The Effect of Bus Rapid Transit on Local Home Prices

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Abstract

Bus Rapid Transit (BRT) systems have become increasingly common in US cities. BRT stations provide a local amenity by improving transportation options for local residents, but may also represent a local nuisance due to noise or displacement of other road users. We estimate whether BRT is priced into local real estate by studying a recently opened BRT project in Vancouver, Washington. We use a difference-in-difference method with both hedonic and repeat sales estimators to test for a price effect. We estimate a 5-7% price premium for homes located within a 20 minute walk of a BRT station. Overall, BRT generated new real estate value that exceeded the project's construction costs by a factor of six. We discuss how government could leverage future residential property value increases to fund construction of BRT projects.

Keywords: Transportation ; Transit ; Bus Rapid Transit ; Real Estate
JEL classification: R30 ; R32 ; R38 ; R40 ; R42

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1 Introduction

Bus Rapid Transit (BRT) systems have become an increasingly common tool in urban public transit planning. BRT systems are meant to improve on conventional bus systems by implementing a set of service improvements (Deng and Nelson, 2011). The presence of a BRT station in a neighborhood represents a potentially valuable local amenity. Access to a station can provide a local resident with improved access to jobs, commercial areas, and other urban destinations. BRT stations may therefore increase local demand for housing, spurring growth in local home prices. On the other hand, a local BRT station may introduce local disamenities such as reduced road space for private vehicles or noise associated with buses and riders. We examine the case of Vancouver, Washington's BRT system to estimate the effect of a new BRT line on local home values.

Estimating the home price effect of BRT is complicated by a number of factors. BRT lines are typically placed along high density, commercial routes. Homes located close to high-density corridors may have particular characteristics that differ from homes elsewhere. Therefore, comparing the prices of homes near BRT lines to those farther away will not provide informative estimates due to omitted variables. Our estimation strategy is a difference-in-difference method, comparing properties near to BRT stations with those farther away, using station openings as a source of temporal variation. We apply two separate estimation approaches. First, using detailed information on housing characteristics, we implement a hedonic estimation model to control for a large array of observable differences across properties and across neighborhoods. Second, to account for the possibility of *unobserved* differences in housing characteristics, we estimate a repeat sales model, allowing us to introduce property-level fixed effects that fully account for both observed and unobserved, time-invariant differences across properties. These approaches are enabled by a complete data set of 70,000 home transactions that span the five years before and the five years after the BRT system opened.

Estimating local home price effects of BRT is important for a number of reasons. First, possible gentrification around new transit lines is a common topic of concern. Sharp increases in housing prices may contribute to neighborhood change, potentially displacing original residents. Conversely, transit could represent a local nuisance and diminish property values. By providing precise price estimates we are able to inform such discussions. Second, land value increases due to transit construction can represent a financial windfall for incumbent homeowners. Research on Land Value Capture (LVC) policies provide possible mechanisms to fund new transit projects from future land value increases. Our estimates provide information on the total real estate value generated by a BRT project and could inform how property tax levies could be used to fund similar projects in the future.

Our paper fits into a growing literature on the home price effects of BRT. Zhang and Yen (2020) conducted a meta-analysis of 23 studies that examined BRT's effect on home and land values. The authors found the majority of studies estimated positive effects. While settings and methodologies differed substantially, estimates of the home price effect of a local BRT station were centered around 5%, with significant dispersion in estimates. Stokenberga (2014) provided a synthesis of literature concerning BRT and urban land values. The authors found the bulk of research has been conducted for BRT systems in South America and Asia. Across varying settings and research methodologies there was general consensus of BRT imparting a positive price effect on local property values.

Much of the prior literature on the local price effects of BRT have focused specifically on the Transmilenio BRT system in Bogota, Columbia. Bogota was an early adopter of BRT, constructing an expansive system in a short period of time. The development of Transmilenio was accompanied by significant local property development. Bocarejo et al. (2013) found that Transmilenio led to densification around BRT stations. Rodriguez et al. (2016) estimated the effect of new BRT systems on land development near stations in Bogota as well as Quito, finding stations significantly increased local development. There is agreement among studies that Transmilenio led to an increase in property values close to BRT stations. Using a hedonic regression method, Rodríguez and Mojica (2009) found a 13-14% price premium for BRT access, with the effect staying roughly constant for properties within one km of a station and falling thereafter. Rodríguez and Targa (2004) found rents climbed by 6-9% for every five-minute reduction in walk time to a BRT station. Munoz-Raskin (2010) also estimated a positive price effect using a hedonic method, and found results were specific to local socioeconomic status, with higher price effects for middle-income areas. Guzman et al. (2021) examined land values in Bogota, finding BRT significantly increased values in low-income neighborhoods but not in high-income neighborhoods. We test for similar neighborhood response heterogeneity in our setting. Finally, Tsivanidis (2018) estimates the welfare effects of Transmilenio, finding welfare benefits to incumbent renters are reduced due to rising local housing costs.

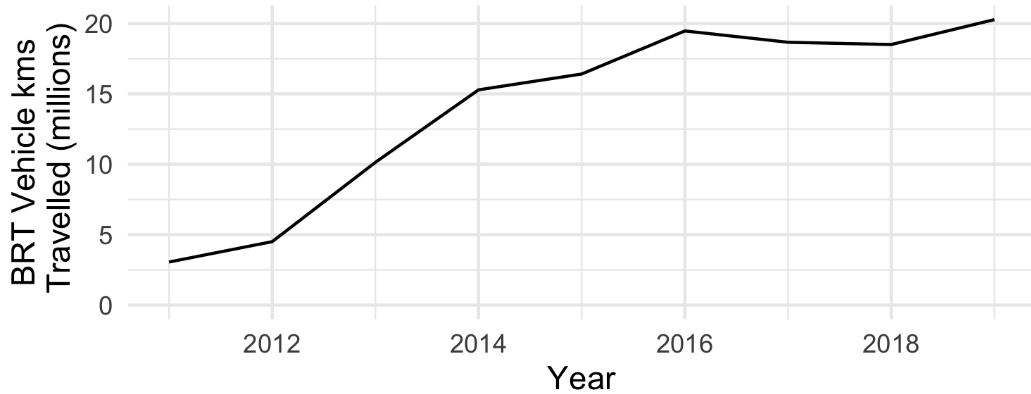
Several studies have examined home price effects of BRT in Asia. Ma et al. (2014) and Deng et al. (2016) both estimated price effects for Beijing's BRT system. Ma et al. (2014) found no effect of local stations on home prices, whereas Deng et al. (2016) estimated a small positive effect. Yang et al. (2020) analyzed a BRT system on Xiamen Island, China, and identified both amenity and disamenity effects and showed the high-price housing market responded more strongly to the disamentiy effects. A BRT system in Seoul, South Korea was studied in Cervero and Kang (2011), with results showing BRT increased the price of land by 10% for properties within 300 meters of a station. Anas et al. (2021) studied both a BRT system and road expansion in Beirut using a structural model, finding the BRT system generated a financial surplus while the road expansion did not.

While there have been a significant number of papers measuring the home price effects of BRT, the evidence comes largely from cities that are very different from the mid-sized US city we study. A set of studies from Australian cities of Sydney and Brisbane may provide a somewhat more comparable setting. Unlike our study area, Sydney and Brisbane operate rail systems, which might affect the desirability of living near a BRT line. Mulley (2014), Mulley and Tsai (2016), and Mulley and Tsai (2017) all study a BRT system opening in Sydney. Mulley and Tsai (2016) used a hedonic approach and found an 11% price premium generated for properties close to new BRT stations. However, the estimates were imprecise. Mulley (2014) used a Geographically Weighted Regression approach, and reported marginally positive effects of BRT proximity on property values. Finally, Mulley and Tsai (2017) estimated effects with a repeat sales model, but did not find significant effects when using this methodology. Mulley et al. (2015), Mulley et al. (2016), and Zhang et al. (2020) all examine the impacts of the BRT system in Brisbane. Mulley et al. (2016) found that a 100 meter reduction in distance to a BRT station increased a home's value by 0.13%-0.14% and Zhang et al. (2020) examined local bus routes that connected to the BRT, finding a 100 meter reduction in distance to one of these stops increased a home's value by 1.6%.

Research into the home price effects of BRT in the US is sparse relative to South America and Asia. However, BRT has experienced strong growth in the US. Figure 1 shows that the miles of BRT service provided in the US has increased dramatically over the past decade. Between 2011 and 2019, the distance travelled by operating BRT vehicles increased by over 500%. The American Public Transportation Association (APTA) reported 13 transit agencies in the US operating BRT systems in 2019.

The home price effects of BRT in North America could be significantly different than in other countries due to differences in travel behaviour. Sidloski and Diab (2020) reviewed general ridership performance of North American BRT systems, finding higher ridership in areas with larger, denser populations. In a study related closely to our own, Acton et al. (2022) used national housing transaction data to test for price effects across 11 US BRT systems, using a hedonic regression approach that made use of system opening dates. Estimates varied significantly across the systems. Using an 800-meter treatment bandwidth, the authors found a local BRT station decreased home values by 7% in one metro but increased home values by 15% in another. The results suggested price effects were more positive for multifamily housing relative to single-family housing. Dubé et al. (2011) studied the BRT system in Quebec City, exploiting the system opening dates for variation, and

Figure 1: Growth in US BRT Systems



Data is from the 2021 APTA Factbook. Vehicle miles include only those where the vehicle was actively providing service to paying passengers.

found positive home price effects ranging from 3-7%. Dubé et al. (2018a) also examined BRT in Quebec City confirming positive home price effects and finding effects were larger in neighborhoods that were denser and more walkable. Tyndall (2018) analyzed bus service upgrades in New York City, which were part of a program to implement several components of BRT. Results showed the service improvements increased local bus ridership and increased local rents but had an insignificant effect on local home prices. Perk and Catala (2009) was an early attempt at quantifying the real estate price effects of a North American BRT system. The authors examined the BRT system in Pittsburgh, finding a $19 price premium for moving a home from 101 to 100 meters away from a BRT station.

As BRT is often seen as an alternative to rail transit projects, this paper is also related to the large literature on the home price effects of urban rail stations. The methodology involved in measuring the effect of a rail station is similar to measuring BRT effects. Studies of US rail systems generally find positive home price effects related to proximity to rail (Baum-Snow and Kahn, 2000; Kahn, 2007; Tyndall, 2021). Dewees (1976) represents an early empirical analysis of home price capitalization effects, demonstrating positive capitalization patterns from the construction of a new subway line in Toronto. Studying light rail in Buffalo, Hess and Almeida (2007) found positive property value capitalization, with effects differing based on neighborhood income. Anas (1995) provided a review of the theory underpinning transport infrastructure investment and changes in land values and Anas (2021) provided a model for understanding travel improvement capitalization effects across different modes.

