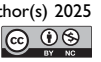
Article

B Urban Analytics and City Science

EPB: Urban Analytics and City Science
2026, Vol. 53(7) 1449–1466
© The Author(s) 2025

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/23998083251389078
journals.sagepub.com/home/epb
Sage

Impacts of bus rapid transit (BRT) on income-segmented housing markets in El Paso, Texas: A spatial hedonic and difference-in-differences analysis

Youngre Noh[1], Hanwool Lee[1], Yang Song[1], Chanam Lee[1] and Wei Li[1]

Abstract

This study evaluates the impact of introducing the Bus Rapid Transit (BRT) system on housing market dynamics across three diverse urban corridors in El Paso, Texas, utilizing spatial hedonic pricing and AITS-DID models. The research aims to understand how the BRT system influences property values, hypothesizing that the effects vary between developed and underdeveloped areas. Initial findings reveal an increase in property values in the affluent Mesa area until the BRT opening in 2014, followed by a decline, suggesting a shift in market perceptions post-implementation. Conversely, less affluent areas along the Alameda and Dyer corridors exhibit a reduction in the negative impact on property values over time, indicating growing appreciation for the BRT and associated urban improvements. The study contributes to urban planning and policy by highlighting the mixed impacts of BRT systems on property values across different urban fabrics and underscores the importance of context-sensitive transit planning. It also points to the necessity for comprehensive communication with stakeholders to ensure transit solutions meet community needs and support equitable urban development.

Keywords

bus rapid transit, hedonic model, economic impact, difference-in-difference, longitudinal analysis, public transportation, sustainability, property value

[1]Department of Landscape Architecture and Urban Planning, Texas A&M University, College Station, TX, USA

Corresponding author:
Youngre Noh, Department of Landscape Architecture and Urban Planning, Texas A&M University, College Station, Texas 77843-3137, USA.
Email: ynoh@arch.tamu.edu

Data Availability Statement included at the end of the article

Introduction

The introduction of Bus Rapid Transit (BRT) systems represents a transformative approach to urban development, impacting housing markets and residential patterns (Basheer et al., 2020). Planners have focused on the BRT systems to mitigate urban congestion and promote efficient mobility using dedicated lanes, traffic signal prioritization, and efficient boarding processes. With these improvements in accessibility, the BRT system influences the dynamics of real estate development and housing, fostering environments favorable to residential growth and revitalization (FTA, 2023b; Hensher and Golob, 2008). By offering an affordable and efficient alternative to private cars and conventional transit, BRT significantly alters property desirability and values, encouraging compact developments and enhancing neighborhood appeal. (Nikitas and Karlsson, 2015; Stokenberga, 2014; U.S. Department of Transportation, 2004).

In the U.S., BRT was first introduced in Pittsburgh in 1977, and it spurred in other metropolitan areas like Los Angeles and Cleveland in the early 2000s (Hidalgo, 2013). Beyond the direct urban mobility benefits, they were expected to revitalize the city's public transit system and attract economic development along their corridors, leading to more holistic and inclusive urban planning (Lucas and Jones, 2012; Venter et al., 2018). This trend is particularly relevant in cities like El Paso, Texas, where BRT is expanding to areas with significant socio-economic divides.

El Paso has experienced substantial growth accompanied by urban sprawl. Bordering the states of Texas, New Mexico, and the Mexican state of Chihuahua, El Paso has a Hispanic dominant population share of 81%, the largest Hispanic population share of any metropolitan area in the U.S. (U.S. Census Bureau, 2021). It also has a unique geographical condition with three major transportation corridors radiating out from its downtown area: Mesa, Alameda, and Dyer. These corridors feature different levels of urban development. The Mesa corridor, located in the western part of the city, is a more affluent region characterized by higher income levels, well-maintained infrastructure, and proximity to commercial centers. On the other hand, the Alameda corridor, stretching southeast of downtown, is situated in a historically underserved community with a rich cultural history, predominantly Hispanic population, and older, more densely packed neighborhoods that have faced economic stagnation. Similarly, the Dyer corridor, located in the northeastern part of El Paso, serves another historically underserved area characterized by lower-income neighborhoods and older housing stock. These areas have had limited accessibility to jobs and amenities, and thus fewer economic opportunities. To mitigate the disparities, enhance mobility and connectivity, and promote more equitable growth across the city, El Paso has introduced a new BRT system along these three corridors.

This research aims to examine the impact of the BRT system, Brio, on the housing market along the three BRT corridors—Mesa, Alameda, and Dyer. Utilizing both spatial hedonic modeling and Adjusted Interrupted Time Series Difference-in-Differences analysis, this study analyzes the difference in the BRT impacts on housing prices across the three corridors temporally and spatially to find causal relationships between the BRT systems and their impact on the housing market, offering insights into relevant planning and policy objectives to guide the city toward more equitable and inclusive growth.

Background and literature review

Bus rapid transit and housing market

Planners and policy makers adopt public transit infrastructure, such as bus, light-rail (LRT), or bus rapid transit (BRT), to enhance accessibility and promote more equitable economic development (Huang et al., 2023). BRT provides fast and efficient service through dedicated lanes, busways,

traffic signal priority, off-board fare collection, elevated platforms, and enhanced stations (FTA, 2023a; 2023b). These features improve ridership, comfort, and satisfaction compared to traditional buses (Stewart et al., 2017; Wirasinghe et al., 2013). BRT systems improve mobility and accessibility to workplaces and amenities, enhance streetscape, attract economic developments, and thus impact the housing market (Stokenberga, 2014).

While various studies have explored the impact of BRT on housing markets, the concentration has largely been on short-term cross-sectional effects. These studies examine the impact on property values and housing demand within a relatively short time frame after the BRT implementation. For example, Perk et al. (2010) showed a considerable premium in areas adjacent to BRT lines 1 year after the BRT implementation. Similar studies showed short-term positive impacts on local housing markets (Acton et al., 2022a; Cervero and Duncan, 2002). However, the long-term effects, impacts across different urban contexts, and causality of the premium remain largely unanswered.

