

Article

Use of Geographically Weighted Regression and Multiscale Geographically Weighted Regression to Account for Spatially Heterogeneous Property Value Impacts of Heavy Rail Transit Stations

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Abstract

This study provides evidence on the impact of a heavy rail-based suburban metro station in Fremont, California, on house prices using geographically weighted regression (GWR) and multiscale geographically weighted regression (MGWR). The dataset comprises sale price, sale date, and property and locational characteristics for single-family houses sold during the January 2000–April 2018 period within two miles of the Warm Springs Station on the San Francisco Bay Area Rapid Transit system. The results demonstrate that, relative to the referent period (2000–2001): (a) the station-led house price impacts are spatially heterogeneous—the house price increased in one pocket only, comprising less than one-tenth of the dataset, not across the entire 0–2 mile station area, (b) the price increase in that pocket began right after the project announcement period, and (c) the price impacts indicated by the MGWR model markedly differ from baseline ordinary least square regression (OLS) estimates. Overall, the study’s findings highlight the need to move beyond average estimation techniques, such as OLS, to those that account for spatially heterogeneous price impacts, such as GWR and MGWR.

Keywords: sustainable transportation; value capture; heavy rail-based rapid transit; house prices; multiscale geographically weighted regression

1. Introduction

While there is renewed interest across the United States (US) to expand the public transit infrastructure, governments at all levels—federal to local—are fiscally constrained and therefore unable to make the large investments required to develop and operate these systems. They eagerly seek new revenue sources. Value capture (VC) is one such source.

One VC tool, a special assessment district (SAD), captures public-infrastructure-led property value increases by levying a fee/assessment on properties within a SAD. Normatively, VC tools rely on the “benefits received” principle, which asserts that property owners who benefit from publicly funded infrastructure or services should bear its costs. When transit improvements increase accessibility, nearby property values rise as accessibility-related benefits are capitalized into property values, resulting in windfall gains for property owners. Therefore, it is contended that such property owners ought to contribute to financing public transit since they directly benefit from its provision [1].

Implementing VC mechanisms, such as SADs, requires robust empirical evidence that public transit improvements have raised the value of nearby properties. Crucially, planners



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must determine whether these value impacts vary spatially across the entire transit station's catchment area. For example, does a station induce a uniform 12% property value increase across its catchment area, or does it generate localized property value increases (e.g., 5% in one section, 7% in the second, and 15% in the third)? Variability in property value increases would call for different property assessment rates across sections of the catchment area. Without empirical estimation, public agencies often make ad hoc assumptions about the likelihood and magnitude of property value increases, such as assuming that the increases stop at one side of a freeway or an arterial road or aligning SAD boundaries with existing neighborhood boundaries, or employing labor-intensive parcel-by-parcel professional appraisals, as was the case for the Seattle Street Car system [2].

Although existing research on public transit has effectively applied econometric models to assess how rail transit investments influence property values, the majority of recent US-based research examines light rail systems [1,3–8]. In addition, aside from a handful of recent studies examining the effects of heavy rail rapid transit on property values [9–11], the majority of research on heavy rail systems dates back several decades [12–20] or focuses on inter-city commuter rail [21].

Two additional research gaps remain in the existing literature. First, many studies do not employ a rigorous research design, as they are typically based on cross-sectional analyses. Second, most studies assume that all properties in the vicinity of a transit station experience the same property value gain (that is, the statistical significance and the coefficient of the proximity-to-transit-station variable in their econometric models are uniform across a distance band from the transit station). While one study advanced research in this field by investigating the price impact of the Warm Springs (WS) Station, located in Fremont, California, across the entire house price spectrum, it still assumed that all properties within a given price range would experience the same property value gain [10]. A few studies, primarily non-US-focused, have relaxed this uniform impact assumption using geographically weighted regression (GWR). For example, one study used GWR to estimate the impact of light rail on property values in Malaysia's Greater Kuala Lumpur region [22]. However, this study is cross-sectional. Furthermore, while GWR assumes a fixed spatial scale (same distance band or same number of nearest neighbors) for all variables, MGWR relaxes this assumption (see the more detailed discussion in the Methodology Section). Hence, it is useful to estimate an MGWR model because it allows property value impacts to vary spatially across the entire transit station's catchment area, thereby helping delineate SAD boundaries and assessment rates that are aligned with the transit station's actual property impacts.

This study aims to fill the three above-noted research gaps using MGWR and GWR to estimate the property value increment resulting from the Bay Area Rapid Transit (BART) system's WS Station in Fremont, California. BART is a heavy rail public transportation system that operates throughout the San Francisco Bay Area in Northern California.

The study focuses on single-family houses for two reasons. First, single-family homeowners, especially those in suburban cities such as Fremont, typically oppose public transit, arguing that it depresses property values. Hence, if this study finds that the WS Station increased single-family home values, it is likely to increase the values of non-single-family homes, such as apartments, condominiums, and townhomes, even more, to the extent their residents are more likely to benefit from improved transit accessibility and less likely to complain about construction-related disruptions and noise, compared to single-family residents. Second, county assessor records are more accurate and complete for single-family homes than for other housing types. For example, assessors' data are often incomplete for apartment- and condominium-complex-level features such as gymnasiums, swimming pools, and parking spaces.

2. Literature Review

Since our focus area, the WS Station, is on the heavy rail-based rapid transit system, BART, that is located in the San Francisco Bay Area region in the US, and the impact of public transit stations can vary by the national context (for example, dense European and Asian versus more sprawling US cities) and by transit type (commuter rail, heavy rail-based rapid transit, and light rail), below, I review the property value impacts of US-based studies published in peer-reviewed journals that examine the house price impacts of heavy rail-based rapid transit systems similar to BART. However, to review the research design and econometric models, I include all recent (2015–2025) global studies on rail transit's impact on property values because the insights from their modeling approaches could be applied globally. Overall, I reviewed 40 US-focused and 82 international studies.

2.1. Impacts of Heavy Rail-Based Rapid Transit Stations on Single-Family Houses' Property Values in the US

Heavy rail transit is characterized by high-speed, high-capacity passenger rail operating on a dedicated right-of-way [11]. While 16 studies reviewed for this paper found positive effects of heavy rail on residential property prices, the impacts varied by urban form, socioeconomic and station area characteristics, and other factors. For example, in metropolitan Atlanta, Georgia, the Metropolitan Atlanta Rapid Transit Authority (MARTA) service area's racial and economic stratification affected the property value impacts, with rail proximity depressing home values in the northern, predominantly white and high-income area, but increasing them in the southern, predominantly Black and low-income area [20]. Another study found similar income-based variation around MARTA stations [23]. On the other hand, while one study found a negative impact of Washington Metro rail stations on house prices [24], other studies observed positive impacts on home prices for the same system across a wider study area [11,25,26]. However, no impact was identified for the Miami Metrorail in Florida [16].

