low-income people out is debatable. However, regardless of the extent of the premium, policymakers should not neglect the property value premium of BSS since, for low-income inhabitants, even a slight price increase can be substantial, and they would need to give up something to live in the neighborhoods.

Unfortunately, only a few government policies in Portland, Oregon, have focused on the BSS-induced premium and potential gentrification risks. For example, several bicycle-related plans in the study area, such as the 2016 Bike Plan, have boosted BSS and bicycling. However, despite the numerous ongoing attempts and investments, there have been few guidelines, such as encouraging researchers to conduct a study to assess the economic benefit and give recommendations. Thus, plans should address BSS-induced gentrification and develop detailed policy schemes, such as Local Improvement Districts and Tax Increment Financing in detail, so that the broader population has an equally accessible and desirable transportation mode.

6. Conclusions

Since bikesharing services (BSS) have offered a variety of benefits, including reduced pollution and congestion, improved accessibility, and improved public health, the positive externalities may be transformed into property values within a reasonable distance of BSS stations. Thus, this study sought answers to the following three research questions: (1) Was proximity to BSS positively associated with residential property value in Portland, Oregon? (2) Did proximity to BSS and public transportation modes, including light rail transit, synergistically affect residential property values? (3) Did the magnitude of the property value premium produced by BSS intensify over time? Employing a spatial hedonic model with a case study of Portland, Oregon, this work contributes to a growing body of empirical research by revealing the following three main findings: (1) a statistically significant premium for proximity to BSS in both single-family and multi-family housing markets with different magnitudes, (2) synergetic effects between BSS and public transportation modes on residential property values, and (3) a stable premium for BSS with a few exceptions. The findings contribute to providing a more detailed picture of the BSS premium, offering pertinent policy implications, and expanding discussions around transportation-induced property value premium.

The study acknowledges limitations and offers future research opportunities. First and foremost, this study employed a cross-sectional analysis, which fails to reveal a causal association. As a result, future research will need to use sophisticated analytical approaches, such as spatial difference-in-differences analysis [83,84]. Second, because BSS station placements can vary and service areas can expand over time, future research should establish alternative matrices besides distance to the nearest BSS station. Third, since different regions in different countries have distinct BSS investment, infrastructure development, and ridership settings, more research with other study areas is required, as the findings may not apply to other places. For instance, further research needs to investigate other cities or nations that have urban structures that are comparable to those found in Portland, and then compare the results to one another. Furthermore, future study is needed to explore the economic impact of BSS in the European context, where bicycling has been a vital and major transportation mode. Fourth, because BSS has been in the city for about six years, this study may only have found an impact on property value in the intermediate term. Thus,
future research should concentrate on the system’s long-term impact as it matures. Fifth, empirical research is needed to answer the additional questions of whether BSS induces gentrification. Sixth, there might be an omitted variable bias in the final models; specifically, the final models did not include all variables influencing housing prices, such as housing qualities, neighboring natural beauty, and school quality. Finally, this study did not offer a sufficient theoretical basis for using interaction terms. Consequently, further research must concentrate on developing the theoretical frameworks and incorporating them into their respective investigations.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The four main data sets used in the analysis of this study are publicly available on websites: (1) https://rlisdiscovery.oregonmetro.gov/ (accessed on 5 April 2022), (2) https://www.census.gov/data/developers/data-sets/acs-5year.html (accessed on 10 May 2022), (3) https://www.epa.gov/smartgrowth/smart-location-mapping (accessed on 25 May 2021), and (4) https://data-usdot.opendata.arcgis.com/datasets/bikeshare/explore (accessed on 15 April 2022). Additionally, Figure 1 used data obtained from https://www.socialexplorer.com/ (accessed on 10 June 2022), data used in Figure 3 was obtained from https://www.biketownpdx.com/system-data/historical (accessed 10 June 2022), and Figure 5 used data from https://biketownpdx.com/system-data (accessed 10 June 2022).