In addition to the numerous studies addressing the impacts of BRT systems on the housing market, there is a growing body of literature studying the context-specific nature of these impacts. Acton et al. (2022b) compared 11 BRT systems in the U.S. and found their mixed impacts on the housing market. Among these systems, three systems had a positive impact, six had an insignificant impact, and two had a negative impact on property values. Zhang et al. (2020) investigated the open-system BRT network where BRT vehicles can operate both on dedicated lanes and regular roadways in Brisbane, Australia, providing evidence that such systems can increase property values in cities with well-integrated BRT networks. A study by Thomas and Bertolini (2014) showed that the introduction of BRT systems did not lead to a universal rise in property values. Their findings suggested that the impacts on the housing market are subject to the context of the socio-economic environment. Overall, prior studies suggested that BRT impacts on property values vary based on factors such as the BRT system usability and ridership, status of other transportation environment, and overall urban development patterns.

Differentiated impact on neighborhoods

Limited research has been conducted on the relationship between the introduction of BRT systems and the housing market in areas with different living conditions across different geographical contexts. The results from these studies are mixed, depending on the specific context of each study.

Within the international context, Mulley et al. (2016) examined the impacts of proximity to transport infrastructure, including BRT and heavy rail networks, on residential property value, in Brisbane, Australia. The results showed that Brisbane experienced a greater increase in property values compared to Sydney's BRT due to its greater BRT network coverage of BRT and weaker competition from rail. Also, distance to train stations was not as prominent as distance to BRT stations, especially when the property was closer to BRT stations. Additionally, Calvo (2017) have demonstrated the possibility of densification and increased land values in peripheral areas where they are newly connected by the system in Bogotá, Colombia.

In the U.S., there is an increasing interest in how rapid transit systems, such as light rail, might address urban disparities. Historically, many low-income neighborhoods in the U.S. have often been overlooked in terms of both public and private sector investments. Infrastructural developments, like light rail systems, have been shown to enhance nearby property values and promote revitalization of surrounding areas (Duncan, 2011). A study by Noh and Li (2022) suggested that low-income neighborhoods within a half-mile radius of light rail stations experienced more positive impacts on housing prices compared to middle and high-income neighborhoods. This trend likely stems from the market capitalizing on development opportunities in areas with lower property values yet with convenient access to public transportation. Moreover, reliable transit options such as

light railways are particularly valued in low-income neighborhoods where commuting alternatives are limited.

Focusing back on BRT studies, Zhang and Yen (2020) conducted a meta-analysis on how BRT systems affect land and property values. Focusing on the characteristics of the BRT systems, accessibility, and spatial and temporal factors, the authors found that the maturity of the BRT system, property type, distance to BRT stations, and geographical location of the system significantly influenced the property value premiums. Their findings confirmed significant variations in housing premium across different contexts, highlighting the need for comprehensive and longitudinal research that compares the BRT impacts across different contexts. They also reviewed research methodologies used in the previous studies, pointing out a reliance on hedonic price modeling approaches and the lack of causal studies that consider the temporal and spatial dimensions.

Previous research has highlighted the immediate benefits of BRT systems, such as increased property values and enhanced accessibility; however, a significant literature gap remains in understanding their long-term effects across various neighborhoods. By analyzing pre- and post-BRT implementation data, this study aims to establish causality, assess housing premiums, and evaluate the differentiated impacts on housing markets.

Methodology

Study area

El Paso, located at the intersection of Texas, New Mexico, and Chihuahua, Mexico, stands as a significant border metropolis. The city extends outwards from its downtown area along three major transportation corridors: Mesa, Alameda, and Dyer. The population is predominantly Hispanic or Latino, making up 81% of the population, which is significantly higher than the U.S. urban average of 20.7% (U.S. Census Bureau, 2021). Economically, El Paso presents below-average statistics compared to other U.S. cities. The median household income is approximately $51,325, significantly lower than the U.S. urban median of $76,330 (U.S. Census Bureau, 2021). The median household income varies from $69,500 for Mesa to $39,100 and $39,300 for Alameda and Dyer, respectively. In terms of the value of owner-occupied units in El Paso, the median value is about $160,000, also significantly lower than the U.S. urban median of approximately $374,000 as of 2021 (U.S. Census Bureau, 2021). The predominant form of public transportation in the city is the bus, accounting for 98.3% of public transit usage.

El Paso's Bus Rapid Transit (BRT) system, BRIO, was first introduced at the Mesa Street Corridor in 2014, followed by Alameda and Dyer in 2019. BRIO features dedicated lanes, priority traffic signals, and modern stations equipped with advanced ticketing systems and real-time information to enhance residents' mobility and connectivity to workplaces. It also aimed to provide the infrastructure needed to accommodate its expanding urban development (Metro, 2024). (Figure 1).

Data collection and study variables

In this study, we collected data on housing market databases, socio-economic, and geographic information. The primary source of housing data was Realtor.com, a prominent platform for property listings in the U.S., where realtors upload data via the Multiple Listing Service (MLS). The housing prices, represented by the asking prices set by realtors, have been shown to closely align with the actual transaction prices, as evidenced by prior studies (Hagerty, 2007; Ibeas et al., 2012; Salon et al., 2014). This is particularly relevant in Texas, a state known for its non-disclosure policy, making actual sales data hard to obtain. Therefore, asking prices are considered a reliable proxy for