Prior research has found positive home price effects of local BRT, though estimated magnitudes vary significantly. We contribute a new estimate from the US, where BRT is relatively understudied. We also focus on a mid-sized city. Existing BRT research focuses most heavily on large cities, while the future growth of BRT in the US is likely to come from mid-sized cities, due to the significantly lower capital costs of BRT versus light rail systems. Our focus on a mid-sized city may provide a useful reference for similar locations. Given rich data, we are able to estimate repeat sales models, which are uncommon in the past literature and may better control for omitted variables. Prior meta-analyses have examined the potential for methodological differences across studies to influence results. We are able to compare estimates across both hedonic and repeat sales methods. We also define our treatment areas according to walk distances rather than geodesic distances, and contrast these two approaches. Our results identify a strong influence of local racial composition in determining price effects. This source of heterogeneity has not been identified in past studies and may be a unique dynamic of US systems. Finally, we extend results to consider whether LVC strategies may be a viable funding tool for future BRT projects, given the significant home capitalization effects we find.

The paper proceeds as follows. Section 2 provides details on the study area and BRT system. Section 3 discusses data sources. Section 4 describes the methodology used to estimate price effects. Section 5 provides results. Section 6 considers the implications for LVC policies and Section 7 concludes.

2 Empirical Setting

2.1 Demographics of Study Area

Our study area is Clark County, Washington. Clark County has a population of 503,000 and is part of the Portland, Oregon metropolitan area, which has a total population of 3.28 million. While we analyze the housing market for all of Clark County, the entirety of the BRT system operates within the City of Vancouver (population 191,000), which is the commercial and employment center for the county. Table 1 provides general demographic information for Clark County, Vancouver, and national figures for comparison. Median household income in Clark County ($75,000) is higher than the national level ($62,843), whereas the share of the population with a college education is comparable. Clark County has a majority white population, with 85% of population identifying as white.

The median home value in Clark County is significantly higher than the national median, though relatively low when compared to other west coast metropolitan areas. We provide detailed data on the housing market in the subsequent section.

The share of commuters who drive alone to work in Clark County (78.5%) is higher

Table 1: Demographic Characteristics of Study Area

	Vancouver, WA	Clark County, WA	USA
Population	190,915	503,311	331,449,281
Median household income ($)	61,714	75,253	62,843
Median house value ($)	286,500	327,000	217,500
College education rate† (%)	29.2	30.6	32.1
Median age	36.9	38.4	38.1
Owner-occupancy rate (%)	51.7	67.0	64.0
White (%)	80.1	84.6	72.5
Black (%)	2.3	1.8	12.7
Asian (%)	5.6	4.6	5.5
Hispanic (%)	13.9	9.6	18.0
Average commute time (minutes)	25	27	27
Commuter mode share:			
Drove alone (%)	76.2	78.5	76.3
Public transportation (%)	3.3	2.2	5.2
Cycling (%)	0.5	0.3	0.6
Walking (%)	2.4	1.8	2.7

Population estimates are from the 2020 US Census. Data for the remaining demographic variables are from the 2019 5-year American Community Survey.
† Bachelor's degree or above, among population 25 years and older.

than the national rate (76.3%), while the rate of public transit commuting in Clark County (2.2%) is less than half the national rate (5.2%), though is typical of many mid-sized US cities. Public transit commuting in the city of Vancouver is slightly higher than elsewhere in the county (3.3%), but still very low.

A significant share of Clark County's workforce commutes to Portland. According to 2013 5-year ACS commuting flow data, 24% of employed workers who lived in Clark County worked in Multnomah County, Oregon, which contains Portland. While Portland is the economic center of the region, the BRT system does not provide direct access to Portland.

2.2 Vancouver's BRT Line

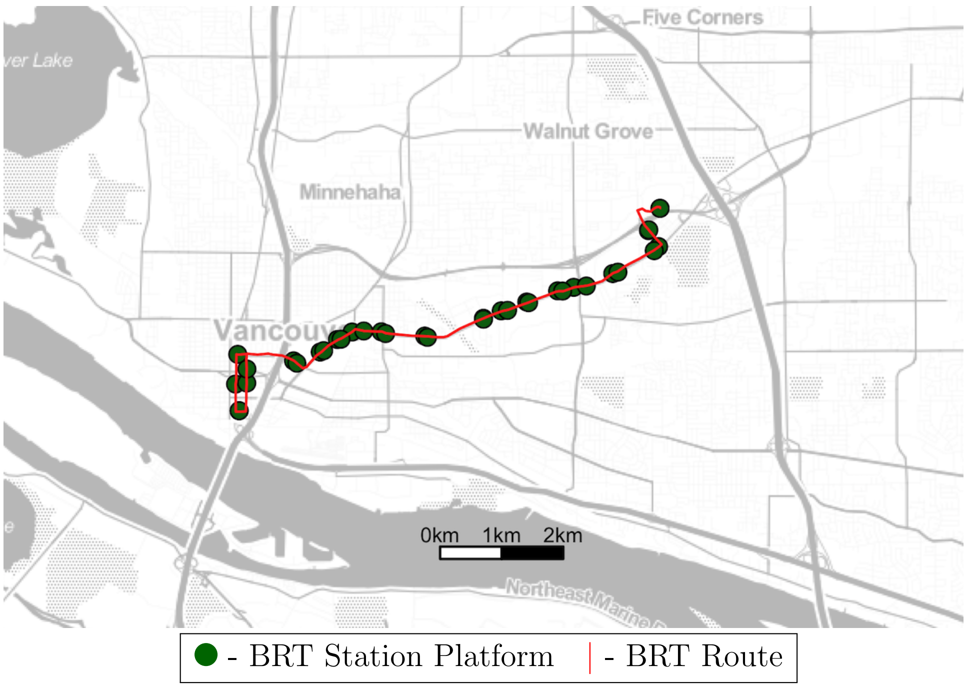
We study the introduction of the first BRT line to open in the Portland metropolitan area. The line consists of 34 station platforms and runs east-west through the City of Vancouver. The system was branded as the *Vine*. Figure 2 provides a map of the station locations.

Planning by public agencies for a possible BRT line in Vancouver extends back to at least 2008.[1] Final approval of the project was granted in 2012 and construction broke ground in

[1] Clark County High Capacity Transit System Study Final Report, Southwest Washington Regional Trans-

2015. On January 8, 2017 the entire 11 kilometer, 34 station-platform line opened to the public. The line connects the city's downtown area in the south-east of the city to a major shopping center (the Vancouver Mall) at the western end of the line. The route passes through both residential and commercial areas. The residential neighborhoods contain both single-family housing and low-rise multi-family developments.

Figure 2: Vine BRT Route



The BRT route and 34 station platforms are shown.

Most BRT systems share some common characteristics such as the ability to avoid traffic via road lanes dedicated exclusively for bus use, traffic signal priority, raised station platforms, pre-boarding payment systems, larger buses, and stops that are spaced farther apart than conventional bus routes to increase travel speed. BRT features provide significant advantages over traditional bus service in terms of speed, reliability, and convenience. Levinson et al. (2003) provided a description of early US BRT systems. The Vine incorporates all of the system features noted here except for dedicated lanes. With the exception of some intersections and station areas, the Vine buses share road space with other vehicles.

The total capital costs of implementing the BRT system was $53 million. 80% of these costs were paid by the Federal Transit Administration, with the remainder of funding coming from the local transit agency (C-Tran) and the state of Washington.

portation Council, December 2008.

Vine buses run with 10-minute headways during peak hours. The cost of a ride during our study period was $1.80, which was consistent with the non-BRT local bus fare. Expansion of the Vine system to include a second route is currently under construction, with plans to open in 2023. The second line will also run east-west through Vancouver but will be located to the south of the original line.

Reaching a Vine station likely involves walking to or from the traveller's origin or final destination. Potentially, a traveller could drive to a station, park, and use the BRT system to complete the remainder of their trip. Some past research has pointed to the importance of "park and ride" infrastructure for BRT systems (Cervero et al., 2010; Currie, 2006). For the Vine system, the stations generally do not include dedicated parking facilities. A "park and ride" program does operate within Clark County. However, there are only two instances of dedicated parking space within 500 meters of a Vine station (Vancouver Mall Terminus Station, and the 65th Avenue Station). These parking facilities are extremely small, providing only 15 and 30 dedicated parking stalls respectively. We therefore assume park and ride users are uncommon in our setting. Travellers could also connect to the BRT system through other bus routes, alternative modes such as cycling, or be dropped off by a driver of a private vehicle.

3 Data

We combine proprietary real estate transaction data from Clark County, Washington with data on BRT stations and local demographics. Our primary data source is a set of real estate transactions for residential properties in Clark County. The Clark County Assessor releases an annual report of sales for the previous calendar year and these transactions were merged with a separate database of property characteristics provided by the Assessor.

The real estate transaction data covers every residential property transaction in Clark County spanning a 10-year period from 2012 to 2021. We remove any transaction where the sale price was below $50,000 in order to remove transactions that were unlikely to be genuine, arm's length transactions. We also remove sales of land without a building. Vacant lots are often purchased and resold after housing has been constructed, which may dramatically change the property's value for reasons unrelated to BRT. We include single-family homes, townhouses and condominiums in our analysis. We do not have access to data on commercial properties or rental apartment buildings so they are not included. Our data does include individual condominium units in multifamily buildings. We remove 988 mobile home transactions from the analysis. We observe no instances of a mobile home transaction near to a BRT station. We also remove 683 transactions that occurred in census blocks for which we do not have local demographic information, as described below. The final set of property transactions includes 70,450 observations for analysis. These transactions cover 55,184 unique properties, with some properties selling multiple times over the study period. The data includes an extensive array of housing characteristic variables including square footage, lot size, number of bedrooms, number of full and half bathrooms, and the year the house was constructed. We make use of these characteristics in our hedonic price analysis. Average home characteristics are summarized in Table 2.

Table 2: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Property Characteristics				
Sale price	385,133	184,938	55,142	4,304,906
Year built	1991	23	1891	2021
Square footage (1,000)	1.897	0.739	0.294	12.008
Lot square footage (1,000)	24.568	76.580	0	3419.460
Bedrooms	3.287	0.820	1	16
Full bathrooms	2.049	0.609	1	12
Half bathrooms	0.530	0.536	0	11
Drive time to Portland (hours)	0.543	0.129	0	1.382
Single family home	0.882	0.323	0	1
Condominium	0.056	0.229	0	1
Townhome	0.063	0.242	0	1
Local Demographics				
Share 18-34 years old	0.199	0.073	0	0.515
Share over 65 years old	0.140	0.074	0.034	0.643
White population share	0.851	0.090	0.504	1
Black population share	0.017	0.028	0	0.231
Asian population share	0.048	0.052	0	0.316
Hispanic population share	0.077	0.073	0	0.45
Median household income	72,562	22,742	19,632	140,625
High school education share	0.925	0.053	0.693	1
College education share	0.297	0.128	0.045	0.623
N		70,450		

Summary statistics for all observed transactions are shown. Demographic characteristics are taken from block group data, but averaged across transactions.