The impacts also varied by station location and characteristics, such as proximity to the central business district (CBD), density, and walkability. One study of urban stations—three Metropolitan Transportation Authority (MTA) stations in Queens, New York—found a 13% increase in house prices [18]. Another study, which used proximity to the CBD as a measure of urban character, found that single-family home prices were 2.4% higher in areas around a station [19].

Similarly, walkability was associated with about a 3% increase in property prices within a 0.6-mile (1 km) radius of all stations in Washington, DC [26]. An earlier study of the same area recorded 8% higher house prices in station areas with higher employment/residential density [26].

A study of mature public transit rail lines in Los Angeles, which are also associated with higher densities of multi-family properties, found 99.55%, 45.95%, and 27.35% increases in property values of multi-family houses with proximities of 0–0.25 miles, 0.25–0.5 miles, and 0.5–1.0 miles, respectively, to mature lines [27]. These larger price increases for multi-family houses compared to single-family homes are, among others, likely because residents of the former housing type might value transit accessibility more than those of the latter.

Focusing on suburban stations, one study estimated a 9% increase in house prices surrounding the Pleasant Hill BART station in the San Francisco Bay Area, and the other found a maximum 21.93% increase in house prices around the WS BART station in Fremont, California [10,18]. However, one study found a negative relationship between station area proximity and house prices in Washington, District of Columbia, with house prices increasing by 2.4% and 4.8% as distance from the station increased. These significant

variations in results for heavy rail's impact in suburban areas necessitate further research of heavy rail's property value impacts in auto-dominated suburban US [24].

Moreover, a few studies focusing on suburban station areas examined the impact of parking facilities or "Park-and-Ride" lots. This additional amenity reduced house prices—stations without parking, that served predominantly inner-city areas, experienced higher single-family house prices [19]. Another study noted a positive relationship between proximity to "Walk-and-Ride" stations and owner-occupied property prices, while "Park-and-Ride" stations were negatively associated with property prices [17]. Finally, in Los Angeles, "Park-and-Ride" stations did not impact the value of single- and multi-family properties [27].

2.2. Research Design and Econometric Models

Among the US-focused studies, 10 used cross-sectional data and 30 employed time-series data. Among the former, one study used the 1980 Census of Housing and Journey to Work dataset [28]. Among the latter, one study examined residential property values around the New Jersey Transit commuter rail stations using data from 1990, 2000, and 2013 [29].

Of the 30 time-series studies, only nine address before-and-after construction periods in their analyses. For example, one study included data from 1970, 1980, 1990, and 2000 to estimate the impact on property values before and after the construction of heavy rail and light rail systems in 14 US cities, employing both time-series and before-and-after data [17]. Only two of these nine studies used time-series data with before-and-after construction periods *and* also addressed spatial dependence [9,10].

Overall, 11 studies, with varying data types, addressed spatial dependence. One of these estimated two types of spatial regression models, yielding different estimates of the house price impact [30]. These results range from a 0.441% decrease in house prices for every 1% increase in proximity to the station area in a spatial autoregressive (SAR) model to a 0.03% decrease in a spatial error model (SEM). Further advanced methodologies, such as GWR, address spatial heterogeneity by conducting local regressions for each house [25].

Among the international literature, 34 studies used only cross-sectional data, and 46 employ time-series data. Thirty-one of these 46 studies employed time-series and before-and-after data. One study utilized cross-sectional data from July 2016 to identify a positive impact of heavy rail and bus systems on apartments and houses in Dalian City, China [31]. Another study used time-series data from 1990 to 2017 for house values and 2004 to 2017 for rental values to capture the pre- and post-construction periods for the Sydney, Australia, Epping-to-Chatswood rail link; the authors found a positive impact on both housing types [32]. Yet another study used time-series data but did not include a before-and-after construction period. This study focused on the Shinkansen in Japan, which opened in 1964 as the first high-speed rail (HSR) system [33].

Furthermore, 52 studies address spatial dependence or heterogeneity, and 15 of these use time-series and before-and-after data. For example, one study analyzes lines 5, 8, and 10 of the Beijing Urban Rail Transit between 2005 and 2011 using a SAR model [34]. Overall, twenty-two studies address spatial heterogeneity using GWR, MGWR, or temporally weighted MGWR models. However, none of the studies use GWR or MGWR for time-series before-and-after data—a limitation this paper seeks to address.

In summary, the literature review highlights the paucity of research that employs time-series before-and-after data and regression models that address spatial heterogeneity to examine the impacts of rail stations on house prices. Finally, the impact of suburban heavy rail stations on house prices varies significantly, underscoring the need for further research on this common, auto-dominated urban form in the United States.

3. Materials and Methods

3.1. Research Questions and Study Area

This study answers the following research questions (RQs):

RQ1: Does the WS Station impact the surrounding house prices?

RQ2: Is the house price impact spatially heterogeneous?

RQ3: What is the total house price impact of the WS Station?

The study area—WS Station—is located on BART's Orange and Green Lines (see Figure 1) in Fremont, Alameda County, California. The last two stations on these lines—Milpitas and Berryessa North San Jose—were under construction during the latter part of this study period. The nearest station to the North—Fremont Station—is about 4.5 miles away, and the closest to the south—Milpitas Station—is approximately 8 miles away. Hence, properties within the study area—a 2-mile radius around the WS Station—are deemed to benefit from the station only.