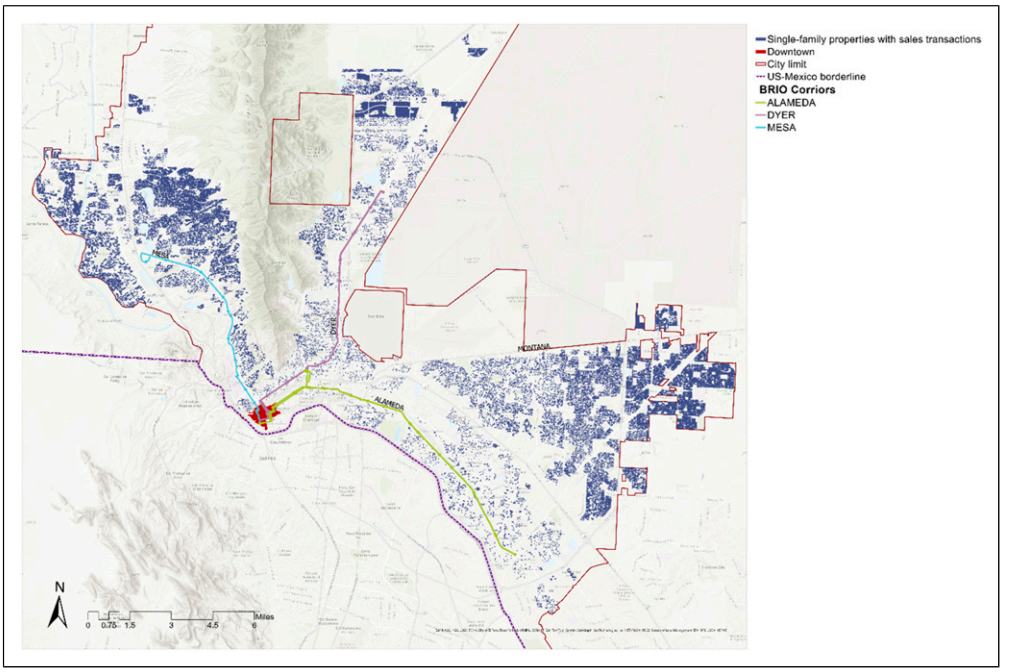


Figure 1. Map of El Paso and Brio line.

analyzing housing market dynamics, accurately reflecting transaction prices (Sohn et al., 2020; Yang et al., 2020). It is important to note that Realtor.com does not capture data from all realtors, and certain types of transactions, such as pre-foreclosures or sales by owners, may not be included. Nevertheless, no significant bias has been reported between the data shared versus not shared on this platform (Realtor.com, 2010; Realtor.com. (n.d).

To ensure the accuracy of the data, a rigorous validation process was implemented, utilizing both visual and numerical checks. This process was supported by external online resources, such as Google Maps and tax assessor data, to verify housing characteristics like address, geographical coordinates, number of bathrooms and bedrooms, square footage, year of construction, and listing price at sale. An initial dataset comprising records of 95,000 single-family homes in El Paso, TX, was obtained from Realtor.com in 2022, which was consistent with the county tax assessor's data (EP CAD, 2023). House data without transaction records was excluded. After the validation process, records with anomalies or missing values were filtered out by plotting data distributions and visually identifying properties with no or more than seven bathrooms, no or more than eight bedrooms, and living spaces either larger than 8,800 square feet or smaller than 800 square feet. The analysis was further refined to include houses sold within a 2-year period from their listing date, resulting in a final dataset of 51,196 single-family home transactions for detailed examination. For the analyses, sales transactions within three miles of BRT stations were included to define the study area encompassing the corridors' influence. In the AITS-DID model, this includes treatment properties within 0.5 miles and control properties between 0.5 and 3 miles. Three miles was selected based on sensitivity tests showing it balances coverage of corridor effects with sufficient sample size, while two miles reduced statistical power and four miles introduced unrelated noise, resulting in 38,195 transactions for the spatial hedonic modeling and 34,532 transactions for the AITS-DID analysis.

The study variables also included distances from the study properties to amenities and dis-amenities using ESRI ArcGIS Pro (i.e., from the centroid of property parcel polygon to the nearest

edge of the amenity/dis-amenity polygon). The shortest routes to the nearest destinations from each single-family residential parcel were captured as either street network distance or Euclidean distance. Network distances were applied to destinations associated with daily activities (e.g., commercial areas, retail outlets, food and drug stores, parks, schools, and BRT stations) where residents travel for specific purposes such as errands, recreation, or utilitarian needs. Euclidean distances were used for land uses and infrastructures that may have broader exposure impacts at the neighborhood level (e.g., highways, refineries, and industrial sites) (Noh et al., 2024). Thus, we measured each property's network distance to the nearest Brio BRT station (in miles) using the shortest path along the road network from the residence to the closest Brio station. Data on the socio-demographic and economic status of neighborhoods were derived from block group-level 5-year American Community Survey (ACS) data (U.S. Census Bureau, 2023). The list of locational and neighborhood variables was derived from previous hedonic literature (Li et al., 2015). Variables with a correlation over 0.6 and a variance inflation factor (VIF) over four were checked for their significance in the regression analysis. Variables that had higher correlation and explained less variance in the dependent variable were excluded from the analysis. For example, income variables were excluded due to high multicollinearity with included neighborhood attributes like percent Hispanic, education levels, and vacancy rates, which capture similar socio-economic effects without reducing model stability; they also did not yield statistically significant coefficients in preliminary tests, and conceptually, the corridors represent income segmentation, Mesa affluent, Dyer middle and low, and Alameda low Table 1.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev	Min	Max
Distance to Brio station (mile)	5.62	3.28	0.086	12.42
Structural characteristic				
Living area (sq_ft)	1905.91	668.79	800	8800.00
Number of bedrooms	3.47	0.65	2	7.00
Number of bathrooms	2.61	1.14	1	6.50
House age at the year of sale (year)	19.30	20.24	0	81.00
Locational characteristic (mile)				
Network distance to downtown	10.48	3.37	0	16.44
Euclidean distance to refinery	8.32	2.85	0.01	15.09
Network distance to industrial site	1.15	0.86	0	3.94
Network distance to Big box retail	0.47	0.29	0	2.33
Network distance to small retail	0.53	0.37	0	2.81
Network distance to park	0.84	0.60	0.01	3.25
Euclidean distance to highway	0.87	0.53	0	3.58
Network distance to elementary school	5.08	3.10	0.02	14.67
Neighborhood characteristics				
Percent of population: Hispanic	78.31	12.84	23.71	100.00
Percent of population: Age under 18	16.34	5.17	0	29.41
Percent of population: Age over 65	4.13	3.60	0	23.00
Percent of population: Degree over college	15.50	5.05	0.85	43.40
Percent of vacant properties	7.26	5.98	0	44.85
Percent of rental properties	23.92	15.91	0	91.69

Year characteristics
Binary variables for fixed effects were employed for each regression. For example, 1 = sale at year 2014
Number of observations 38,195

Method

Spatial hedonic pricing model with longitudinal data set

The Hedonic Pricing Model is used to determine the implicit prices of individual characteristics that make up a composite good. This model analyzes the price of a good based on its various intrinsic and environmental attributes. The approach has been extensively discussed and developed in the literature, with significant contributions from Can (1992), Freeman (2003), and Rosen (1974).