**Conflicts of Interest:** The author declares no conflict of interest.

**References**

1. Sheller, M.; Urry, J. Mobilizing the New Mobilities Paradigm. *Appl. Mobilities* **2016**, *1*, 10–25. [CrossRef]
2. Chen, Y.; Zha, Y.; Wang, D.; Li, H.; Bi, G. Optimal Pricing Strategy of a Bike-Sharing Firm in the Presence of Customers with Convenience Perceptions. *J. Clean. Prod.* **2020**, *253*, 119905. [CrossRef]
3. Qian, X.; Jaller, M.; Niemeier, D. Enhancing Equitable Service Level: Which Can Address Better, Dockless or Dock-Based Bikeshare Systems? *J. Transp. Geogr.* **2020**, *86*, 102784. [CrossRef]
4. Teixeira, J.F.; Silva, C.; Moura e Sá, F. Empirical Evidence on the Impacts of Bikesharing: A Literature Review. *Transp. Rev.* **2021**, *41*, 329–351. [CrossRef]
5. Alonso, W. A Theory of the Urban Land Market. *Urban Reg. Econ.* **1960**, *6*, 83–91. [CrossRef]
6. Alonso, W. *Location and Land Use: Toward a General Theory of Land Rent*; Harvard University Press: Cambridge, MA, USA, 1964.
7. Mills, E.S. *Studies in the Structure of the Urban Economy; Resources for the Future, Inc.*: Washington, DC, USA, 1972.
8. Muth, R.F. *Cities and Housing: The Spatial Pattern of Urban Residential Land Use*; UC Berkeley Transportation Library: Berkeley, CA, USA, 1969.
9. Wingo, L. *Transportation and Urban Land*, 1st ed.; Routledge: Abingdon-on-Thames, UK, 1961; ISBN 978-1-138-96267-5.
10. Tomkins, J.; Topham, N.; Twomey, J.; Ward, R. Noise versus Access: The Impact of an Airport in an Urban Property Market. *Urban Stud.* **1998**, *35*, 243–258. [CrossRef]
11. Cervero, R.; Duncan, M. Benefits of Proximity to Rail on Housing Markets: Experiences in Santa Clara County. *J. Public Transp.* **2002**, *5*, 1–18. [CrossRef]
12. Giuliano, G.; Gordon, P.; Pan, Q.; Park, J. Accessibility and Residential Land Values: Some Tests with New Measures. *Urban Stud.* **2010**, *47*, 3103–3130. [CrossRef]
13. Allen, M.T.; Austin, G.W.; Swaleheen, M. Measuring Highway Impacts on House Prices Using Spatial Regression. *J. Sustain. Real Estate* **2019**, *46*, 859–882. [CrossRef]
14. Bowes, D.R.; Bilanfeldt, K.R. Identifying the Impacts of Rail Transit Stations on Residential Property Values. *J. Urban Econ.* **2001**, *50*, 1–25. [CrossRef]
15. Kay, A.J.; Noland, R.B.; DiPetrillo, S. Residential Property Valuations near Transit Stations with Transit-Oriented Development. *J. Transp. Geogr.* **2014**, *39*, 131–140. [CrossRef]
16. Seo, K.; Salon, D.; Kuby, M.; Golub, A. Hedonic Modeling of Commercial Property Values: Distance Decay from the Links and Nodes of Rail and Highway Infrastructure. *Transportation* **2019**, *46*, 859–882. [CrossRef]
17. Pan, Q. The Impacts of an Urban Light Rail System on Residential Property Values: A Case Study of the Houston METRORail Transit Line. *Transp. Plan. Technol.* **2013**, *36*, 145–169. [CrossRef]
18. Qiao, S.; Gar-On Yeh, A.; Zhang, M. Capitalisation of Accessibility to Dockless Bike Sharing in Housing Rentals: Evidence from Beijing. *Transp. Res. Part D Transp. Environ.* **2021**, *90*, 102640. [CrossRef]
19. Zhou, Z.; Li, H.; Zhang, A. Does Bike Sharing Increase House Prices? Evidence from Micro-Level Data and the Impact of COVID-19. *J. Real Estate Financ. Econ.* **2022**, *1*, 30. [CrossRef]
20. Zhao, Y.; Ke, J. The Impact of Shared Mobility Services on Housing Values near Subway Stations. Transp. Res. Part D Transp. Environ. 2021, 101, 103097. [CrossRef]

21. Lee, S.; Golub, A. The Residential Property Value Premium of the Proximity to Carsharing and Bikesharing Services: Evidence from New York City. Transp. Res. Interdiscip. Perspect. 2021, 11, 100427. [CrossRef]

22. El-Geneidy, A.; van Liepen, D.; Wasfi, R. Do People Value Bicycle Sharing? A Multilevel Longitudinal Analysis Capturing the Impact of Bicycle Sharing on Residential Sales in Montreal, Canada. Transp. Policy 2016, 51, 174–181. [CrossRef]

23. Chu, J.; Duan, Y.; Yang, X.; Wang, L. The Last Mile Matters: Impact of Dockless Bike Sharing on Subway Housing Price Premium. Manag. Sci. 2021, 67, 297–316. [CrossRef]

24. Buehler, R.; Pucher, J. Cycling to Work in 90 Large American Cities: New Evidence on the Role of Bike Paths and Lanes. Transportation 2012, 39, 409–432. [CrossRef]

25. Shi, W. The Impacts of the Bicycle Network on Bicycling Activity: A Longitudinal Multi-City Approach. Ph.D. Thesis, Portland State University, Portland, OR, USA, 2020.

26. Portland Bureau of Transportation. Portland Bicycle Plan for 2030; Portland Bureau of Transportation: Portland, OR, USA, 2010.

27. Eudaly, C.; Warner, C.; Pearce, A.; Igarta, D.; Geller, R.; Phillips, T.; Serrietta, M. Portland Bicycle Plan for 2030: 2019 Progress Report; Portland Bureau of Transportation: Portland, OR, USA, 2019; p. 66.

28. Bertini Ruas, E. The Influence of Shared Mobility and Transportation Policies on Vehicle Ownership: Analysis of Multifamily Residents in Portland, Oregon. Ph.D. Thesis, Portland State University, Portland, OR, USA, 2019.