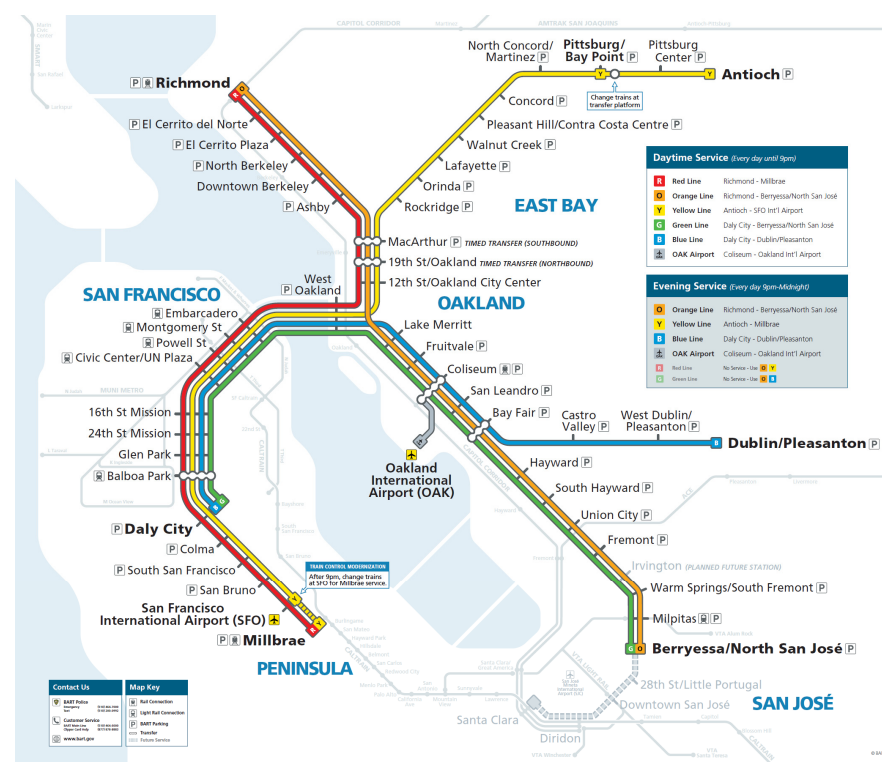


Figure 1. BART system map [35].

Finally, I took two additional steps to conservatively estimate the WS Station's impact on property values. First, all properties to the north were deemed to benefit more from the older and well-established Fremont station. Second, public agencies made many improvements to the I-880 freeway, which is west of the WS Station. Therefore, properties east of the freeway and west of a major arterial road—Warm Springs Boulevard—were deemed to benefit from these improvements. In summary, the study area includes a 2-mile radius to the south and east and up to Warm Springs Boulevard to the west of the station (see Figure 2).

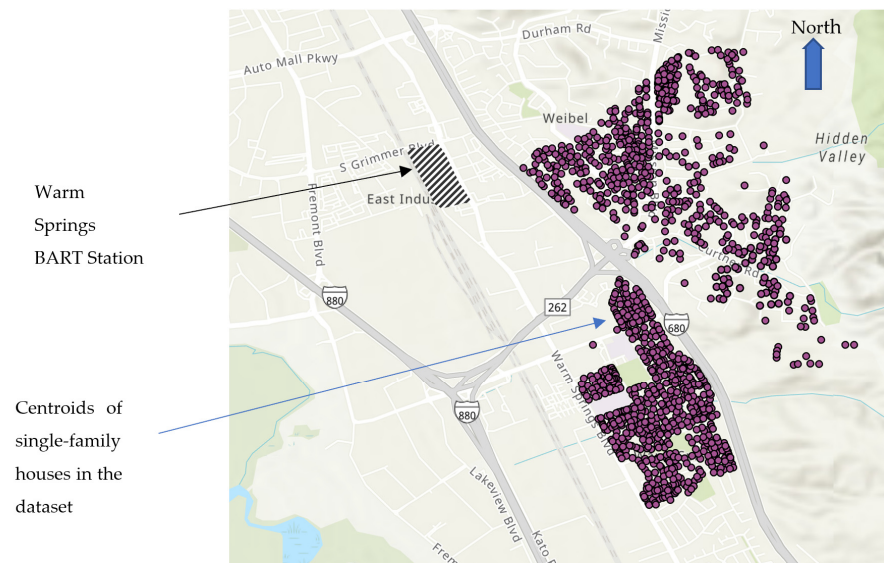


Figure 2. Case study area.

3.2. Timeline

The 5.4-mile railway track, related improvements (such as construction of over- and underpasses), and construction of the station constitute the \$800 million Warm Springs Extension (WSX) project [9]. The entire project can be divided into the following five periods:

The years 1991–2001 represent the initial phase of interest, beginning with BART proposing the project in 1991 to ease congestion on Interstate 880, during which an environmental impact report (EIR) was also completed. BART then considered several possible rail alignments, and in 2000, voters in Alameda County approved using sales tax revenues to finance the WSX project [36].

WSX became broadly known in the 2002–2006 period. The state of California completed its environmental review in 2003. In 2004, the WSX project qualified for federal funding, and multiple EIRs were drafted and approved between 2005 and 2006 [36].

The City of Fremont completed a few construction projects in 2007–2009 to separate rail and non-rail traffic [37]. However, major construction was undertaken in the 2010–2014 period, including the construction of the station and an underground rail tunnel beneath the main city park and laying the tracks [38].

The post-construction but pre-station-opening period was from 2015 to February 2017, during which all the project systems were tested [38]. The station opened for service in March 2017 [39].

3.3. Dataset

The dataset contains information on sales, as well as structural and locational characteristics, for 1274 single-family homes sold during 2000–April 2018 within a 0–3.2 km (0–2-mile) radius of the WS Station, as described in Section 3.2. The structural attributes of each house include the lot and house size, number of bedrooms and bathrooms, and age. Data on various locational attributes included proximity to the WS Station, freeways, and arterial roads; the elementary school attendance zone; and proximity to multiple uses, such as multi-family housing, neighborhood parks, offices, industrial, and commercial uses. Finally, I included socioeconomic data from the US Census.

I took several steps to clean the data. First, I removed observations where a home had zero bedrooms, bathrooms, or lot size, as these were likely cottages, studio apartments, or other building types miscoded as single-family homes. Next, homes with more than

6 bedrooms were excluded because they are likely to be large, luxury properties that do not represent the typical single-family housing market in the study area.

Since the dataset included sales over eighteen years (2000–2018), I normalized the sale price using the Bureau of Labor Statistics' (BLS) non-housing consumer price index (CPI) for San Francisco–Oakland–Hayward. Final sale prices are in 2018 constant-dollar terms. Finally, I excluded data with standardized predicted values and residuals that were both less than -3 and greater than $+3$ in the baseline OLS model.

Preliminary models included a large number of locational attributes; I included those listed in Table 1 in the final models because they were statistically significant or used in previous studies of this station [9,10]. The descriptive statistics of the ratio-level independent variables are in Table 2.

Table 1. Description of the independent variables.