For single-family houses, the factors contributing to the price can be categorized into three main groups: (1) structural attributes (physical characteristics such as size, number of rooms, type of construction, age), (2) neighborhood characteristics (surrounding environment including schools, proximity to amenities, socio-economic status), and (3) locational attributes (geographical location such as distance from the city center, accessibility to public transport, proximity to major highways or landmarks).

In this study, the dataset was segmented into nine 2-year subsets for the Mesa area and seven 2-year subsets for the Dyer and Alameda areas. Two-year subsets maintain a balance between having enough sales transactions for robust spatial analysis and avoiding the loss of a significant portion of sales data due to repeated transactions at the same property. When creating a spatial matrix, only one sales transaction for each property can be employed in the matrix, which leads to losing repeated sales. Two-year periods provide higher temporal resolution than 3-year subsets, which would reduce periods and granularity for detecting pre- and post-changes as supported by McMillen (2008) and Noh and Rogers (2016). One-year subsets were tested but yielded insignificant coefficients due to small samples and poor fit, while 2-year subsets better align with the hedonic model's market equilibrium assumption by capturing short-term dynamics. Testing for spatial autocorrelation is essential when conducting spatial analyses to ensure that the model adequately captures spatial dependencies in the data (Anselin, 2002). The use of Moran's I, Geary's C, and Lagrange Multiplier tests is well-established in spatial econometrics for identifying spatial patterns in both dependent variables and error terms. Moran's I and Geary's C test for global spatial autocorrelation, while Lagrange Multiplier tests help detect potential spatial dependence in the error structure (Cliff and Ord, 1981; Kissling and Carl, 2008).

Due to the presence of significant spatial autocorrelation in the dependent variable and error terms confirmed by these test, Spatial Autoregressive model with Autoregressive errors (SARAR/SAC) models were employed for each subset (Badinger and Egger, 2011). SARAR/SAC models fit regressions that include spatial lags of the dependent variable with spatial autoregressive errors on lattice and areal data (Badinger and Egger, 2011; Kelejian and Prucha, 2010; Kissling and Carl, 2008; Noh and Rogers, 2016). For the spatial analysis, spatial weighting matrices, inverse-distance, were created for each subset of the data using coordinates of each property (Anselin, 2002).

The spatial hedonic model can be written as follows:

$$y = \beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \cdots + \beta_{n-1} \mathrm{X}_{n-1} + \beta_n \mathrm{W}y + (1 - \rho \mathrm{W})^{-1} \varepsilon$$

where β is coefficient, W is the spatial weighting matrix, Wy is the spatial lag of dependent variable, capturing how nearby property prices influence each other. The autoregressive error term, denoted by $(\mathrm{I}- \rho\mathrm{W})^{-1}$ ε accounts for spatial dependence in the error terms.

Adjusted Interrupted Time-Series Difference-in-Difference (AITS DID) model

El Paso, with its unique geographic attributes and varied developments across its three corridors, presents a distinctive case for study. This research aims to analyze the differential impacts of the BRT system on its neighborhoods: one that's well-developed and two that are comparatively underdeveloped. Given the different timelines of the BRT station's launch, variations in the housing market, and the distinct qualities of each neighborhood, several factors were crucial when choosing the appropriate analysis model.

The AITS-DID model was identified as the most suitable approach due to its ability to handle complex temporal and spatial dynamics (Galster et al., 2004); this hybrid model extends the adjusted interrupted time-series method from Galster et al. (2004) by incorporating difference-in-differences elements for causal inference, similar to applications in Koschinsky (2009), Noh et al. (2024), Noh (2019), and Woo and Lee (2016). This model is particularly adept at distinguishing variations based on market, time, and region. By facilitating a comparative analysis of price differences between impact areas and the rest of the region, the AITS-DID model evaluates price variations between proximate areas and those farther away, both before and after the completion of the BRT system (Koschinsky, 2009).

This model is an extension of the hedonic price model, encompassing all attributes of the hedonic price model except for the "distance to BRT station" attribute. Instead, it includes micro-neighborhood factors, binary distance bands, and time variations. This approach is particularly suited to El Paso's unique circumstances, such as the phased BRT introduction and varying neighborhood developments. The phased introduction of the BRT allows for the model to capture the effects over different time periods and across neighborhoods with varying levels of development. It provides a comprehensive understanding of how the BRT influences housing prices within different urban settings by accounting for temporal shifts and localized impacts. It partially validates causality by comparing the impact and control areas (Noh, 2019). Unlike traditional models, the AITS-DID can isolate the specific impact of the BRT system by differentiating between pre- and post-implementation periods and between impacted and control zones. It offers further insights from conventional distance coefficients and shows the direct impact of BRT on housing markets.

The equation for the Adjusted Interrupted Time Series Difference-in-Differences (AITS-DID) model is represented as follows:

$$P(h) = f(S_h, N_h, L_h, T_{ht}\, \beta, \delta, \gamma, \theta) + \tau_1 PreImpactLevel + \tau_2 PostImpactLevel + \tau_3 PreImpactTrend + \tau_4 PostImpactTrend + \varepsilon$$

In this model, the variables explicitly account for localized effects by incorporating binary and continuous variables for proximity and timing of the intervention.

- *Pre-Impact Price Level* (binary variable): Indicates whether a property transaction occurred within a defined micro-neighborhood (a half-mile radius from a BRT station) before the opening of the BRT station. This captures baseline property value differences in the immediate vicinity of the station before any potential impact.
- *Post-Impact Price Level* (binary variable): Denotes property transactions within the micro-neighborhood after the BRT station became operational, thus allowing assessment of immediate changes in property values directly attributable to the opening of the station.
- *Pre-Impact Price Trend* (continuous variable): Represents the elapsed years from the initial year of the study period to the sale date, for transactions occurring within the micro-neighborhood before the BRT station opening. This captures the underlying property value trend over time before the intervention. For Mesa corridor, the trend spans values from 0 to 7, corresponding to 7 years before BRT conversion within the 16-year analysis period. Alameda and Dyer Streets, each analyzed over an 8-year span, employ trend ranges of 0 to 3.
- *Post-Impact Price Trend* (continuous variable): Measures the number of years from the BRT station opening date to the transaction date, specifically for post-opening sales occurring within the micro-neighborhood. It provides insights into how property value trends evolve over time after the station opening. Similar to pre-impact trends, Mesa Street's post-impact trends range from 0 to 7, and Alameda and Dyer Streets range from 0 to 3.