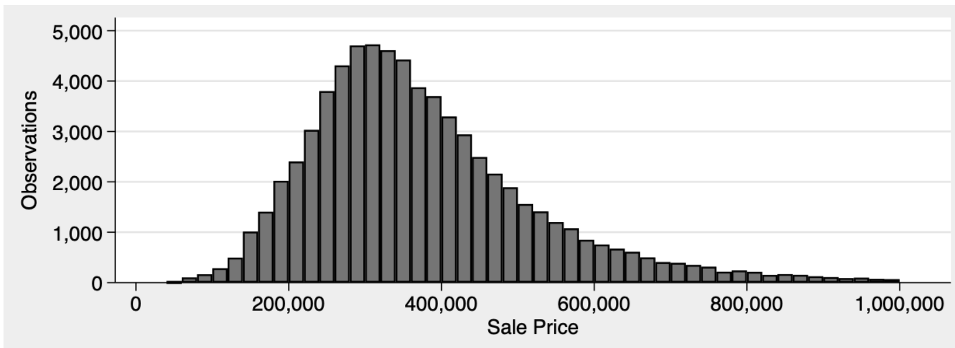
The median sales price across homes in Clark County during the study period was \$329,970.[2] Figure 3A provides a histogram showing the distribution of sale prices. The distribution has a rightward skew in part due to the prices being mechanically truncated at \$50,000. In regression analysis we will use the log-transformed sale price. The distribution

[2]All home sales figures have been inflation adjusted to 2020 USD.

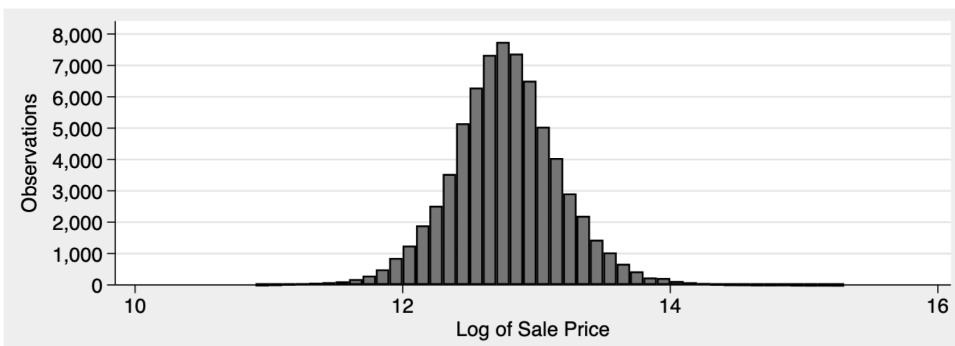
of the logged prices are shown in Figure 3B. The logged prices roughly follow a normal distribution.

Figure 3: Sale Price Distribution

A. Sale Prices



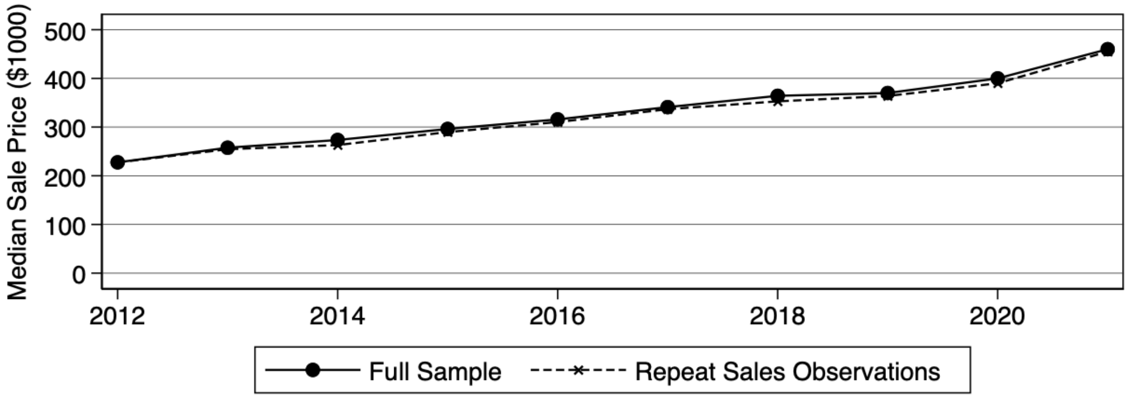
B. Logged Sale Prices



Panel A shows the distribution of sale prices, across all years in the sample. Panel A truncates the data at $1,000,000. Panel B shows the distribution of logged sale prices, which will be the variable used in analysis. All prices are in 2020 USD.

Figure 4 shows the trend in median sales price for homes in Clark County over the study period. Clark County experienced sustained home price appreciation over the period. The median sales price increased by 102% from 2012 to 2021 in real terms. In addition to the annual median sales price, Figure 4 also plots the median sales price among properties that sold multiple times over the study period. Some analysis will be limited to the set of properties that sold multiple times. The price level and trend between the repeated sales and the full sample of sales are very closely correlated, suggesting the repeat sales sample is generally representative of the complete set of home sales.

Figure 4: Trend in Clark County Median Sales Price



The Clark County housing market experienced steady price appreciation over the study period. All prices are in 2020 USD.

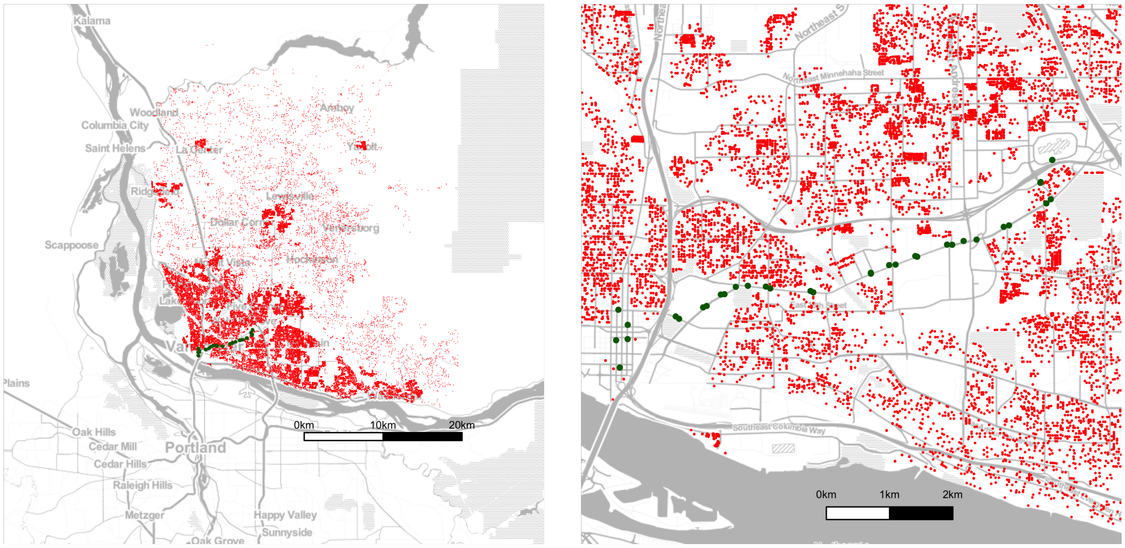
We add latitude and longitude coordinates onto each transacted property. Using the street address of each observation, we make use of the online geocoding service HERE to convert street addresses to precise geographic coordinates. Figure 5 maps the locations of transacted properties. Transactions cover the entirety of Clark County, but occur more frequently in the south part of the county, which contains the more densely populated city of Vancouver.

In addition to home transaction data we use spatial data on the location of all Vine BRT stations. We download the location of BRT stations from the publicly available General Transit Feed Specification (GTFS). The BRT line includes a total of 34 station platforms, which we refer to as stations. However, these include 16 named stations with eastbound and westbound platforms, plus two terminus stations. We use the centroid of all 34 station platforms to represent access points to the BRT system. Station locations are shown in Figures 2 and 5.

We combine the transaction data with the BRT station data by calculating the distance to the nearest station platform for every transacted property. We use two methods to accomplish this. First, we construct a matrix of every property-platform pair and compute the geodesic distance separating the locations. We then take the distance to the nearest platform as a measure of BRT proximity. Second, we repeat the matrix calculation but rather than calculate geodesic distances, we calculate pedestrian walk times. Geodesic distances may give a misleading indication of proximity because the presence of highways, buildings and natural features will force pedestrians to take longer routes to reach a station. We again use the HERE API to calculate walk times from properties to every station platform and

Figure 5: Locations of BRT Stations and Property Transactions

A. B.



● - BRT Station ● - Property Transaction

All 55,184 transacted properties from the final data set are represented in Panel A. Transactions cover all populated areas of Clark County, WA. Panel B shows the same data, but limited to the area around the BRT stations.

subsequently calculate the walking time required to reach the nearest station. The walk time algorithm assumes pedestrians adhere strictly to sidewalks, paths and designated road crossings, which may inflate estimated walk times if pedestrians are able to find shorter routes in practice. We contrast the effect of using geodesic or walk time distances, but our main results make use of walk times. These measurements will allow us to group property transactions into treated and untreated groups by identifying transactions that occurred near to a BRT station.

After collecting both geodesic and walking distances from homes to stations, we generate dummy variables for each property according to whether the property is within a certain radius of a platform. For example, we generate a dummy variable that takes a value of one for properties that are within a 20-minute walk of a BRT platform, as one indicator of system proximity. We generate such variables at 10-minute intervals for walk times ranging from 10 to 50 minutes, and we generate variables using geodesic distance to a platform at intervals of 500 meters ranging from 500 to 2,500 meters. Table 3 shows the share of transacted properties that are near to platforms, based on the various definitions. For example, we find that 4.2% of transactions (2,932 transactions) are located within a 20 minute walk of a BRT station location. Because half of our study period is before the BRT system opened, only 1,679 transactions are observed for properties within a 20 minute walk of an open BRT platform, while 1,253 are within 20 minutes of the site of a future operating platform.

Table 3: Share of Transactions Within "X" of a Station Location

X	**Share of Transactions**
10 minutes walk	0.016
20 minutes walk	0.042
30 minutes walk	0.069
40 minutes walk	0.096
50 minutes walk	0.131
500 meters	0.022
1,000 meters	0.059
1,500 meters	0.093
2,000 meters	0.136
2,500 meters	0.172
N	70,450

The table indicates the share of properties within the defined radius of a station location. For example, 6.9% of the 70,450 observed transactions were within a 30-minute walk of a station location.

Proximity to Portland may be a confounding variable in our model. A significant portion of Clark County's population commutes to the city of Portland. Portland was undergoing economic growth during this period, which could generate a source of spurious correlation in prices across space. For example, homes closer to Portland may have experienced higher price appreciation over this period, and the Vine route happens to be in the area of Clark County that is close to Portland. Using the HERE API we calculate the time it takes to drive from each property in our dataset to Portland's Central Business District (CBD). Drive times are estimated according to typical traffic conditions faced by a driver departing home at 8 am on a Wednesday. We use the address of Portland City Hall as a proxy for Portland's CBD. Drive times from Clark County properties to the Portland CBD range from 20 to 83 minutes, and average 33 minutes (Table 2).