Variables	Description
Lot Size	Size of the parcel size on which the house is constructed (sq. ft.)
Living Space	Size of the living space of the house (sq. ft.)
Bedrooms	Number of bedrooms in the house
Bathrooms	Number of bathrooms in the house
Age	Age of the house at the time of sale (year)
WSBART	Euclidean distance from the house to the Warm Springs BART station (meter)
LnHwy	Natural log of the distance from the house to the nearest highway (meter)
LnCommr	Natural log of the distance from the house to the nearest commercial use (meter)
LnMF	Natural log of the distance from the house to the nearest multi-family housing (meter)
LnPark	Natural log of the distance from the house to the nearest neighborhood park (meter)
Art100	Dichotomous (dummy) variable (= 1 if a house is within 100 m of an arterial road; otherwise, 0)
Asia2000	Percent Asian population for the census block group in which the house is located as per the American Community Survey 2000
Elem School	Dichotomous (dummy) variable for the elementary school attendance area in which the house is located
Winter	Dichotomous (dummy) variable indicating whether the house was sold in winter
Spring	Dichotomous (dummy) variable indicating whether the house was sold in spring
Summer	Dichotomous (dummy) variable indicating whether the house was sold in summer

Table 1. *Cont.*

Variables	Description
Y2002-06	Dichotomous (dummy) variable indicating whether the house was sold in years 2002 to 2006
Y2007-09	Dichotomous (dummy) variable indicating whether the house was sold in years 2007 to 2009
Y2010-14	Dichotomous (dummy) variable indicating whether the house was sold in years 2010 to 2014
Y2015-F17	Dichotomous (dummy) variable indicating whether the house was sold in years 2015 to February 2017
YM17-A18	Dichotomous (dummy) variable indicating whether the house was sold in March 2017 to April 2018
WY200206	Interaction variable created by interacting WSBART with Y2002-06
WY200709	Interaction variable created by interacting WSBART with Y2007-09
WY201014	Interaction variable created by interacting WSBART with Y2010-14
WY2015F17	Interaction variable created by interacting WSBART with Y2015-F17
WYM17ON	Interaction variable created by interacting WSBART with YM17-A18

Table 2. Descriptive statistics of ratio-level independent variables.

Variables	Minimum	Maximum	Mean	Standard Deviation
Lot size (sq. ft.)	1556	23,470	8389.7	3693.1
Living space (sq. ft.)	1000	3641	2071.5	589.6
Bedrooms (number)	2	6	3.8	0.7
Bathrooms (number)	1	4	2.5	0.5
Age (years)	0	60	29.3	12
WSBART (meter)	473	3198	1991.6	637.6
Distance to nearest highway (meter)	5	1998	636.5	432.3
Distance to nearest commercial use (meter)	1	1852	712.9	434.5
Distance to nearest multi-family housing (meter)	1	1884	662.1	324.3
Distance to nearest neighborhood park (meter)	1	1130.7	423.8	283
Percent Asian population (%)	0	91.4	49.5	21.1

N = 1274.

3.4. Methodology

I employed the following four-step methodology to answer the research questions.

Step 1

I used the WS Station's development timeline (from the preliminary interest period to one year after the beginning of the service), as delineated in Section 3.2. This timeline helped identify the various time periods for the statistical analysis described in Steps 2 and 3. The extant literature suggests the following periods for consideration: the pre-station announcement period, the period from the announcement to the start of construction, the construction period, the post-construction period until the start of service, and the post-service commencement period.

Step 2

I estimated a baseline ordinary least squares regression (OLS) similar to the ones used in previous studies of this station [9,10]. This baseline model helped identify the

variables (e.g., house- and neighborhood-level characteristics) that affect the sale price of single-family homes around the WS Station.

Under the OLS approach, the main estimation equation (see Equation (1) below) estimated the impact of the structural and locational attributes (lc_i) of house i on its sale price (p_i). These attributes include the proximity of the house to the WS Station (see Equation (1)). α_0 is the constant, α_i is the coefficient of lc_i , and ξ_i is the error term.

$$p_i = \alpha_0 + \alpha_i lc_i + \xi_i \quad (1)$$

Step 3

Using a subset of independent variables included in the OLS model, I estimated GWR and MGWR models. I excluded statistically insignificant (p -value less than 0.10) and spatial dummy variables from the GWR and MGWR models due to multicollinearity, without affecting the magnitude or significance of the coefficients for the variables of interest.

Under GWR, the main estimation equation (see Equation (2) regresses the sale price of a house i at location s [$p_i(s)$] on its structural and locational attributes (lc_i) such that the coefficients of the intercept and each independent variable also vary by location s .

$$p_i(s) = \alpha_0(s) + \sum(\alpha_i(s) lc_i(s) + \xi_i \quad (2)$$

GWR assumes that all independent variables impact the dependent variable at the same spatial scale; for example, in this research, it would assume that proximity to highways and multi-family residences would impact house prices to the same spatial extent. Therefore, I ran MGWR to relax this assumption. MGWR estimates a different bandwidth (b_i) for each independent variable i (see Equation (3)).

$$p_i(s) = \alpha_0(s) + \sum(\alpha_{bi}(s) lc_i(s) + \xi_i \quad (3)$$

Step 4

Since the GWR and MGWR models identified spatially heterogeneous property value impacts, I displayed their spatial distribution through maps. Finally, I used the statistically significant coefficients from the local regression equations, created by interacting the distance to the WS Station with the time dummy variables, to compute the total house price impact of the WS Station.

4. Results and Discussion

4.1. Model Structure

I estimated four regression models (see Table 3). The first, the OLS Model (Model 1), includes all the structural and locational variables used in the previous studies of this station [9,10] to develop a comparable OLS fixed-effects model. Apart from the variable capturing houses' structural and locational attributes, dichotomous (dummy) variables were used to account for the season of sale and the time period within the WSX project timeline when the house was sold. The 2000–2001 initial interest period served as the referent category. These dichotomous variables also captured changes in the housing market in the study area, both by season of sale and over time. Finally, I interacted the WSBART variable with the time dummy variables to create interaction variables. These are the primary variables of interest because they capture the marginal effect of the proximity to the WS Station compared to the referent period.

Table 3. Regression results.

	OLS Model 1	OLS Model 2: OLS Model 1 minus school and other spatial dummy variables and statistically insignificant variables	GWR Model (same set of independent variables as OLS Model 2)	MGWR Model (same set of independent variables as OLS Model 2)
	Model 1	Model 2	Model 3	Model 4
Variables		Coefficient (std. error ^a)	Mean Coefficient (Min to Max Coefficients)	Mean Coefficient (Min to Max Coefficients)
Lot Size	15.0 *** (2.2)	14.1 *** (2.1)	5.8 (−21.8 to 19.0)	5.3 (−20.5 to 18.8)
Living Space	327.6 *** (15.9)	325.7*** (15.9)	251.9 (136.0 to 394.7)	249.4 (126.1 to 403.4)
Bedrooms	9912 (8346)	11,787 (8383)	8453 (−100,030 to 65,400)	6447 (−134,227 to 68,783)
Bathrooms	−48,493 *** (12,712)	−50,785 *** (13,382)	−27,342 (−131,881 to 80,492)	−22,644 (−142,534 to 104,242)
Age	−2489.3 *** (650.6)	−3146.5 *** (639.3)	−2271.1 (−8337.38 to 5566.27)	−1455.3 (−10,449.4 to 11,097.3)
WSBART	−75.5 *** (24.8)	−46.6 ** (23.5)	91.4 (−358.6 to 790.8)	124.1 (−435.9 to 1309.3)
LnHwy	71,305 *** (7142.9)	65,137 *** (4847.9)	−69,033 (−1,661,100 to 150,396)	−164,909 (−3,132,878 to 173,406)
LnCommr	15,435 ** (6182.9)	13,642 ** (6283.5)	87,125 (−242,846 to 1,769,571)	162,235 (−140,467 to 3,215,448)
LnMF	16,696 * (8799.3)	14,141 * (7864.3)	34,508 (−476,345 to 281,361)	15,131 (−693,193 to 334,07)
LnPark	−4811.2 (5530.90)			
Art100	−43,788 *** (10,484)			
Asia2000	1266.2 *** (413.22)			
Elem School	48,926 (32,297)			
Winter	−31,117 ** (14,051)	−35,099 *** (10,813)	−29,517 (−95,524 to 31,103)	−26,163 (−110,174 to 57,534)
Spring	13,433 (12,842)			
Summer	−1065.5 (13,104)			