29. Blythe, A. Bikeshare Cycle-Ology: Portland’s Nike BIKETOWN and Public-Private Partnerships. Ph.D. Thesis, Lewis & Clark College, Portland, OR, USA, 2017.

30. Biketown MORE TO EXPLORE! Available online: http://www.biketownpdx.com/blog/biketown-expands-east-1 (accessed on 22 February 2022).

31. Biketown Service Area Expansion. Available online: http://www.biketownpdx.com/blog/system-expansion (accessed on 22 February 2022).

32. Simone, A.G.D. Complement or Substitute? An Analysis of Bikeshare’s Effect on Transit Ridership in Portland. Ph.D. Thesis, University of Washington, Seattle, WA, USA, 2019.

33. El-Assi, W.; Salah Mahmoud, M.; Nurul Habib, K. Effects of Built Environment and Weather on Bike Sharing Demand: A Station Level Analysis of Commercial Bike Sharing in Toronto. Transportation 2017, 44, 589–613. [CrossRef]

34. Eren, E.; Üz, V.E. A Review on Bike-Sharing: The Factors Affecting Bike-Sharing Demand. Sustain. Cities Soc. 2020, 54, 101882. [CrossRef]

35. Gebhart, K.; Noland, R.B. The Impact of Weather Conditions on Bikeshare Trips in Washington, DC. Transportation 2014, 41, 1205–1225. [CrossRef]

36. Noland, R.B.; Smart, M.J.; Guo, Z. Bikeshare Trip Generation in New York City. Transp. Res. Part A Policy Pract. 2016, 94, 164–181. [CrossRef]

37. Venigalla, M.; Kaviti, S.; Brennan, T. Impact of Bikesharing Pricing Policies on Usage and Revenue: An Evaluation through Curation of Large Datasets from Revenue Transactions and Trips. J. Big Data Anal. Transp. 2020, 2, 1–16. [CrossRef]

38. Debrezion, G.; Pels, E.; Rietveld, P. The Impact of Railway Stations on Residential and Commercial Property Value: A Meta-Analysis. J. Real Estate Financ. Econ. 2007, 35, 161–180. [CrossRef]

39. Mohammad, S.I.; Graham, D.J.; Melo, P.C.; Anderson, R.J. A Meta-Analysis of the Impact of Rail Projects on Land and Property Values. Transp. Res. Part A Policy Pract. 2013, 50, 158–170. [CrossRef]

40. Yan, S.; Delmelle, E.; Duncan, M. The Impact of a New Light Rail System on Single-Family Property Values in Charlotte, North Carolina. J. Transp. Land Use 2012, 5, 60–67.

41. Foster, N.; Morsere, C.M.; Dill, J.; Clifton, K. Level-of-Service Model for Protected Bike Lanes. Transp. Res. Rec. 2015, 2520, 90–99. [CrossRef]

42. Liu, J.H.; Shi, W. Impact of Bike Facilities on Residential Property Prices. Transp. Res. Rec. 2017, 2662, 50–58. [CrossRef]

43. Bhat, C.R.; Gossen, R. A Mixed Multinomial Logit Model Analysis of Weekend Recreational Type Episode Choice. Transp. Res. Part B Methodol. 2004, 38, 767–787. [CrossRef]

44. Gehrke, S.R.; Wang, L. Operationalizing the Neighborhood Effects of the Built Environment on Travel Behavior. J. Transp. Geogr. 2020, 82, 102561. [CrossRef]

45. Kim, K.; Lab, M.L. The impact of Hudson-Bergen Light Rail on residential property appraisal. Pap. Reg. Sci. 2014, 93, 579–597. [CrossRef]

46. Duncan, M. Comparing Rail Transit Capitalization Benefits for Single-Family and Condominium Units in San Diego, California. Transp. Res. Rec. 2008, 2067, 120–130. [CrossRef]

47. McQueen, M.; Lee, T. Bike Share Capitalization in Portland Is Down 72.7% During the Pandemic. Available online: https://trec.pdx.edu/news/bike-share-ridership-portland-down-727-during-pandemic (accessed on 22 February 2022).

48. Lee, S.; Wang, L.; Golub, A. Effect of COVID-19 on Property Value Premium of Light Rail Transit: A Case Study of the Portland Metropolitan Area. Sustainability 2020, 12, 9107. [CrossRef]

49. Dong, H. Were Home Prices in New Urbanist Neighborhoods More Resilient in the Recent Housing Downturn? J. Plan. Educ. Res. 2015, 35, 5–18. [CrossRef]

50. Court, A.T. Hedonic Price Indexes with Automotive Examples. In The Dynamics of Automobile Demand; General Motors Corporation: New York, NY, USA, 1939; pp. 99–117.

51. Griliches, Z. (Ed.) Hedonic Price Indexes for Automobiles: An Econometric Analysis of Quality Change. In Price Indexes and Quality Change; Harvard University Press: Cambridge, MA, USA, 1961; pp. 173–196. ISBN 978-0-674-59258-2.

52. Rosen, S. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. J. Political Econ. 1974, 82, 34–55. [CrossRef]