Each property's status is defined based on its spatial proximity, within or outside the micro-neighborhood, and timing, before or after the BRT opening, facilitating causal inference regarding the impact of BRT stations on housing values (Galster et al., 2004; Koschinsky, 2009; Woo and Lee, 2016).

The micro-neighborhood vicinity is determined to be a half-mile from the BRT stations. Previous literature shows that the influence of an LRT station is most pronounced for properties within a half-mile radius (Noh and Li, 2022). Other research indicates varying distances for the influence of open spaces and train stations on property values (Crompton, 2001; Dubé et al., 2013). A sensitivity test between one-quarter-mile, half-mile, and one-mile vicinities validated the half-mile as providing a more statistically sound model. Additionally, we tested the parallel trend assumption by regressing property prices on a binary group indicator (pre-impact price level), a continuous time variable (time), and their interaction exclusively during the pre-intervention period. The statistically insignificant interaction term confirmed parallel pre-treatment trends, thereby validating the use of the Difference-in-Differences methodology (See Appendix).

Results

Longitudinal spatial hedonic modeling analysis

The property value impacts across the Mesa, Alameda, and Dyer BRT corridors show distinct patterns, particularly when comparing pre- and post-opening periods. The Mesa corridor, which opened in 2014, exhibited different trends compared to the Alameda and Dyer corridors, which both opened in 2019.

In the Mesa corridor, properties located closer to BRT stations consistently showed a significant positive premium on property values. Before the BRT's opening in 2014, property values increased significantly, with premiums ranging from $14,277 per mile closer to the station in 2006-2007 to $41,976 in 2014-2015, suggesting strong anticipation of the BRT system. After the BRT became operational, the premium decreased, dropping to $11,511 in 2016-2017, before rebounding to $25,227 per mile closer in 2020-2021 (Table 2, Supplement Figure 2).

In contrast, the Alameda corridor showed a more complex relationship with proximity to the BRT. Before its opening in 2019, proximity to Alameda stations was associated with significant negative impacts on property values. For example, between 2014 and 2015, property values decreased by $24,455 per mile closer to the station. However, after the BRT's opening in 2019, the negative impact lessened, with premiums improving from - $24,455 in 2014-2015 to - $10,223 in 2016-2017, and further recovery to $12,523 per mile closer in 2020-2021.

The Dyer corridor showed the most persistent negative impact on property values throughout the study period. Before its opening in 2019, proximity to Dyer stations led to significant reductions in property values, with the most substantial negative impact of $23,736 per mile closer to the station in 2016-2017. Following the BRT's opening, the negative impacts moderated, with property value declines reducing to $11,147 in 2018-2019 and $12,475 per mile closer in 2020-2021. While the negative trend persisted, the magnitude of the decline decreased after the BRT became operational. The full sets of coefficients for all control variables are available in the Appendix (Supplemental Table 3, 4, and 5).[1]

AITS-DID analysis

The AITS-DID model shows coefficients that align closely with those from the spatial hedonic models discussed earlier, except for the Mesa corridor area. The key variables in the AITS-DID are the pre-impact price level, post-impact price level, pre-impact price trend, and post-impact price trend. Each of these variables captures the effects both before and after the introduction of Brio. All coefficients are statistically significant.

Table 2. Longitudinal spatial hedonic result.

Year			2006-2007	2008-2009	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019	2020-2021
Distance to Mesa Brio			−14277.6**	−26026.2***	−27403.9***	−37894.4***	−41975.8***	−11511.2*	3685.183	−25227.4***
Distance to Alameda Brio					24200.4***	19813.3***	24455.3***	10223.1**	−902.2	12522.8***
Distance to Dyer Brio					19226.9**	3860.7	14768.4***	23736.0***	11146.7***	12475.7**
Mesa Brio	Number of obs		621	673	697	862	1144	1186	1742	992
	Pseudo R2		0.8631	0.8164	0.8181	0.8181	0.8016	0.8014	0.7777	0.7792
	Wald test of spatial error terms	chi2 (2)	15.03	18.77	27.3	38.5	47.94	84.42	875.25	38.57
		Prob>chi2	0.0005	0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
	Moran's I test	Prob>chi2	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Alameda Brio	Number of obs				307	382	522	535	974	537
	Pseudo R2				0.7188	0.7422	0.7073	0.6930	0.7265	0.7609
	Wald test of spatial error terms	chi2 (2)			8.55	14.86	9.15	81.19	196.09	46.44
		Prob>chi2			0.0035	0.0001	0.0025	<0.0001	<0.0001	<0.0001
	Moran's I test	Prob>chi2			<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Dyer Brio	Number of obs				307	382	522	535	974	537
	Pseudo R2				0.7188	0.7422	0.7073	0.6930	0.7265	0.7609
	Wald test of spatial error terms	chi2 (2)			8.55	14.86	9.15	81.19	196.09	46.44
		Prob>chi2			0.0035	0.0001	0.0025	<0.0001	<0.0001	<0.0001
	Moran test	Prob>chi2			<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

***denotes p < 0.01, ** denotes p < 0.05, * denotes p < 0.10.

In all regions combined, the pre-impact price level for properties within a half-mile radius of the BRT stations is negative, with a coefficient of -$9,887. This suggests a price disadvantage for properties near the stations relative to the control group, properties located more than a half-mile distance from the BRT stations. This negative impact worsens after the BRT's introduction, with the post-impact price level showing a coefficient of -$20,768. The pre-impact trend indicates an annual decrease in property values, with a coefficient of -$1,306. This trend converted after the BRT became operational, with the post-impact trend showing an annual premium increase of $6,109 (Table 3, Supplement Figure 3).

In the Mesa corridor, the pre-impact price level is significantly negative, with a coefficient of -$44,260. This indicates a substantial price disadvantage for properties near the stations compared to those farther away. The post-impact price level remains negative with a coefficient of -$39,979. The pre-impact trend shows an annual increase in property values, with a coefficient of $3,140 as the BRT opening approached. After the BRT became operational, the post-impact trend indicates an annual premium increase of $4,513.