Table 3. Cont.

Y2002-06	59,600 (47,892)	78,426 (48,955)	79,089 (−715,368 to 791,740)	42,993 (−1,107,022 to 862,182)
Y2007-09	151,350 *** (50,955)	162,789 *** (52,607)	237,207 (−654,902 to 963,126)	219,150 (−818,383 to 1,067,297)
Y2010-14	35,736 (49,586)	51,501 (51,485)	197,500 (−581,753 to 1,595,908)	153,932 (−1,043,358 to 1,142,409)
Y2015-F17	488,620 *** (52,615)	503,529 *** (53,329)	576,928 (−449,954 to 1,332,173)	560,210 (−736,466 to 1,349,727)
YM17-A18	574,730 *** (71,412)	606,225 *** (71,862)	831,362 (−211,087 to 2,534,073)	768,715 (−514,694 to 2,038,007)
WY200206	22.9 (25.1)	12.9 (25.6)	15.27 (−318.8 to 424.3)	29.92 (−540.2 to 2,038.0)
WY200709	19.8 (26.6)	13.0 (27.5)	−26.05 (−377.72 to 406.15)	−15.94 (−625.8 to 478.6)
WY201014	58.6 ** (26.2)	52.0 * (27.2)	−25.51 (−555.5 to 325.7)	−13.33 (−469.9 to 469.7)
WY2015F17	26.9 (27.2)	22.9 (27.7)	−30.7 (−424.6 to 503.7)	−28.3 (−636.4 to 639.4)
WYM17ON	43.4 (35.2)	31.6 (35.7)	−78.27 (−692.8 to 448.2)	−55.42 (−939.2 to 593.7)
Adj. R ²	0.793	0.789	0.837	0.844
N	1274	1274	1274	1274

^a White's heteroscedasticity-consistent standard errors. *** Statistically significant at the $p = 0.01$ level. ** Statistically significant at the $p = 0.05$ level. * Statistically significant at the $p = 0.10$ level.

Due to multicollinearity, the GWR and MGWR models failed to run when I included all the variables from Model 1, especially the spatial dummy variables (Art100, Asia2000, and Elem School). Hence, I removed these variables first. When I still could not estimate the GWR and MGWR models due to multicollinearity, I removed statistically insignificant variables (LnPark, Spring, and Summer). I estimated another OLS model (Model 2) to check whether removing the spatial and statistically insignificant variables from OLS Model 1 impacted the signs and coefficients of the variables of interest—the interaction variables created by interacting WSBART with the time dummies. As Table 3 shows, the coefficients of all the variables common to Models 1 and 2 are within two standard errors of each other. Moreover, the adjusted R-squares of the two models are very similar—0.793 and 0.789 for Models 1 and 2, respectively. Therefore, I used the reduced set of variables from Model 2 to run the GWR and MGWR models (Models 3 and 4, respectively). Finally, I used the MGWR model results since they provided a higher adjusted R-square and did not constrain the spatial scale of the independent variables.

I estimated OLS Models 1 and 2 using White's heteroscedasticity-consistent standard errors to minimize the violation of homoscedasticity. Furthermore, a statistically significant Global Moran's I test indicated spatial heterogeneity. I used Gradient Search for bandwidth selection in MGWR, with the optimal number of neighbors determined for each independent variable during the regression estimation.

4.2. Results and Discussion

The number of observations is 1274, and the adjusted R-squares of Models 1 to 4 are 0.793, 0.789, 0.837, and 0.844. Since the adjusted R-square of the MGWR model is higher than that of the GWR model, I will focus on the former in the rest of the paper.

The large majority of statistically significant variables have expected signs. For example, the Model 1 results (see Table 3) show that lot and house sizes, proximity to the WS Station, and the percent Asian population are positively associated with house prices. Older homes and those located closer to freeways, commercial areas, or multi-family residences tend to have lower property values—findings supported by several other studies [40–42]. Furthermore, houses within 100 m of an arterial road sell for lower prices than those farther away, and those sold in winter sell for lower prices than those sold in other seasons. Counterintuitively, the number of bathrooms negatively impact house prices, perhaps reflecting peculiarities of this dataset, where an average house is 2071 square feet in size, has 3.8 bedrooms, and already has 2.5 bathrooms. In such a scenario, an additional bathroom may not be needed.

The number of bedrooms does not impact house prices. Empirical research finds an inconsistent impact of the number of bedrooms on housing prices. A meta-analysis of 40 studies finds that the number of bedrooms has a positive impact on housing prices in 21 studies, a negative impact in nine, and no impact in 10 [43,44].

The main variables of interest—formed by combining distance to the WS Station with the time dummy variables—are mostly statistically insignificant in Models 1 and 2, except for the 2010–2014 time period, which is statistically significant at the $p = 0.05$ level for Model 1 and at the $p = 0.10$ level in Model 2, and has a positive sign, indicating that the sale prices increase as the distance from the station site increases. This is perhaps indicative of the construction-related nuisance (such as noise and traffic delays) of the WSX project on properties close to the station, an assertion indirectly supported by empirical studies that find a negative impact of noise and traffic congestion on property values [45–47]. Notably, previous studies that estimated the price impacts of the WS Station, comparing its impact on properties within a 0–2-mile radius with properties 2–5 miles away, found that apart from the 2002–2006 period, when the proximity to the station had no discernible impact compared to the 2000–2001 period, the proximity increased house prices for all other time periods [9,10]. So, simply looking at the findings of Models 1 and 2 and previous studies [9,10], one may conclude that all properties within the 0–2-mile radius of the station were equally impacted by proximity to the station across the 2007–April 2018 period, except during 2010–2014. However, the MGWR results reveal (a) significant spatially heterogeneous price impacts, (b) that the sale prices of only a small minority of the houses are impacted (these are the houses for which the interaction variable created by interacting WSBART with time period dummy variable is significant at the $p = 0.05$ level), and (c) the overall price impact is much smaller than that estimated in a previous study of this station [9]. Below, I discuss each of these three findings in more detail.