We will test for heterogeneity in price effects of BRT across different neighborhood types. To classify properties into neighborhoods, we use the US Census Tiger shapefiles for block groups in Clark County. We assign each property to a Census block group. We also use

American Community Survey 2016 5-year estimates at the block group level to capture average local demographic conditions, including income, race and education levels. The 2016 data includes survey responses covering 2012-2016, which capture conditions immediately before the introduction of BRT. Neighborhood demographic characteristics for the average transacted property are provided in Table 2.

4 Methodology

The main regression equation follows a difference-in-difference design (Equation 1). We first describe the hedonic estimation approach. $\log(P_{it})$ is the log sale price of housing transaction i that was transacted at time t in municipality $I(i)$. S_i is a dummy variable indicating whether property i is near to the site of a BRT station. We will test several cutoff distances to classify whether a property is near to a station. O_t is a dummy variable that takes a value of one if the sale occurred after the BRT system opened (January 8, 2017). Ψ_i is a vector of property characteristic control variables including year of house construction, square footage, lot size, number of bedrooms, number of full bathrooms, number of half bathrooms and the driving time to Portland's CBD. Ψ_i also includes separate dummy variables if the home is a condominium or a townhome. Π_i is a fixed effect for the census block group where the sale occurred and Λ_t is a fixed effect for the year-month when the sale occurred. The census block group fixed effects capture any time-invariant characteristics of neighborhoods that may affect home prices, while time fixed effects capture changes to home prices over time that occurred across the entire market. We include two time trend controls to capture differential appreciation trends that may be unrelated to the BRT project. First, we include a municipality level time trend, by interacting municipality dummy variables with a variable capturing the number of months elapsed since the start of the study period ($\Omega_{I(i)t}$). We observe transactions across 10 municipalities in Clark County. Second, we include a distance to Portland time trend (C_{it}), generated by interacting the number of minutes it takes to drive to the Portland CBD at rush hour by the number of months elapsed since the start of the study period. The coefficient of interest is β_1, which captures the partial effect of an operating local BRT station on the sale price of a home.

$$\log(P_{it}) = \beta_0 + \beta_1(S_i \times O_t) + \beta_2 S_i + \beta_3 O_t + \Psi_i + \Pi_i + \Lambda_t + \Omega_{I(i)t} + \beta_4 C_{it} + \varepsilon_{it} \qquad (1)$$

We define treatment status based on the distance of a property transaction from a BRT station. For example, our main specification will adopt a 20 minute walking distance definition of treatment, wherein properties within a 20 minute walk of an operating BRT station are considered treated ($O_t = 1$). We draw control observations from pre-BRT transactions and those properties that are more than 20 minutes from a station. In order to maintain the Stable Unit Treatment Value Assumption (SUTVA) we remove observations that are within 10 minutes walking distance of the edge of our treatment area. For the case of a 20 minute treatment definition, we remove all observations that are between 20 and 30 minutes from a station site across the entire study period. Therefore, we contrast price appreciation between properties within 20 minutes of a station, to those more than 30 minutes from a station. When using alternative treatment distances, we similarly remove observations that fall within the 10 minute ring that is directly outside of the treatment area.

In addition to estimating the average effect of a BRT station on local home prices, we also estimate heterogeneous effects based on local demographics. Estimating heterogeneous effects is accomplished through a triple-difference model, shown by Equation 2.

$$\begin{aligned}\log(P_{it}) = \alpha_0 + \alpha_1(S_i \times O_t) + \alpha_2(S_i \times O_t \times D_i) + \alpha_3(O_t \times D_i) + \alpha_4(S_i \times D_i) + \\ + \alpha_5 S_i + \alpha_6 O_t + \Psi_i + \Pi_i + \Lambda_t + \Omega_{I(i)t} + \alpha_7 C_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

The elements of Equation 2 match those of Equation 1 with the exception of D_i. D_i is the value of a demographic variable for the census block group where transaction i occurred. For example, D_i could capture the share of the local population who are white, with 0 indicating 0% of the population is white and 1 indicating 100% of the population is white. In this case, α_1 would capture the partial effect of BRT treatment on a home in a neighborhood with a 0% white population share and $\alpha_1 + \alpha_2$ would represent the effect for a home in a neighborhood with a 100% white population share. We will estimate this model for several different neighborhood demographic variables.

Our Equation 1 specification is a standard difference-in-difference specification, where the dimensions are time, and proximity to a BRT station location. The cell of this two-by-two matrix where an observation is both close to a station and observed after the station is open, represents a treated observation in this context. Equation 2 represents a triple-difference model with a continuous treatment variable. The dimensions are time, BRT station proximity, and a demographic characteristic. α_2 identifies the unique causal effect pertaining to observations that are near a station location, when the station is open, and the demographic characteristic takes a value of one.

In addition to the above hedonic models, we estimate repeat sales models. When estimating repeat sales models we essentially repeat Equations 1 and Equation 2 but add property-level fixed effects. When estimating the repeat sales models we remove all time-invariant control variables, including building characteristics, from the estimation equations because they are perfectly multicollinear with the property fixed effects. In this case, we isolate the average difference in logged price experienced by a specific property ($\ln(P_{t+\Delta}) - \ln(P_t)$), due to BRT station treatment occurring between two sales of the same property. We estimate the repeat sales model on properties that sold more than once over the study period. Selecting for only repeat sales reduces the sample size from 70,450 transactions to 28,533 transactions.

The repeat sales models are superior to the hedonic models in their ability to control for time-invariant differences across properties that may be correlated with BRT proximity. On the other hand, using only repeat sales forfeits over half of our sample, potentially drastically reducing estimation power. Additionally, the frequency with which a home transacts may be correlated with unobserved characteristics, suggesting the repeat sales sample could be less representative of the overall market. However, Figure 4 suggests the levels and trends are very similar between the two samples. Because we face a trade-off between the two methods we elect to present results from both approaches.

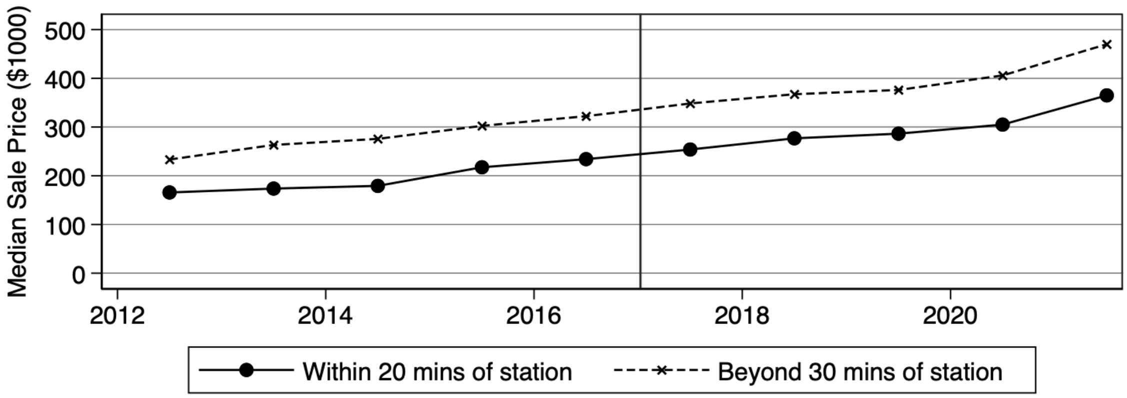
Our empirical approach differs from much of the existing literature by applying a conventional difference-in-difference design rather than a spatial econometric approach. Methodologically, our approach is similar to Dubé et al. (2018a). We are able to estimate clear effects without the need to impose a spatial weighting matrix on the model. Gibbons and Machin (2008) demonstrated that the difference-in-difference approach is efficient for valuing spatial amenities in closely related contexts. The inclusion of a repeat-sales estimator is easily combined with the difference-in-difference approach to yield more precise estimates that are unaffected by unobserved property characteristics.

We allow for the possibility that the model's error term is correlated across space and through time by clustering the standard errors. We estimate two-way clustered standard errors in all regressions. Spatially, we cluster standard errors at the block group level for hedonic regressions and at the property level for repeat sales regressions. Temporally, we cluster at the month-year level for all regressions.

The methodology we propose assumes a parallel trend assumption, wherein the price appreciation trend of properties near to BRT stations were similar to that of properties farther from BRT stations, prior to the BRT system opening. Figure 6 plots the median price of properties within a 20 minute walk of a BRT platform against the price trend of properties that were more than a 30 minute walk away. The figure also indicates the point when the BRT system began operating. We find the two sub-markets experienced very similar levels of price appreciation prior to the system opening, suggesting the parallel trends assumption is reasonable.

A related challenge to identifying the effect of the route on home prices is the existence

Figure 6: Parallel Trend



Properties within a 20 minute walk of a BRT station location and those more than a 30 minute walk from a station location followed parallel price trends prior to the opening of the BRT system. The vertical line indicates the time when the BRT system began operating. Median prices are plotted at the respective year's mid-point.

of anticipation effects among those involved in the local housing market.[3] Because planning for the BRT began in 2008 and construction began in 2015, price effects may show up before the 2017 opening date. We would expect anticipation effects to reduce our estimated effects, as the effect of the BRT is already partially capitalized in the pre-treatment period. Therefore, the positive price effects we find may be conservative estimates. We will provide a robustness check where we omit years directly prior to the opening of the BRT system to limit the anticipation effects.

5 Results

5.1 Estimating Average Home Price Effect of BRT

Table 4 provides hedonic model results, using Equation 1. Our treatment definition depends on defining a threshold of proximity to the BRT platforms by walking time. Table 4 presents results by increasing the treatment definition in increments of 10 minutes with definitions

[3]Damm et al. (1980) conducted an empirical analysis of the land capitalization effects of a DC metro expansion, noting that price capitalization likely begins before construction is completed and the premium for an operating station is likely different than for a prospective station. Dubé et al. (2018b) studied an upgrade from BRT service to Light Rail Transit (LRT) service along a corridor in Dijon, France, finding apartment prices rose in anticipation of the future LRT line during its construction. In a recent study of a rail expansion in New York City, Gupta et al. (2022) provide a discussion on real estate anticipation effects. We provide some empirical analysis of anticipation effects in our setting in the Appendix.

ranging from 10 to 50 minute walk times. While we examine effects up to a 40-50 minute range, we hypothesise the positive effect of BRT access will be limited to walkable distances close to the stations. As described in the previous section, regressions exclude observations from a 10 minute buffer along the outer edge of the treated area. Across all five treatment definitions we find that BRT proximity has a positive effect on local property values.