The Alameda corridor shows a similar pattern, with the pre-impact price level being negative, as indicated by a coefficient of -$20,709. The post-impact price level, while still negative, shows a lessened impact with a coefficient of -$17,824. The pre-impact trend reveals a moderate annual increase in property values, with a coefficient of $1,656. After the BRT became operational, the post-impact trend shows a significant annual premium increase of $6,928.

In the Dyer corridor, the pre-impact price level is also negative, with a coefficient of -$30,166. After the BRT became operational, the post-impact price level shows a reduction in the negative impact, with a coefficient of -$23,347. The pre-impact trend indicates a moderate annual increase in property values, with a coefficient of $1,356. This positive trend strengthens after the BRT's introduction, with the post-impact trend showing a significant annual premium increase of $7,248 (Table 3, Supplement Figure 4). The full set of coefficients for all control variables is available in the Appendix (Supplemental Table 6).

Discussion

Integration of hedonic and AITS-DID models

This study's methodological approach provides two different perspective analyses of the impact of BRT stations on property values by analyzing longitudinal spatial hedonic models with the AITS-DID model. The spatial hedonic models provide a cross-sectional view of the general impact, capturing the relationship between property values and their proximity to BRT stations. However, these models do not fully capture the temporal trend of this relationship or isolate the direct impact of BRT on property value changes. The AITS-DID model complements this by examining the level

Table 3. AITS-DID result.

	All region	Mesa	Alameda	Dyer
pre_price_level	−9887.1**	−44260.0***	−20708.5***	−30165.6***
post_price_level	−20768.0**	−39979.1***	−17824.4***	−23347.3***
pre_price_trend	−1305.7***	3139.6***	1655.8***	1356.0***
post_price_trend	6109.0***	4512.9***	6927.7***	7248.5***
Number of Obs	34,532	7972	2570	3408
R-squared	0.7721	0.7713	0.7235	0.75

***denotes p < 0.01, ** denotes p < 0.05, * denotes p < 0.10.

and trend of property values within a specified radius of the BRT stations, both before and after the BRT opening. This approach helps explain the trend of changes and causality by comparing BRT-impacted areas with control areas. These two methods offer different approaches to examining how property values have changed over time in response to the new BRT stations.

Mesa area

The longitudinal analysis for the Mesa area reveals an interesting trend: a consistent increase in housing premiums until the opening of the Mesa Brio in 2014, followed by a decrease. This suggests a shift in perceptions or values associated with the BRT service over time. Initially, the anticipation of the new transit service likely contributed to property value increases. However, after the opening, factors such as increased traffic and noise might have altered residents' perceptions, leading to a decrease in housing premiums (Noh and Li, 2022). This trend might also reflect a market adjustment to the new transit infrastructure, balancing initial expectations with the practical implications of living near a transit station. The period of 2018-19, showing an insignificant coefficient, indicates that other uncaptured external factors might have impacted the housing market. Examples could be the opening of two other Brio lines in 2019. However, there is limited prior literature that suggests the opening of additional transit/BRT services contributes negatively to the housing values along the existing corridor.

The AITS-DID model for Mesa presents opposite results, indicating a negative premium for living within a half-mile radius of the BRT stations. This suggests that while a moderate distance is perceived positively, immediate proximity to the stations is not desirable, especially in more affluent areas like Mesa. This also can mean that the direct use value of BRT service by living very close to the stations may not be significant, but having BRT services available in the neighborhood may be a more positive attribute contributing to the property value premium. This complexity in predicting the impact of transit developments on property values highlights the importance of considering both the anticipation and reality phases of public transit projects, along with their specific socio-economic context.

Alameda and Dyer areas

In the longitudinal analysis for Alameda and Dyer, the diminishing negative impact of proximity to these street corridors on property values over time may reflect growing recognition and appreciation of the BRT service and its associated environmental improvements, such as sidewalks, lighting, crosswalks, and bus shelters with amenities. Being relatively less affluent and less developed, compared to Meas, these areas are more likely to benefit from the BRT service itself and the additional environmental enhancements and development projects. Prior literature suggests that improvements such as better streetscapes and general urban maintenance may contribute to a gradual enhancement of the neighborhood's perception among home buyers (Acton et al., 2022b; Wirasinghe et al., 2013).

The AITS-DID analysis corroborates these findings, showing a decrease in the negative impact of proximity on property values and a shift towards positive trends following the introduction of the BRT stations in 2019. The substantial increase in the coefficients of post-trend variables for both Alameda and Dyer indicates residents' positive expectations towards the introduction of BRT service and the additional improvements and developments to follow.

Socio-economic implications

In affluent areas like Mesa, the initial increase in property values followed by a subsequent decrease suggests that while BRT systems can initially enhance property values due to improved accessibility,

the practical realities of increased traffic and noise can diminish these benefits over time. This highlights the need for urban planners to address potential negative externalities to maintain the positive impact of BRT systems on property values. Conversely, in less affluent areas such as Alameda and Dyer, the consistently positive impact of BRT on property values indicates that BRT systems can serve as catalysts for urban renewal and increased accessibility, which are critical for promoting social equity. Improved transportation infrastructure in these areas can enhance connectivity to economic opportunities, education, and healthcare, which in turn can contribute to the overall socio-economic advancement of historically underserved communities (Lucas and Jones, 2012).

BRT systems can stimulate economic development by attracting investments in commercial and residential projects (Venter et al., 2018). The findings suggest that in less developed areas, BRT systems not only improve mobility but also enhance the attractiveness of these neighborhoods, leading to increased property values. This can drive further investments and spur comprehensive urban revitalization efforts. However, while the increase in property values in less affluent areas can be seen as a positive development, it also raises concerns about potential displacement and gentrification. As property values rise, long-term residents might face increased property taxes and living costs, potentially leading to displacement. Policymakers need to consider measures such as affordable housing programs and property tax relief to mitigate these adverse effects and ensure that the benefits of BRT systems are equitably distributed and negative and inequitable impacts are minimized.

The varied impacts of BRT systems across different socio-economic contexts underscore the importance of context-sensitive urban planning. Planners must consider the unique characteristics and needs of different neighborhoods to design transit solutions that maximize benefits while minimizing negative impacts. This includes integrating BRT systems with broader sustainability initiatives, such as green infrastructure and community development programs. Furthermore, effective communication and engagement with local communities are crucial for the successful implementation of BRT systems. Understanding community concerns and expectations can help in designing transit solutions that are well-received and beneficial to the local housing market. Continuous stakeholder engagement can also foster community ownership and support for public transit projects.