First, Figures 3–7 show the spatially heterogeneous price impacts. In Figure 3, a group of houses to the south-east of the station site is negatively impacted by proximity to the station site during the 2002–2006 period, perhaps indicative of the disamenity effect of the vacant site. However, Figure 4 and onward show a gradual but consistent increase in the sale prices of a group of houses to the east–north-east of the station—from two houses in the 2007–2009 period (see Figure 4) to four in 2010–2014 (see Figure 5), to 23 in 2015–February 2017 (see Figure 6) and to 71 in the post-station-operation period of March 2017–April 2018 (see Figure 7). Notably, the cluster of houses negatively impacted by the station site decreases in size between 2002–2006 and the March 2017–April 2018 period from 54 (see Figure 3) to 28 (see Figure 7).

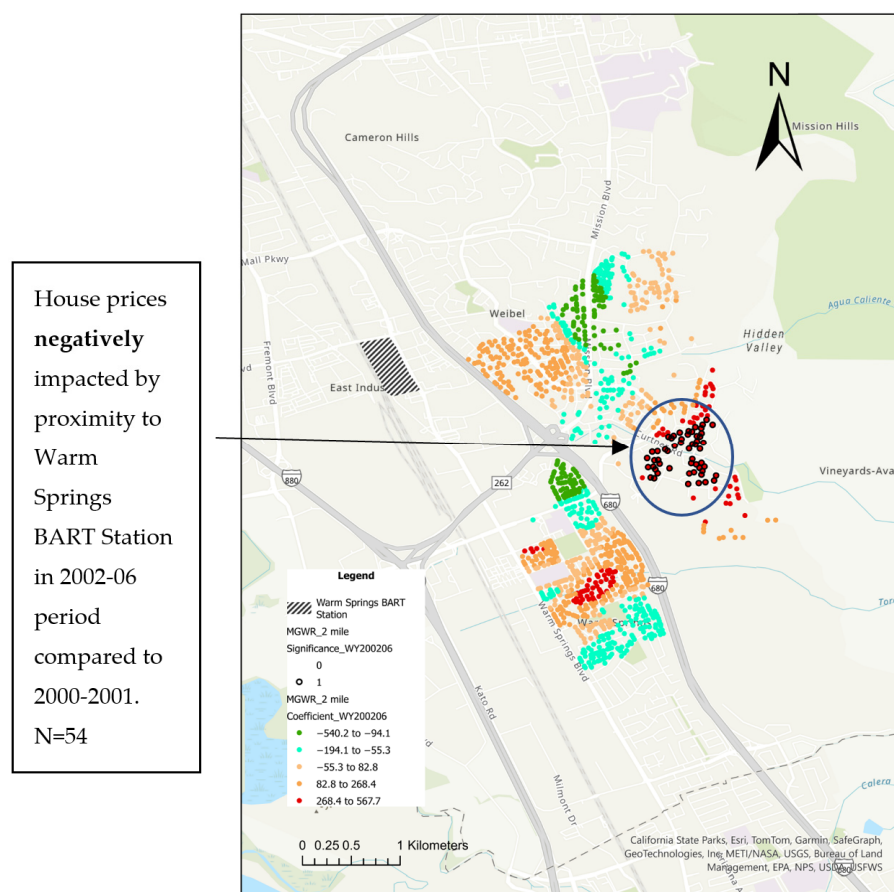


Figure 3. House price impacts during the 2002–2006 period.

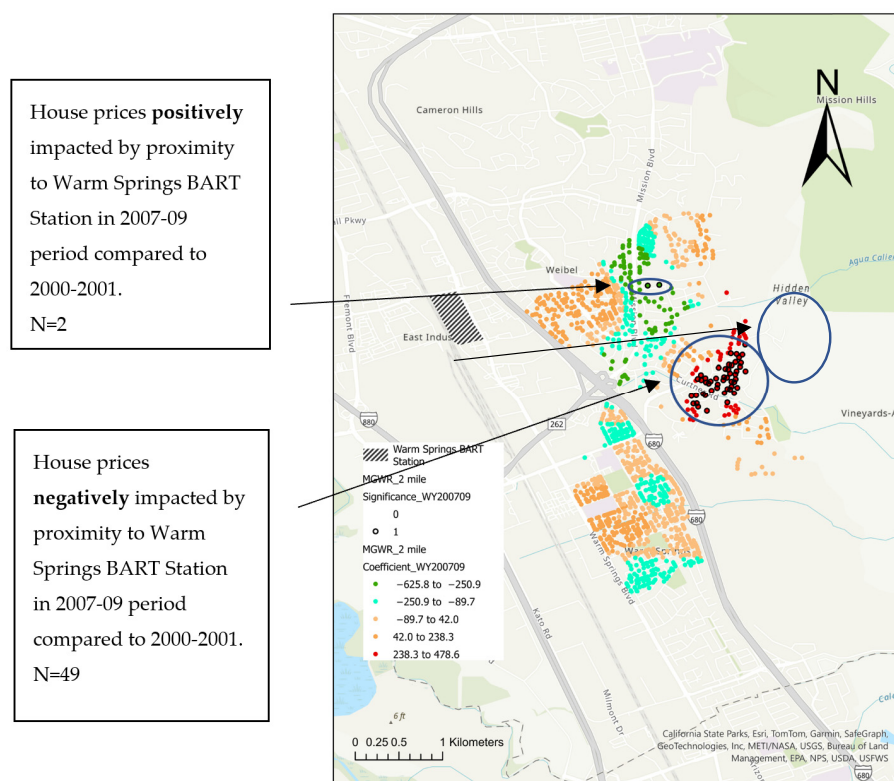


Figure 4. House price impacts during the 2007–2009 period.