Table 4: Hedonic Regression Results

	Within 10 Mins	Within 20 Mins	Within 30 Mins	Within 40 Mins	Within 50 Mins
Near station x post	0.052*	0.068**	0.064**	0.053**	0.045**
	(0.024)	(0.017)	(0.014)	(0.012)	(0.011)
Near station	-0.065*	-0.068	-0.108**	-0.145*	-0.150*
	(0.031)	(0.052)	(0.038)	(0.056)	(0.073)
Post treatment	-0.008*	-0.006	-0.009*	-0.006	-0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year built	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Square footage (1,000)	0.242**	0.241**	0.241**	0.240**	0.240**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lot square footage (1,000)	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bedrooms	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Full bathrooms	0.085**	0.084**	0.086**	0.085**	0.085**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Half bathrooms	0.007	0.008	0.008	0.005	0.007
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Drive time to Portland (hours)	0.535**	0.521**	0.499**	0.453**	0.465**
	(0.178)	(0.176)	(0.173)	(0.160)	(0.164)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
R^2	0.832	0.834	0.835	0.837	0.834
N	68890	68721	68788	68212	68603

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

For properties within a 10 minute walk of a new BRT platform, we estimate a sale price premium of 5.3%. Expanding the treatment bandwidth to include homes within a 20 minute walk, we find a larger price premium of 7.0%. Expanding the bandwidth farther, we find the effect diminishes consistently. The pattern of coefficient estimates as the treatment area expands is suggestive that BRT stations provide a valuable local amenity, though they may also impart a negative congestion externality on properties very close to stations. This pattern is consistent with some prior literature examining the real estate effects of transit stations (Higgins and Kanaroglou, 2016). We return to the estimation of a spatial decay in estimates below.

Table 5 provides estimates among repeated sale properties, with the regressions including property-level fixed effects as discussed in Section 4. We estimate a very similar pattern of effects when using the repeat sales method. For example, the hedonic method estimated a 7.0% price premium for properties within a 20 minute walk of a platform, while the repeat sales method estimates a 5.4% premium. The correspondence of results between the two estimation methods provides some evidence for the robustness of our results to estimation methodology.

Table 5: Repeat Sales Results

	Within 10 Mins	Within 20 Mins	Within 30 Mins	Within 40 Mins	Within 50 Mins
Near station x post	0.042**	0.053**	0.056**	0.050**	0.045**
	(0.013)	(0.008)	(0.006)	(0.006)	(0.005)
Post treatment	0.027	0.028	0.029	0.024	0.012
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)
Drive time to Portland price trend	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y	Y
R^2	0.967	0.968	0.968	0.968	0.968
N	27860	27775	27823	27563	27682

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

Our estimates may differ from past studies due to our unique empirical setting of a mid-sized US city. However, our main finding of a 5-7% price premium for local access to a BRT station is in line with the literature from other settings. For example, the meta-analysis of Zhang and Yen (2020) catalogues estimates from a variety of studies that are centered around this range. Mulley et al. (2016) estimated a slightly larger premium of 11% in Brisbane. Dubé et al. (2011) estimated approximately the same effect magnitude in Quebec City. Estimates of the effect of Bogota's system are generally larger (Rodriguez et al., 2016); for example, Rodríguez and Mojica (2009) estimated a 13-14% price premium.

We estimate treatment areas using estimated walk times between properties and station platforms. The method should better capture the distance faced by pedestrians in accessing

BRT compared to using geodesic distances, which do not account for physical barriers facing pedestrians. In Appendix A, we provide alternative tables that use geodesic distances rather than walk times. We find results are very similar using this approach, consistent with the two measures of proximity being highly correlated.

While the above estimates test for the robustness of results to differing treatment bandwidths, they do not clearly indicate the spatial decay of the effect. The positive and significant effects at the larger bandwidths in Tables 4 and 5 may be driven by properties close to the stations. As most users likely walk to reach the BRT station, we expect price effects to fall quickly over space, and be negligible beyond reasonable walking distances. As a more direct test, we divide our treatment areas into treatment "donuts." We assign properties to unique donuts based on their proximity to the nearest station, in ten-minute intervals. For example, properties within a 10 minute walk of a station are in one treatment area, properties farther than 10 minutes but within 20 minutes are in a second treatment area, and we continue this classification method up to the properties that are between a 40 and 50 minute walk to the nearest BRT platform. In these specifications we omit all observations that are inside of the treatment donut, as well as removing observations from the 10 minute ring directly outside of the treatment ring. For example, the 20 minute specification considers properties within 10-20 minutes of an open station to be treated, and uses properties more than 30 minutes from the station as a control group.

Table 6 provides estimated effects for each of the donuts. Column 1 simply repeats our Table 4, column 1 estimate for comparison. Table 6 column 2 shows the effect of being within the 10 to 20 minute donut and subsequent columns proceed accordingly. We find that BRT has a significant price effect for the inner three donuts but an insignificant effect for the outer two donuts. Beyond 30 minutes, we find no statistically significant property value effects. The convergence of the estimated effect to zero for larger donuts is consistent with the spatial decay of amenity effects of BRT. We find the largest price effect, a 7.5% premium, for properties between 10 and 20 minutes of a station. The finding provides support for there being large positive amenity effects of BRT, but highly localized disamenity effects around stations. The pollution generated by buses, or the noise generated by buses or waiting passengers may present a nuisance effect (Zhang et al., 2020). Such effects would only be relevant for homes very near to the stations, consistent with our results.

Figure 7 provides a visual representation of the spatial decay effect. Panel A captures results reported in Table 6, while Panel B captures analogous results when using the repeat sales method. We again find very consistent results between the two methods. Using the repeat sales method, we find that positive price effects also peak in the 10-20 minute range. Using the repeat sales method, we are also able to identify a statistically significant effect

Table 6: Hedonic Regression Results, Donut Method

	0-10 Mins	10-20 Mins	20-30 Mins	30-40 Mins	40-50 Mins
Near station x post	0.052*	0.071**	0.048**	0.022	0.005
	(0.024)	(0.019)	(0.014)	(0.017)	(0.018)
Near station	-0.065*	-0.054*	-0.040*	-0.104*	-0.048
	(0.031)	(0.025)	(0.016)	(0.045)	(0.032)
Post treatment	-0.008*	-0.005	-0.008*	-0.005	-0.008
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year built	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Square footage (1,000)	0.242**	0.241**	0.241**	0.241**	0.241**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lot square footage (1,000)	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bedrooms	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Full bathrooms	0.085**	0.084**	0.085**	0.085**	0.085**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Half bathrooms	0.007	0.008	0.008	0.005	0.007
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Drive time to Portland (hours)	0.535**	0.532**	0.529**	0.496**	0.530**
	(0.178)	(0.177)	(0.175)	(0.163)	(0.177)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
R^2	0.832	0.834	0.835	0.837	0.834
N	68890	68721	68788	68212	68603

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

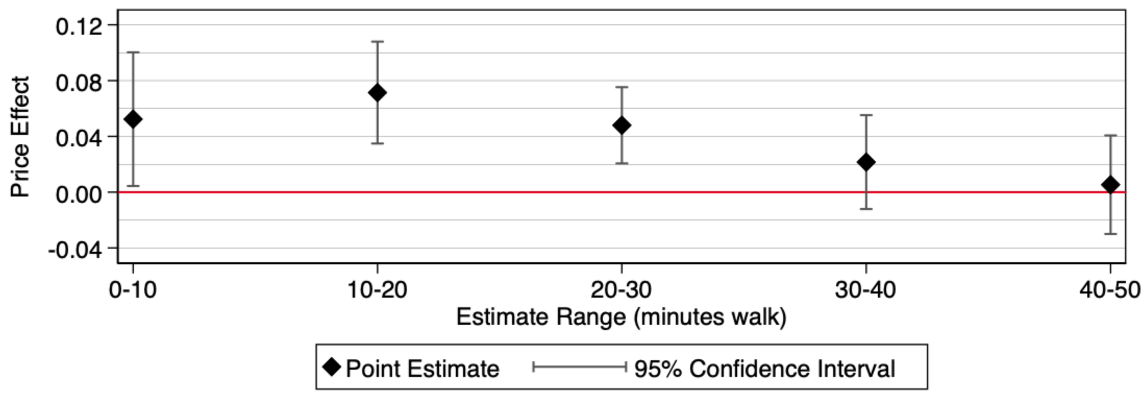
for the 30-40 minute donut of 2.8%. However, the difference between estimates for the 10-20 and 20-30 minute donuts are not significantly different under hedonic or repeat sales methodologies.

Our main methodology does not account for the possible presence of anticipation effects. In Appendix B, we provide alternative results where we omit years directly prior to the 2017 opening of the BRT line. We find results are larger when more pre-opening years are omitted. For example, if we omit transactions that occurred during the period of BRT system construction (2015 and 2016) we estimate a price effect of 8.7% for properties within a 20 minute walk of a station. These results suggest anticipation effects are relatively small, but that our main results marginally underestimate the true effect.

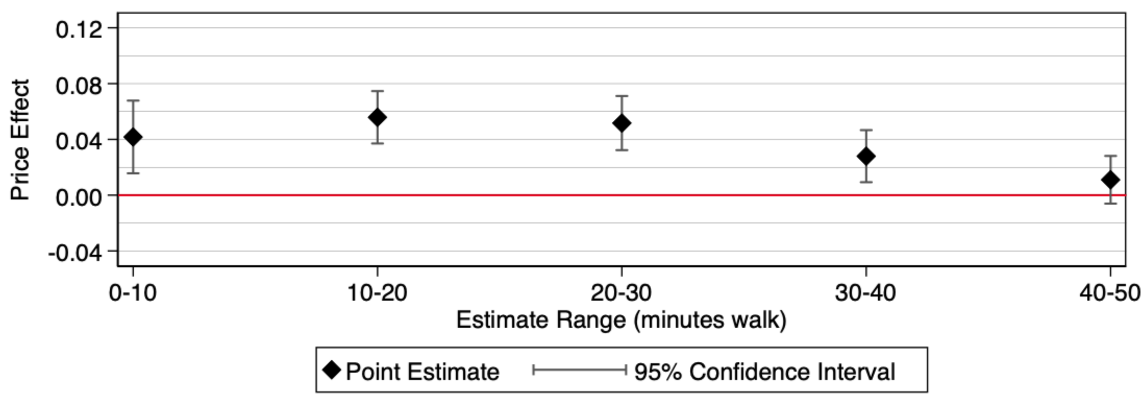
Our data set includes all of Clark County, and we draw from the full county sample to

Figure 7: Partial Effect of Proximity, Donut Method

A. Hedonic Method



B. Repeat Sales Method



Coefficients from five separate regressions are shown in each panel. Proximity to BRT platforms is calculated using walking distances.

construct our control group. Properties very far from the BRT line may provide a relatively poor control group, as the local neighborhood characteristics and appreciation trends may be unique. We re-ran the model on a limited sample that only included the municipality of Vancouver. We found consistent results; for example, we estimated a 5.8% premium for homes within 20 minutes of a station using the hedonic regression approach.

Our price estimates capture the full effect of BRT on home values, which includes mechanisms beyond the direct capitalization of local public transit amenities and disamenities. For example, commercial development induced by BRT stations could be a component of the estimated price effects. Endogenous sorting of households could affect neighborhood composition, which could in turn affect neighborhood demand and prices. Therefore, our estimates are specific to a setting that experienced endogenous capital and demographic sorting similar to that of Vancouver.