Conclusion

This study examined the impact of BRT on property values across different urban corridors within the same city. In Mesa, a relatively affluent area, property values initially increased until the Mesa Brio opened in 2014, after which values declined. This shift suggests altered market perceptions due to increased traffic and noise from the BRT service. The AITS-DID model also identified a negative premium for properties within a half-mile of BRT stations in Mesa, emphasizing a nuanced relationship between proximity and housing desirability. Conversely, the less affluent Alameda and Dyer areas showed significantly reduced negative impacts of proximity to BRT corridors over time, reflecting growing appreciation of the service and associated environmental benefits.

The study's findings have significant policy implications for urban planning and development. In affluent regions like Mesa, urban planners might need to focus on mitigating potential negative impacts of BRT systems, such as noise and congestion, to maintain property values. In less developed areas like Alameda and Dyer, the emphasis should be on utilizing BRT systems to attract urban redevelopment projects and protect/enhance property values. The mixed market reactions to BRT stations across different corridors also suggest that public transit design and implementation should be context-sensitive considering the specific needs and conditions of each service area (Thomas and Bertolini, 2014). Effective communication with residents and stakeholders in all areas affected by BRT implementation is crucial for understanding community concerns and expectations, which can help develop transit solutions that are well-received by and beneficial to the specific local housing market.

This study has some limitations. The use of listing prices from Realtor.com in this study, due to Texas being a non-disclosure state, may introduce some limitations in terms of data completeness and accuracy in the bid function of hedonic modeling. The study's temporal scope, while adequate for observing short- to medium-term trends, may not capture the long-term impacts of BRT systems on housing markets. The findings are specific to El Paso, Texas, and may not be directly applicable to other cities with different urban dynamics and socio-economic contexts. Additionally, the study does not extensively delve into the relationship between BRT ridership levels and housing market impacts, which could be a significant factor in understanding the full effects of BRT systems. If the ridership data is available, future research should explore long-term impacts and ridership data to understand the full effects of BRT systems. Further studies could also investigate the potential displacement and gentrification effects associated with increased property values in less affluent areas to suggest measures that ensure equitable benefits from BRT systems.

In conclusion, this research contributes valuable insights into the complex dynamics between BRT systems and housing markets, offering guidance for future urban planning and public transit initiatives. The differentiated impacts observed across various corridors of El Paso highlight the importance of context-sensitive approaches in urban housing, development, and transit planning.

- The datasets generated and analyzed during the current study are not publicly available due to restrictions imposed by the funding agency, as the project is ongoing and data sharing is currently limited to ensure compliance with grant requirements. However, data are available from the corresponding author upon reasonable request.

ORCID iDs

Youngre Noh https://orcid.org/0000-0002-5971-4644
Yang Song https://orcid.org/0000-0001-6044-7881

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study is supported by National Institutes of Health; 1R01CA228921â€“01.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

The datasets generated and analyzed during the current study are not publicly available due to restrictions imposed by the funding agency, as the project is ongoing and data sharing is currently limited to ensure compliance with grant requirements. However, data are available from the corresponding author upon reasonable request.

Supplemental Material

Supplemental material for this article is available online.

Note

1. All coefficients for Housing, locational, neighborhood characteristics correspond to previous literature.

References

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

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

Anselin L (2002) Under the hood issues in the specification and interpretation of spatial regression models. *Agricultural Economics* 27(3): 247–267.

Badinger H and Egger P (2011) Estimation of higher-order spatial autoregressive cross-section models with heteroscedastic disturbances. *Papers in Regional Science* 90(1): 213–235.

Basheer MA, Boelens L and Bijl Rv. d. (2020) Bus rapid transit system: a study of sustainable land-use transformation, urban density and economic impacts. *Sustainability* 12(8): 3376.

Calvo JAP (2017) The effects of the bus rapid transit infrastructure on the property values in Colombia. *Travel Behaviour and Society* 6: 90–99.

Can A (1992) Specification and estimation of hedonic housing price models. *Regional Science and Urban Economics* 22(3): 453–474.

Cervero R and Duncan M (2002) Transit's value-added effects: light and commuter rail services and commercial land values. *Transportation Research Record: Journal of the Transportation Research Board* 1805(1): 8–15.

Cliff AD and Ord JK (1981) *Spatial processes: models & applications*. Pion.

Crompton JL (2001) The impact of parks on property values: a review of the empirical evidence. *Journal of Leisure Research* 33(1): 1–31.

Dubé J, Thériault M and Des Rosiers F (2013) Commuter rail accessibility and house values: the case of the Montreal south shore, Canada, 1992–2009. *Transportation Research Part A: Policy and Practice* 54: 49–66.

Duncan M (2011) The synergistic influence of light rail stations and zoning on home prices. *Environment and Planning A: Economy and Space* 43(9): 2125–2142.

EP CAD, E. P. C. A. D (2023). https://epcad.org/

Freeman AM (2003) Economic valuation: what and why. In *A Primer on Nonmarket Valuation*. Springer, 1–25.

FTA U (2023a). https://www.transit.dot.gov/research-innovation/bus-rapid-transit

FTA U (2023b) Issues in bus rapid transit. *Document in support of the FTA Bus Rapid Transit Demonstration Program January* 15(1998): 27.

Galster G, Temkin K, Walker C, et al. (2004) Measuring the impacts of community development initiatives: a new application of the adjusted interrupted time-series method. *Evaluation Review* 28(6): 502–538.

Hagerty JR (2007) How good are zillow's estimates? *Wall Street Journal* 2(14): 476–478.

Hensher DA and Golob TF (2008) Bus rapid transit systems: a comparative assessment. *Transportation* 35: 501–518.

Hidalgo D (2013) Bus rapid transit: worldwide history of development, key systems and policy issues. In: *Transportation Technologies for Sustainability.* Springer, 235–255.

Huang Y, Parker DC and Anglin P (2023) Estimating household demand for transit-oriented development: a two-stage hedonic analysis in kitchener-waterloo, Canada. *Environment and Planning B: Urban Analytics and City Science* 51(2): 401–418.