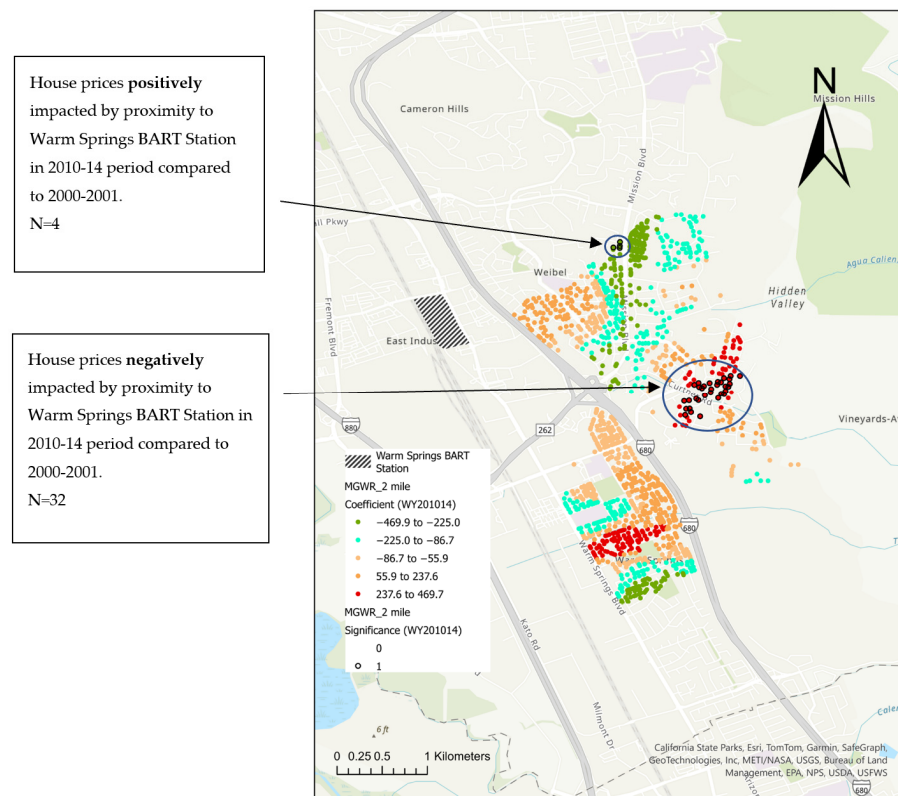


Figure 5. House price impacts during the 2010–2014 period.

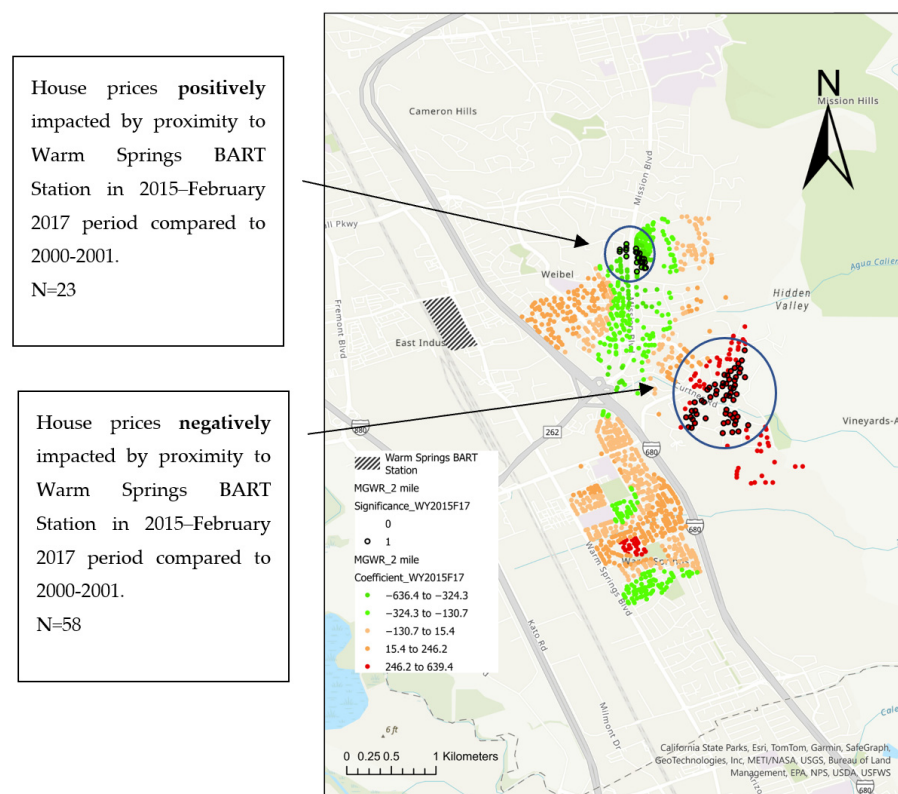


Figure 6. House price impacts during the 2015–February 2017 period.

Second, of the 1274 houses in the dataset, only a small minority are impacted (negatively or positively) by proximity to the station site—ranging from 2.5% in 2010–2014 to 7.7% in the post-station-operation period of March 2017–April 2018 (see Table 4, column 4).

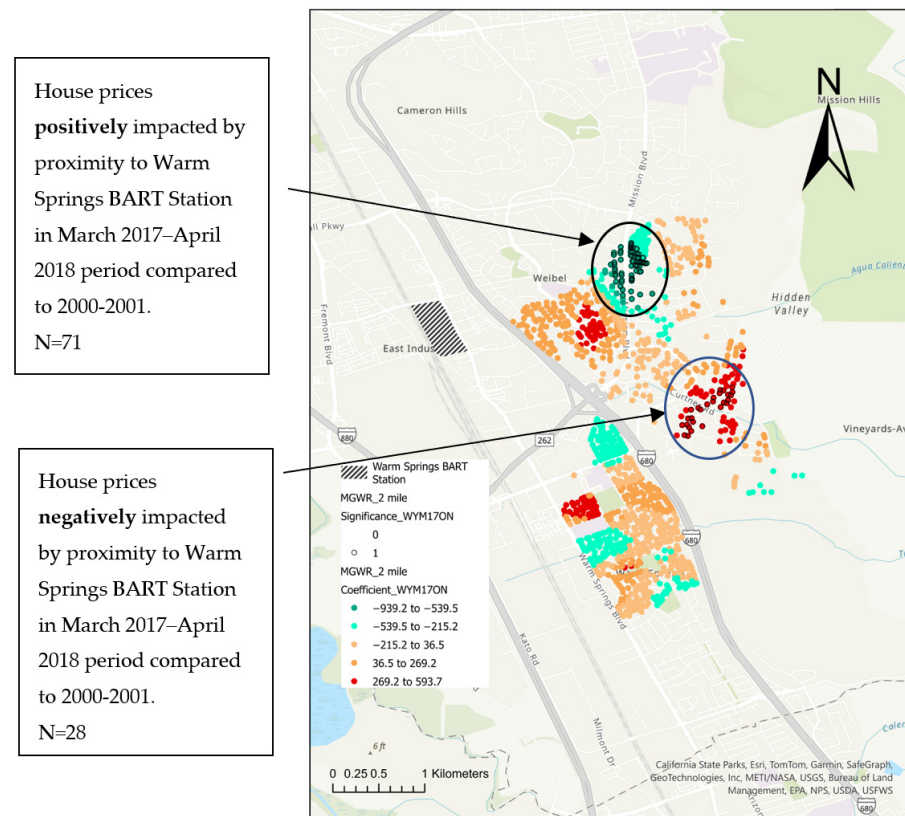


Figure 7. House price impacts during the March 2017–April 2018 period.