Investment in a BRT system may serve as a signal to local real estate developers that the government intends to make infrastructure investments along the proposed route. Additionally, developers may foresee BRT leading to increased local housing demand. These mechanisms may encourage new real estate development around stations. We look for a possible increase in new housing transactions around stations sites after the BRT system was completed. Table 7 shows the share of housing transactions that are newly built housing. We classify a home as newly built if it transacted in the same year construction was completed. Across the sample, 4.5% of transactions were newly built units. We find very few new home transactions around stations in the post-BRT period, suggesting new housing construction around BRT stations was not a significant factor in the for-sale market. Main results are robust to dropping all new construction transactions.

Table 7: Share of Housing Transactions that were Newly Constructed Units

	Before BRT Opening	After BRT Opening
Walking distance from BRT station site:		
>10 minutes	6.51%	3.01%
<10 minutes	1.05%	0.15%

Very few newly constructed homes transacted around BRT stations after the BRT system opened.

5.2 Estimating Heterogeneous Effects Based on Neighborhood Characteristics

While we find large average effects of BRT on local home prices, it is possible that not all areas benefit equally from BRT in terms of property value appreciation. For example, BRT may be a larger amenity in areas with high rates of transit use, as these populations are more likely to make direct use of the system. As discussed, a BRT station may provide both amenities and disamenities to the surrounding area. Different groups may value these (dis)amenities to different extents. As a result, the net effect of a station, as well as the spatial decay of effects, may differ across neighborhoods of differing characteristics.

An obvious amenity of a BRT station is the ability to use BRT for work commuting. However, only 3.3% of Vancouver's population use transit to get to work (Table 1), meaning that BRT commuting is unlikely to be a relevant amenity for the large majority of households. In Table 8 we implement the triple-difference approach shown in Equation 2, interacting the share of the local population that commutes by transit. We find that estimated price effects are not sensitive to local commuter transit mode share, based on the insignificant estimates of

α_2. Because public transit commuting is relatively rare in the sample area, transit commuting may represent an amenity for only a very small share of the population. Additionally, there may be insufficient statistical variation to identify a heterogeneous effect; this is supported by the large estimated standard errors on α_2.

Table 8: Heterogeneous Effects by Transit Mode Share, Hedonic Results

	Within 10 Mins	Within 20 Mins	Within 30 Mins	Within 40 Mins	Within 50 Mins
Near station x post	0.061	0.061*	0.051*	0.037*	0.024
	(0.039)	(0.026)	(0.020)	(0.018)	(0.016)
Near station x post x public transit share	-0.105	0.163	0.339	0.464	0.680
	(0.594)	(0.449)	(0.358)	(0.363)	(0.365)
Post x public transit share	-0.047	-0.054	-0.056	-0.098	-0.084
	(0.114)	(0.113)	(0.111)	(0.104)	(0.107)
Near station x public transit share	-0.262	-2.953	-2.005*	1.039	1.322
	(1.043)	(2.188)	(0.858)	(2.332)	(1.931)
Post treatment	-0.007	-0.005	-0.008*	-0.005	-0.012*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Near station	-0.056	0.020	-0.036	-0.177	-0.197
	(0.042)	(0.083)	(0.048)	(0.123)	(0.134)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property characteristic controls	Y	Y	Y	Y	Y
R^2	0.832	0.834	0.835	0.838	0.835
N	68890	68721	68788	68212	68603

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

In Table 9 we test for a heterogeneous effect based on the neighborhood's median household income. Lower-income households are less likely to own a private vehicle, may be more reliant on transit for work as well as non-work trips, and therefore may place a higher value on transit access. Similar to the transit mode share results, our triple-interaction term is insignificant, suggesting the impact of a BRT station on home prices is similar in areas of low or high income.

In Table 10 we identify heterogeneous effects based on local white population share. Unlike estimates for transit share or income, we find large differences in the effect of a BRT station on home prices based on the white population share of the neighborhood the home is located in. Using a 20 minute walk distance as the treatment definition, we estimate that a local BRT station increased property values in neighborhoods with a 60% white population share by 16.8%, much larger than the average effect. For a neighborhood with a 95% white

Table 9: Heterogeneous Effects by Income, Hedonic Results

	Within 10 Mins	Within 20 Mins	Within 30 Mins	Within 40 Mins	Within 50 Mins
Near station x post	0.080	0.091	0.089*	0.059	0.038
	(0.095)	(0.058)	(0.040)	(0.031)	(0.030)
Near station x post x median household income (1,000)	-0.002	-0.001	-0.001	-0.001	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Post x median household income (1,000)	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Near station x median household income (1,000)	0.003	0.001	0.003	0.004	0.010
	(0.002)	(0.003)	(0.002)	(0.004)	(0.006)
Post treatment	0.104**	0.104**	0.101**	0.104**	0.100**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Near station	-0.164	-0.077	-0.240	-0.356	-0.720
	(0.105)	(0.184)	(0.131)	(0.274)	(0.402)
Drive time to Portland price trend	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property characteristic controls	Y	Y	Y	Y	Y
R^2	0.834	0.835	0.836	0.839	0.836
N	68890	68721	68788	68212	68603

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

population share we estimate that a local BRT station *reduced* property values by an average of 1.0%. This strong heterogeneity in causal effect suggests that while BRT is considered a large amenity for some neighborhoods, it may be a small disamenity in others. Figure 8 maps the white population share of block groups in Clark County. The Vine BRT line passes through block groups which range from a 58% white population share to a 96% white population share. Table 11 provides the white population share triple-difference results but adopts a repeat sales method rather than the hedonic method, and finds similar results.

While we identify a strong heterogeneous effect based on local racial composition, the methodology does not demonstrate the mechanism that is driving this effect. Transit use is significantly correlated with race. In Vancouver, 5.3% of Black residents reported using transit for commuting, while only 2.9% of white residents, 2.6% of Hispanic residents and 1.7% of Asian residents used transit for commuting.[4] However, Table 8 showed no strong heterogeneity based on transit mode share by commuters. There may be more demand for non-commuting trips within communities with lower white population shares. Concerns regarding the possible disamenity effects of BRT could also differ across race. For example,

[4]2019 5-year ACS data.

Table 10: Heterogeneous Effects by White Population Share, Hedonic Results

	Within 10 Mins	Within 20 Mins	Within 30 Mins	Within 40 Mins	Within 50 Mins
Near station x post	0.495**	0.440**	0.370**	0.282**	0.223*
	(0.149)	(0.106)	(0.094)	(0.090)	(0.107)
Near station x post x white population share	-0.558**	-0.474**	-0.384**	-0.285**	-0.218
	(0.192)	(0.130)	(0.112)	(0.108)	(0.128)
Post x white population share	-0.071	-0.063	-0.062	-0.059	-0.041
	(0.045)	(0.046)	(0.046)	(0.047)	(0.048)
Near station x white population share	0.930*	-0.231	0.391	-0.544	-1.087
	(0.375)	(0.815)	(0.447)	(0.378)	(0.952)
Post treatment	0.052	0.048	0.043	0.044	0.022
	(0.037)	(0.037)	(0.038)	(0.039)	(0.039)
Near station	-0.800**	0.127	-0.427	0.324	0.812
	(0.298)	(0.636)	(0.372)	(0.277)	(0.787)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property characteristic controls	Y	Y	Y	Y	Y
R^2	0.832	0.834	0.835	0.838	0.835
N	68890	68721	68788	68212	68603

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

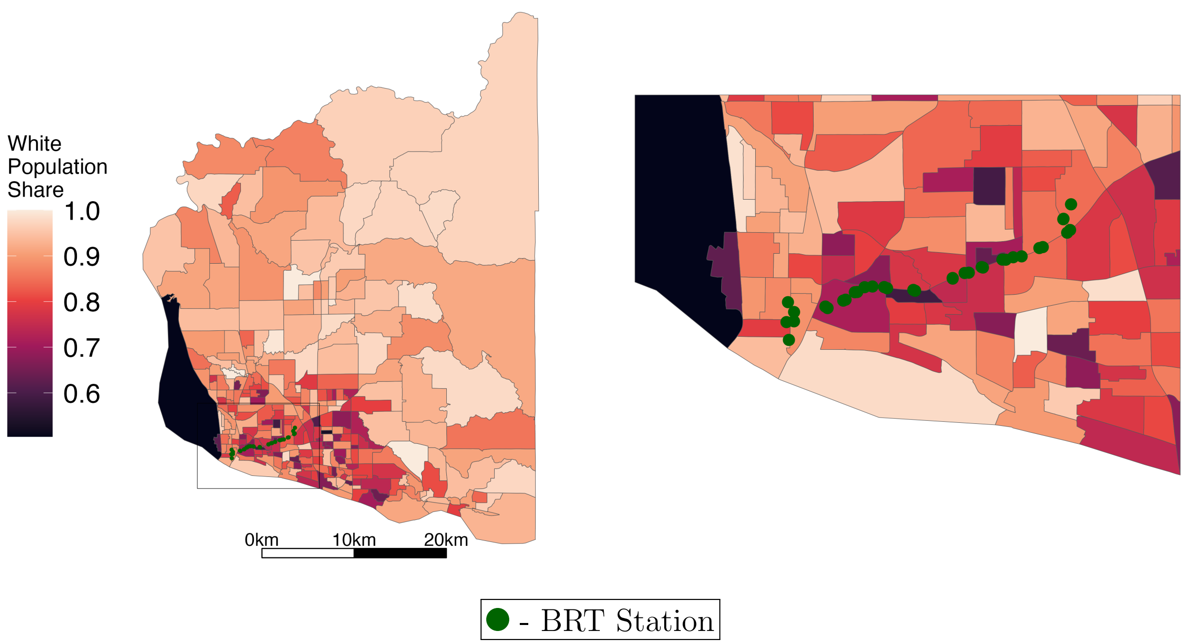
Table 11: Heterogeneous Effects by White Population Share, Repeat Sales Results

	Within 10 Mins	Within 20 Mins	Within 30 Mins	Within 40 Mins	Within 50 Mins
Near station x post	0.586**	0.501**	0.375**	0.265**	0.234**
	(0.112)	(0.074)	(0.066)	(0.060)	(0.047)
Near station x post x white population share	-0.675**	-0.563**	-0.397**	-0.266**	-0.233**
	(0.136)	(0.092)	(0.083)	(0.075)	(0.058)
Post x white population share	0.043*	0.050*	0.052*	0.068**	0.078**
	(0.020)	(0.020)	(0.021)	(0.022)	(0.023)
Post treatment	-0.010	-0.015	-0.016	-0.034	-0.055*
	(0.024)	(0.024)	(0.025)	(0.026)	(0.025)
Drive time to Portland price trend	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y	Y
R^2	0.967	0.968	0.968	0.968	0.968
N	27789	27704	27752	27492	27611

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

Figure 8: White Population Share by Census Block Group

A. B.



The census block groups surrounding the BRT line have lower white population shares compared to more suburban areas of the region (Panel A). Panel B provides a larger scale version, showing that blocks with low white population shares are located around the center of the BRT line.

white households are more likely to own private vehicles and be concerned about street parking displacement, or white households may have different assumptions regarding the connection between local transit service and crime.

We estimated similar models (not shown) to test for heterogeneous effects based on local car ownership, the local rate of college education, and local median home value but found no significant heterogeneity of effect for any of these regressions.

Overall, we find that local BRT systems represent a large positive amenity and this amenity is priced into the cost of local real estate. Results are robust to either hedonic or repeat sales methods, and are robust to either geodesic or walk-time defined treatment areas. Price effects are larger in areas with high non-white population shares. In the next section we explore how the large increase in property values are distributed spatially and discuss how real estate capitalization effects could be leveraged in order to fund system construction.

6 Land Value Capture

In this section we provide a rough comparison of the total land value created by the BRT line relative to the costs of the system. The back-of-the-envelope estimate is meant to demonstrate whether BRT system costs could be funded by the resulting land value uplift. An international survey of Land Value Capture (LVC) policies was undertaken in OECD/Lincoln Institute of Land Policy (2022). The LVC framework we envision falls within the category of an infrastructure levy, where incumbent landowners would pay to support infrastructure, but those payments are offset by appreciation in their land asset.[5]

Medda (2012) provided a discussion of LVC approaches in funding transportation infrastructure, noting that the preferred approach heavily depends on the context. The authors discuss the successful implementation of infrastructure levies (ie "betterment taxes") in many contexts, including the US. Anas and Duann (1985) described a structural model applied to the Chicago area, finding new rail infrastructure raised property values enough to cover 26-36% of capital costs. McMillen and McDonald (2004) analyzed the same setting, finding land value uplift amounted to 47% of construction costs.

Table 6 results provide estimates of significant property value increases for properties within a 30 minute walk of a BRT platform. In this section we estimate the full value of residential real estate uplift that can be attributed to the new BRT line. We classify every block group based on the walking distance from the centroid of the block group to the nearest BRT platform. We then calculate the total value of residential real estate in each block group by multiplying the average value of a home in the transaction data by the number of housing units reported in that block group in the 2016 5-year ACS. By multiplying a block group's estimated price appreciation by the block group's aggregate home value and summing across block groups, we are able to calculate the total residential real estate value created by the BRT system for areas within a 30 minute walk of a station platform.

We identify eight block groups with a centroid within a 10 minute walk of a platform, 16 block groups between 10 and 20 minutes, and nine block groups between 20 to 30 minutes. Using the estimated aggregate residential value of these blocks and the Table 6 columns 1-3 coefficient estimates, we estimate the BRT project generated $345 million in new real estate value for residential properties within a 30 minute walk of a station platform. As noted above, the total construction cost of the project was $53 million. We therefore estimate that the project's benefits, in terms of generated residential real estate value, were more than six times the project's costs. This approach fails to account for the full benefits of

[5] As noted in OECD/Lincoln Institute of Land Policy (2022), LVC policies, including infrastructure levies, have been successfully implemented in the US but often face legal challenges from homeowners.

the project, as the transportation benefits may accrue to individuals who do not own real estate within the vicinity but do use the BRT system. We also ignore commercial real estate effects. Concerning costs, this comparison does not consider the ongoing operating costs of maintaining the BRT system. However, operating costs are likely comparable to the traditional bus service which was replaced, meaning the change in operating costs is likely small overall and small compared to the $345 million in real estate value generated.

We estimate a large ratio of property uplift to construction costs when compared to past US studies of rail systems. The costs of a BRT system are very small compared to rail infrastructure. Therefore, even modest land value uplift can exceed needed construction costs for BRT. The large gap between land value benefits and project costs suggest that this project, or similar projects elsewhere, create value well in excess of cost. Furthermore, such projects could be financed with a local increase in property taxes. Such a financing mechanism could pay for project construction while also making the average local homeowner significantly better off in terms of home equity.

A one-year only property tax levy equal to 0.9% of pre-BRT property values, assessed only on properties within a 30 minute walk of a station, would have generated enough capital to pay for all construction costs.[6] The average incumbent homeowner in that area would have enjoyed a 6.6% increase in their property value (Table 4), meaning after the property tax levy and BRT construction they would still receive a windfall equal to 5.7% of the value of their home.

If we suppose the transit agency has access to financing at a 5% rate of interest, the project could be funded with a permanent property tax increase on all properties within a 30 minute walk of a station platform equal to 0.05% of property value. For the median valued house in the area ($252,798) this would amount to a $118 annual assessment. Notably, the same home would expect to receive $796 annually if they were able to convert the new equity in their property into a perpetuity at a 5% discount rate.

A tax on only properties that experienced home value capitalization from the BRT system is potential pareto efficient as it could result in all homeowners being financially better off. However, there may be practical hurdles in implementing a LVC policy. If the $53 million BRT system was funded through a County-wide lump sum tax, the necessary tax would require $107 per Clark County resident, or $288 per household.

[6] We express the property tax increases in terms of pre-BRT home prices. As the existence of the BRT system raised property values, the needed tax in terms of post-BRT home values is slightly lower. Accounting for the estimated change in home values within a 30 minute walk of the station, the needed tax in terms of post-BRT values would be only 0.88% of home values, rather than the 0.93% of pre-BRT values. The tax itself may also be capitalized into home prices. However, the magnitude of this effect would be very small relative to the home price. Assuming the tax is fully capitalized into home values would imply the need for a tax equal to 0.94% of pre-BRT home values.

The analysis in the section stops short of a full cost-benefit analysis due to data limitations and a relatively narrow focus on property value effects. However, the magnitude of the property value effects suggests that the value of BRT to the local population is large relative to costs.

7 Conclusion

As more cities move forward with BRT implementation there is a growing need for research regarding the basic effects these systems have on neighborhoods and housing markets. The current literature provides relatively little guidance regarding the land value impacts of BRT in the US, and prior research provides some conflicting results. We use property level data surrounding a significant BRT project in Vancouver, Washington and examine the effect BRT stations have on surrounding home values. We find that homes located near to new stations underwent a large and significant increase in value after the stations were opened. We find particularly large capitalization effects in neighborhoods with low white population shares. The results suggest that white households may react more strongly to the negative externalities generated by BRT stations.

We examine the effect of differing methodologies to estimate price effects. We contrast a hedonic and repeat sales approach, and contrast treatment areas defined by walking times and geodesic distances. Across these approaches we find consistent results. The consistency of results suggests that other studies that examine local BRT effects, or other neighborhood amenities in similar settings, should expect consistent results across these methods.

Our estimation strategy has some limitations. We are not able to fully account for endogenous development decisions that could also impact home prices. The BRT line may have increased local housing supply, or spurred local commercial retail investment. While a positive housing supply response would temper the price effect, neighborhood investment by firms could raise the home price premium by bidding up land, or creating gentrification from the amenities of new businesses. Our price estimates therefore include the combined effect of the improved local transportation, as well as any other endogenous market responses.

The Vancouver BRT system generated new residential property value that we estimate to be six times larger than the construction costs of implementing the BRT system. The large land uplift suggests that the benefits of the system outweigh the costs. Local jurisdictions may have enjoyed some small fiscal returns through land value uplift, as higher property values may lead to higher property tax bills. However, the property value benefits largely represent a windfall for incumbent local homeowners. We suggest that the local government could have recovered much more of the new land value if they had implemented a property tax levy on properties that benefited from BRT. Transit budgets are typically low in the US, and new projects require complex coordination between several levels of government, and sometimes require unique funding streams such as local sales tax levies. The imposition of a local property tax levy could have paid for the entirety of the *Vine* BRT system while still leaving incumbent homeowners significantly wealthier than if the system had not been constructed. We suggest that LVC policies could be effective to fund future BRT systems in the US.

References

Acton, B., Le, H. T., and Miller, H. J. (2022). Impacts of bus rapid transit (BRT) on residential property values: A comparative analysis of 11 US BRT systems. *Journal of Transport Geography*, 100:103324.

Anas, A. (1995). Capitalization of urban travel improvements into residential and commercial real estate: simulations with a unified model of housing, travel mode and shopping choices. *Journal of Regional Science*, 35(3):351–376.

Anas, A. (2021). Transportation improvements and property prices. *International Encyclopedia of Transportation*, 1:337–346.

Anas, A., De Sarkar, S., and Timilsina, G. R. (2021). Bus rapid transit versus road expansion to alleviate congestion: A general equilibrium comparison. *Economics of Transportation*, 26:100220.

Anas, A. and Duann, L. S. (1985). Dynamic forecasting of travel demand, residential location and land development. In *Papers of the Regional Science Association*, volume 56, pages 37–58. Springer.

Baum-Snow, N. and Kahn, M. E. (2000). The effects of new public projects to expand urban rail transit. *Journal of Public Economics*, 77(2):241–263.

Bocarejo, J. P., Portilla, I., and Pérez, M. A. (2013). Impact of Transmilenio on density, land use, and land value in Bogotá. *Research in Transportation Economics*, 40(1):78–86.

Cervero, R. and Kang, C. D. (2011). Bus rapid transit impacts on land uses and land values in Seoul, Korea. *Transport Policy*, 18(1):102–116.

Cervero, R., Murakami, J., and Miller, M. (2010). Direct ridership model of bus rapid transit in los angeles county, california. *Transportation Research Record*, 2145(1):1–7.

Currie, G. (2006). Bus rapid transit in australasia: Performance, lessons learned and futures. *Journal of public transportation*, 9(3):1–22.

Damm, D., Lerman, S. R., Lerner-Lam, E., and Young, J. (1980). Response of urban real estate values in anticipation of the washington metro. *Journal of Transport Economics and Policy*, pages 315–336.

Deng, T., Ma, M., and Nelson, J. D. (2016). Measuring the impacts of bus rapid transit on residential property values: The Beijing case. *Research in Transportation Economics*, 60:54–61.

Deng, T. and Nelson, J. D. (2011). Recent developments in bus rapid transit: a review of the literature. *Transport Reviews*, 31(1):69–96.

Dewees, D. N. (1976). The effect of a subway on residential property values in toronto. *Journal of Urban Economics*, 3(4):357–369.

Dubé, J., Andrianary, E., Assad-Déry, F., Poupart, J., and Simard, J. (2018a). Exploring difference in value uplift resulting from new bus rapid transit routes within a medium size metropolitan area. *Journal of Transport Geography*, 72:258–269.

Dubé, J., Des Rosiers, F., Thériault, M., and Dib, P. (2011). Economic impact of a supply change in mass transit in urban areas: a Canadian example. *Transportation Research Part A: Policy and Practice*, 45(1):46–62.

Dubé, J., Legros, D., and Devaux, N. (2018b). From bus to tramway: Is there an economic impact of substituting a rapid mass transit system? an empirical investigation accounting for anticipation effect. *Transportation Research Part A: Policy and Practice*, 110:73–87.

Gibbons, S. and Machin, S. (2008). Valuing school quality, better transport, and lower crime: evidence from house prices. *oxford review of Economic Policy*, 24(1):99–119.

Gupta, A., Van Nieuwerburgh, S., and Kontokosta, C. (2022). Take the Q train: Value capture of public infrastructure projects. *Journal of Urban Economics*, 129:103422.

Guzman, L. A., Enríquez, H. D., and Hessel, P. (2021). Brt system in bogotá and urban effects: More residential land premiums? *Research in Transportation Economics*, 90:101039.