Third, using the methodology adopted in a previous study of this station [9] (p. 556, Table 11), I estimated the total house price impacts of the proximity to the station site during each time period (see Table 4, Column 9). Next, I calculated the house price impacts based on my study. For this, I multiplied (a) the coefficients of all statistically significant variables created by interacting the distance to the WS Station with the time dummy variables by (b) the distance to the WS Station. For example, for the post-station-operation period of March 2017–April 2018, the coefficient of the variable WYM17ON was statistically significant for 71 houses (see Table 4, Column 2). So, for each of these 71 houses, I multiplied this coefficient by the house's distance from the WS Station. The sum of all these products was \$53.23 million (see Table 4, Column 5)—the total price increase of these 71 houses. Next, because the \$53.23 million price increase was from a sample of 1274 houses, while there are 10,775 houses in the study area [9], I multiplied \$53.23 million by the ratio of 10,775 and 1274 to calculate the total house price impact in the study area—\$450.19 million (see Table 4, Column 6). Notably, this amount is about 3.75 times smaller than the \$1.69 billion estimated by the previous study of this station (see Table 4, Column 9) [9]. Even if we omit the houses located south-east of the station that experienced price decrease even in the initial 2002–2006 period (assuming that the disamenity effect of the station site and other omitted variables, such as temporal changes in crime rates and changes in school quality, might have caused this price impact), the total price increase during the March 2017–April 2018 period would be \$687.68 million (see Table 4, Column 8)—about 2.5 times smaller than the previous estimate [9]. Importantly, this extrapolation of the study's findings to the entire 2-mile radius around the WS Station is a rough, not precise, estimate because it assumes that the houses in the dataset represent those in the entire 2-mile radius with respect to property and location characteristics and price appreciation. However, since this extrapolation was adopted in a previous study of this station [9], it provides a consistent basis for comparing this paper's findings with those of the previous study.

Table 4. House price impact of the Warm Springs BART Station over the entire study area.

Time Period	No./Percent of Statistically Significant Observations with Price Increase Due to Proximity to the Warm Springs BART Station	No./Percent of Statistically Significant Observations with Price Decrease Due to Proximity to the Warm Springs BART Station	Total no./Percent of Statistically Significant Observations	Total Property Value Increase in the Dataset Due to Proximity to the Warm Springs BART Station Compared to 2000–2001	Pro-Rated Property Value Increase in the Study Area Due to Proximity to the Warm Springs BART Station Compared to 2000–2001	Total Property Value Increase in the Dataset Due to Proximity to the Warm Springs BART Station Compared to 2000–2001 Based on Only Houses Experiencing Price Increases	Pro-Rated Property Value Increase in the Study Area Due to Proximity to the Warm Springs BART Station Compared to 2000–2001 Based on Only Houses Experiencing Price Increases	Previous Estimates of the Property Value Increase Due to Proximity to the Warm Springs BART Station [9]
(Column 1)	(Column 2)	(Column 3)	(Column 4)	(Column 5)	(Column 6)	(Column 7)	(Column 8)	(Column 9)
WY200206	0/0%	54/4.2%	54/4.2%	−\$52 million	−\$439.82 million	\$0	\$0	\$0
WY200709	2/0.2%	49/3.8%	51/4.0%	−\$44.46 million	−\$376 million	\$1.744 million	\$18.80 million	\$1057.89 million
WY201014	4/0.3%	32/2.5%	36/2.8%	−\$21.53 million	−\$182.10 million	\$2.78 million	\$23.51 million	\$1132.45 million
WY2015F17	23/1.8%	58/4.6%	81/6.4%	−\$44.73 million	−\$378.29 million	\$19.88 million	\$167.94 million	\$2218.57 million
WYM17ON	71/5.6%	27/2.1%	98/7.7%	\$53.23 million	\$450.19 million	\$81.31 million	\$687.68 million	\$1690.60 million

5. Conclusions

This study finds that the WS Station increased single-family house prices in the 0–2-mile radius by about \$450–\$680 million. Furthermore, this price increase was not uniformly spread across the station area. In fact, it was concentrated in one eastern pocket. Accurate, spatially fine-grained analysis of the impacts of public infrastructure and services on property values is critical for policy makers and professionals to develop tools to capture such impacts (when values increase) or to devise mitigation measures (when they decrease).

The above findings also highlight the need to progress from average estimation techniques, such as OLS, to those that consider spatial heterogeneity in price impacts, such as GWR and MGWR, and to create maps, such as Figures 3–7, that depict the geographical distribution of these impacts, which will help develop nuanced tools to capture price increases or tailor mitigation measures. For example, such maps may support a higher assessment rate in core beneficiary zones (where the price increase is highest), a lower rate in secondary beneficiary zones (where the price increase is lower), and no assessments in zones that do not benefit from the station's proximity. Moreover, funds collected from these assessments may be used to mitigate factors, such as noise and traffic congestion, that might be leading to the negative price impact of the station in some zones. Furthermore, these funds can be used to enhance the quality of the station area and transit service—such as feeder bus service to the station, upgrades to the rail transit service, infrastructure that enhances walkability and bikability, and affordable housing in transit-oriented development—thereby strengthening the “beneficiary-to-pay principle” of SADs.

Finally, future research could estimate econometric models that address the spatially heterogeneous price impacts of transit stations across quintiles of house prices, using techniques such as geographically weighted quintile regression (GWQR), as employed in a study to identify the determinants of housing rents in Amsterdam and Warsaw [48].

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Abbreviations

The following abbreviations are used in this manuscript:

BART	Bay Area Rapid Transit
CBD	Central business district
CPI	Consumer price index
EIR	Environmental impact report
GWR	Geographically weighted regression
GWQR	Geographically weighted quintile regression
HSR	High-speed rail
OLS	Ordinary least squares
MARTA	Metropolitan Atlanta Rapid Transit Authority
MGWR	Multiscale geographically weighted regression
MTA	Metropolitan Transportation Authority
RQs	Research questions
SADs	Special assessment districts
SAR	Spatial autoregressive
SEM	Spatial error model

VC	Value capture
WS	Warm Springs
WSX	Warm Springs Extension

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