Hess, D. B. and Almeida, T. M. (2007). Impact of proximity to light rail rapid transit on station-area property values in buffalo, new york. *Urban studies*, 44(5-6):1041–1068.

Higgins, C. D. and Kanaroglou, P. S. (2016). Forty years of modelling rapid transit's land value uplift in North America: Moving beyond the tip of the iceberg. *Transport Reviews*, 36(5):610–634.

Kahn, M. E. (2007). Gentrification trends in new transit-oriented communities: Evidence from 14 cities that expanded and built rail transit systems. *Real Estate Economics*, 35(2):155–182.

Levinson, H. S., Zimmerman, S., Clinger, J., and Gast, J. (2003). Bus rapid transit: Synthesis of case studies. *Transportation Research Record*, 1841(1):1–11.

Ma, L., Ye, R., and Titheridge, H. (2014). Capitalization effects of rail transit and bus rapid transit on residential property values in a booming economy: Evidence from Beijing. *Transportation Research Record*, 2451(1):139–148.

McMillen, D. P. and McDonald, J. (2004). Reaction of house prices to a new rapid transit line: Chicago's midway line, 1983–1999. *Real Estate Economics*, 32(3):463–486.

Medda, F. (2012). Land value capture finance for transport accessibility: a review. *Journal of Transport Geography*, 25:154–161.

Mulley, C. (2014). Accessibility and residential land value uplift: Identifying spatial variations in the accessibility impacts of a bus transitway. *Urban Studies*, 51(8):1707–1724.

Mulley, C., Ma, L., Clifton, G., Yen, B., and Burke, M. (2015). Spatial variations of the effects of bus rapid transit on residential property values. *Working Paper*.

Mulley, C., Ma, L., Clifton, G., Yen, B., and Burke, M. (2016). Residential property value impacts of proximity to transport infrastructure: An investigation of bus rapid transit and heavy rail networks in brisbane, australia. *Journal of Transport Geography*, 54:41–52.

Mulley, C. and Tsai, C.-H. (2017). Impact of bus rapid transit on housing price and accessibility changes in Sydney: A repeat sales approach. *International Journal of Sustainable Transportation*, 11(1):3–10.

Mulley, C. and Tsai, C.-H. P. (2016). When and how much does new transport infrastructure add to property values? Evidence from the bus rapid transit system in Sydney, Australia. *Transport Policy*, 51:15–23.

Munoz-Raskin, R. (2010). Walking accessibility to bus rapid transit: Does it affect property values? the case of Bogotá, Colombia. *Transport policy*, 17(2):72–84.

OECD/Lincoln Institute of Land Policy (2022). Global compendium of land value capture policies.

Perk, V. A. and Catala, M. (2009). Land use impacts of bus rapid transit: Effects of BRT station proximity on property values along the Pittsburgh Martin Luther King, Jr. East Busway. Technical report.

Rodríguez, D. A. and Mojica, C. H. (2009). Capitalization of brt network expansions effects into prices of non-expansion areas. *Transportation Research Part A: Policy and Practice*, 43(5):560–571.

Rodríguez, D. A. and Targa, F. (2004). Value of accessibility to Bogotá's bus rapid transit system. *Transport Reviews*, 24(5):587–610.

Rodriguez, D. A., Vergel-Tovar, E., and Camargo, W. F. (2016). Land development impacts of brt in a sample of stops in Quito and Bogotá. *Transport Policy*, 51:4–14.

Sidloski, M. and Diab, E. (2020). Understanding the effectiveness of bus rapid transit systems in small and medium-sized cities in North America. *Transportation Research Record*, 2674(10):831–845.

Stokenberga, A. (2014). Does bus rapid transit influence urban land development and property values: A review of the literature. *Transport Reviews*, 34(3):276–296.

Tsivanidis, J. N. (2018). The aggregate and distributional effects of urban transit infrastructure: Evidence from Bogotá's Transmilenio. Technical report, University of Chicago.

Tyndall, J. (2018). Bus quality improvements and local commuter mode share. *Transportation Research Part A: Policy and Practice*, 113:173–183.

Tyndall, J. (2021). The local labour market effects of light rail transit. *Journal of Urban Economics*, 124:103350.

Yang, L., Chu, X., Gou, Z., Yang, H., Lu, Y., and Huang, W. (2020). Accessibility and proximity effects of bus rapid transit on housing prices: Heterogeneity across price quantiles and space. *Journal of Transport Geography*, 88:102850.

Zhang, M. and Yen, B. T. (2020). The impact of Bus Rapid Transit (BRT) on land and property values: A meta-analysis. *Land Use Policy*, 96:104684.

Zhang, M., Yen, B. T., Mulley, C., and Sipe, N. (2020). An investigation of the open-system bus rapid transit (brt) network and property values: The case of brisbane, australia. *Transportation Research Part A: Policy and Practice*, 134:16–34.

Appendix A

Appendix A provides the main results of the paper but rather than use local walking distances as the measure of BRT access, geodesic distances are used. Treatment definitions are varied between 500 meters and 2,500 meters across Table A1. Similar to the method using walk times, we remove observations in a boundary area separating treated and control observations. In this case we use 500 meter radius buffers. For example, when using the 500 meter treatment definition we remove all observations between 500 and 1,000 meters of a station site.

Table A1 shows hedonic results, Table A2 shows repeat sales results, and Table A3 shows triple-difference results based on the local white population share. We find estimates that are consistent with the main results of the paper. Using geodesic distances provides coefficient estimates that are more precisely estimated. We hypothesise that walk times may introduce noise to the measurement. When considering short local walks, pedestrians may cut across empty lots, or cross roads mid-block. The HERE API used to generate walk times assumes that pedestrians strictly adhere to rules of the road, which may cause the estimates to overstate the true walk times in some cases. Nevertheless, we find very similar results across approaches.

Table A1: Hedonic Results, Geodesic Distances

	Within 500m	Within 1000m	Within 1500m	Within 2000m	Within 2500m
Near station x post	0.070**	0.070**	0.057**	0.045**	0.046**
	(0.021)	(0.016)	(0.012)	(0.011)	(0.010)
Near station	-0.025	-0.084	-0.071**	-0.319	-0.152
	(0.023)	(0.079)	(0.026)	(0.184)	(0.084)
Post treatment	-0.007*	-0.007*	-0.007	-0.012**	-0.011*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Year built	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Square footage (1,000)	0.240**	0.241**	0.239**	0.241**	0.241**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lot square footage (1,000)	0.001**	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bedrooms	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Full bathrooms	0.084**	0.086**	0.085**	0.084**	0.085**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Half bathrooms	0.008	0.008	0.005	0.007	0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Drive time to Portland (hours)	0.533**	0.505**	0.403**	0.484**	0.428**
	(0.178)	(0.177)	(0.152)	(0.160)	(0.153)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
R^2	0.832	0.836	0.838	0.835	0.834
N	68082	68264	67694	68093	68353

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

Table A2: Repeat Sales Results, Geodesic Distances

	Within 500m	Within 1000m	Within 1500m	Within 2000m	Within 2500m
Near station x post	0.062**	0.061**	0.050**	0.047**	0.047**
	(0.011)	(0.007)	(0.006)	(0.005)	(0.004)
Post treatment	0.029	0.027	0.028	0.020	0.015
	(0.017)	(0.017)	(0.017)	(0.017)	(0.015)
Drive time to Portland price trend	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property fixed effects	Y	Y	Y	Y	Y
R^2	0.967	0.968	0.968	0.968	0.968
N	27524	27620	27255	27498	27717

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

Table A3: Heterogeneous Effects by White Population Share, Hedonic Results, Geodesic Distances

	Within 500m	Within 1000m	Within 1500m	Within 2000m	Within 2500m
Near station x post	0.497**	0.397**	0.259**	0.250*	0.283**
	(0.117)	(0.100)	(0.096)	(0.106)	(0.096)
Near station x post x white population share	-0.547**	-0.412**	-0.252*	-0.252	-0.292*
	(0.154)	(0.118)	(0.114)	(0.128)	(0.115)
Post x white population share	-0.066	-0.062	-0.057	-0.027	-0.002
	(0.045)	(0.046)	(0.047)	(0.049)	(0.045)
Near station x white population share	0.311	1.215	-0.137	-3.606**	-0.382
	(0.393)	(0.797)	(0.122)	(0.874)	(0.887)
Post treatment	0.048	0.045	0.041	0.012	-0.009
	(0.037)	(0.038)	(0.039)	(0.041)	(0.037)
Near station	-0.268	-1.085	0.048	2.827**	0.171
	(0.311)	(0.634)	(0.088)	(0.696)	(0.691)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y	Y
Property characteristic controls	Y	Y	Y	Y	Y
R^2	0.832	0.836	0.838	0.837	0.835
N	68082	68264	67694	68093	68353

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.

Appendix B

Participants in the local housing market may have considered the property value effects of the BRT system even before the service began. Buyers may have been willing to pay a premium for the expectation of future local BRT service. Therefore, property value capitalization may have occurred prior to the 2017 system opening. Table B1 tests for anticipation effects by removing data from years directly preceding the system opening. The table adopts a 20 minute treatment ring definition. Column 1 provides the full sample regression for comparison. Column 2 removes 2016 data from analysis, column 3 removes 2015-2016 data, and column 4 removes 2014-2016 data. Removing this data should reduce the influence of anticipation effects by limiting the pre-treatment years to a period well before the BRT system was completed. We find that the estimated effects increase as data are removed from the years preceding the system opening. The result is consistent with the presence of anticipation effects. We also observe the precision of estimates decreasing as we reduce the sample size.

Table B1: Testing Anticipation Effects

	2017 Cutoff	2016 Cutoff	2015 Cutoff	2014 Cutoff
Near station x post	0.072**	0.076**	0.083**	0.098**
	(0.019)	(0.024)	(0.029)	(0.032)
Near station	-0.070	-0.067	-0.070	-0.086
	(0.054)	(0.057)	(0.059)	(0.066)
Post treatment	-0.005	-0.006	-0.007	-0.007
	(0.004)	(0.004)	(0.004)	(0.004)
Year built	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Square footage (1,000)	0.240**	0.240**	0.238**	0.235**
	(0.007)	(0.007)	(0.007)	(0.007)
Lot square footage (1,000)	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Bedrooms	-0.001	-0.001	-0.003	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Full bathrooms	0.083**	0.083**	0.083**	0.082**
	(0.006)	(0.006)	(0.006)	(0.006)
Half bathrooms	0.008	0.008	0.008	0.007
	(0.006)	(0.005)	(0.005)	(0.005)
Drive time to Portland (hours)	0.533**	0.524**	0.528**	0.565**
	(0.177)	(0.171)	(0.165)	(0.171)
Drive time to Portland price trend	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	Y	Y	Y	Y
Block group fixed effects	Y	Y	Y	Y
Municipality time trends	Y	Y	Y	Y
Property type fixed effects	Y	Y	Y	Y
Property type time trends	Y	Y	Y	Y
R^2	0.833	0.836	0.838	0.838
N	67573	59757	53109	47708

Significance levels: $*$: 5% $**$: 1%. Two-way clustered standard errors in parentheses.