Ibeas Á, Cordera R, Dell'Olio L, et al. (2012) Modelling transport and real-estate values interactions in urban systems. *Journal of Transport Geography* 24: 370–382.

Kelejian HH and Prucha IR (2010) Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics* 157(1): 53–67.

Kissling WD and Carl G (2008) Spatial autocorrelation and the selection of simultaneous autoregressive models. *Global Ecology and Biogeography* 17(1): 59–71.

Koschinsky J (2009) Spatial heterogeneity in spillover effects of assisted and unassisted rental housing. *Journal of Urban Affairs* 31(3): 319–347.

Li W, Joh K, Lee C, et al. (2015) Assessing benefits of neighborhood walkability to single-family property values: a spatial Hedonic study in Austin, Texas. *Journal of Planning Education and Research* 35(4): 471–488.

Lucas K and Jones P (2012) Social impacts and equity issues in transport: an introduction. *Journal of Transport Geography* 21: 1–3.

McMillen DP (2008) Changes in the distribution of house prices over time: structural characteristics, neighborhood, or coefficients? *Journal of Urban Economics* 64(3): 573–589.

Metro S (2024) Sun metro brio | about. In: *Sun Metro*. https://www.sunmetroBrio.net/about.html

Mulley C, Ma L, Clifton G, et al. (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.

Nikitas A and Karlsson M (2015) A worldwide state-of-the-art analysis for bus rapid transit: looking for the success formula. *Journal of Public Transportation* 18(1): 1–33.

Noh Y (2019) Does converting abandoned railways to greenways impact neighboring housing prices? *Landscape and Urban Planning* 183: 157–166.

Noh Y and Li W (2022) Impact of light rail: a spatial-temporal assessment of neighboring residential property values in Los Angeles. *Journal of Planning Education and Research* 44(3): 1634–1649.

Noh Y and Rogers G (2016) Recovery of the value of natural amenities: from oil fields to nature preserve. *Land Use Policy* 57: 11–22.

Noh Y, Kim T and Woo A (2024) Spillover effects of business improvement districts on residential housing values: a focus on the northern region in Los Angeles county California. *International Journal on the Unity of the Sciences* 29: 1–19.

Perk V, Mugharbel M and Catalá M (2010) Impacts of bus rapid transit stations on surrounding single-family home values: study of east busway in Pittsburgh, Pennsylvania. *Transportation Research Record* 2144(1): 72–79.

Realtor.com (2010) Does realtor.com show all listings? https://www.homesteadingtoday.com/threads/does-realtor-com-show-all-listings.341228/

Realtor.com (n.d.) *My Listing Isn'T Appearing on Realtor.Com*. https://support.realtor.com/s/article/What-should-I-do-if-my-listing-isn-t-on-realtor-com

Rosen S (1974) Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy* 82(1): 34–55.

Salon D, Wu J and Shewmake S (2014) Impact of bus rapid transit and metro rail on property values in guangzhou, China. *Transportation Research Record: Journal of the Transportation Research Board* 2452(1): 36–45.

Sohn W, Kim HW, Kim J-H, et al. (2020) The capitalized amenity of green infrastructure in single-family housing values: an application of the spatial hedonic pricing method. *Urban Forestry and Urban Greening* 49: 126643.

Stewart OT, Moudon AV and Saelens BE (2017) The causal effect of bus rapid transit on changes in transit ridership. *Journal of Public Transportation* 20(1): 91–103.

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.

Thomas R and Bertolini L (2014) Beyond the case study dilemma in urban planning: using a meta-matrix to distil critical success factors in transit-oriented development. *Urban Policy and Research* 32(2): 219–237.

U.S. Department of Transportation, Federal Transit Administration. (August 2004). Characteristics of Bus Rapid Transit for Decision-Making (Report No. FTA-VA-26-7222-2004.1). Office of Research, Demonstration, and Innovation.

U.S. Census Bureau (2021) *2020 population and housing state data*. U.S. Department of Commerce. Available at: https://www.census.gov

U.S. Census Bureau (2023) American Community Survey 5-year data (2018–2022). U.S. Department of Commerce. https://www.census.gov/programs-surveys/acs

Venter C, Jennings G, Hidalgo D, et al. (2018) The equity impacts of bus rapid transit: a review of the evidence and implications for sustainable transport. *International Journal of Sustainable Transportation* 12(2): 140–152.

Wirasinghe SC, Kattan L, Rahman MM, et al. (2013) Bus rapid transit – a review. *International Journal on the Unity of the Sciences* 17(1): 1–31.

Woo A and Lee S (2016) Illuminating the impacts of brownfield redevelopments on neighboring housing prices: case of cuyahoga county, Ohio in the US. *Environment and Planning A: Economy and Space* 48(6): 1107–1132.

Yang L, Chau K, Szeto W, et al. (2020) Accessibility to transit, by transit, and property prices: spatially varying relationships. *Transportation Research Part D: Transport and Environment* 85: 102387.

Zhang M and Yen BT (2020) The impact of bus rapid transit (BRT) on land and property values: a meta-analysis. *Land Use Policy* 96: 104684.

Zhang M, Yen BT, Mulley C, et al. (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.

Author biographies

Dr. Youngre Noh is an assistant professor at Texas A&M University. He is also a member of the American Institute of Certified Planners. His work aims to quantify the social equity, environmental, and housing implications of physical planning using large data sources that include longitudinal historical records. His publications include analyzing longitudinal impact of planning decisions on nearby housing values, comparing different methodological measures for spillover effects of physical planning, and examining causality of the spillover effects.

Dr. Hanwool Lee is a post-doctoral research associate at Texas A&M University. His major is urban planning and design. He is interested in measuring/quantifying urban form and other elements of urban environments and their impact on pedestrian behavior. He is especially an expert in the handling of GIS data.

Dr. Yang Song specializes in landscape architecture, community planning, and urban design, focusing on public placemaking's impact on community health and resilience. With a strong interest in digital technology and data science, he applies these tools to study urban space usage and develop human-centered design theories that promote active living and economic resilience. His work has garnered national and international recognition, including the Honor of Research Award from the American Society of Landscape Architects and a Research Excellence Certificate from the Environmental Design and Research Association.

Dr. Chanam Lee, Professor of Landscape Architecture and Urban Planning at Texas A&M University and founding director of Design Research for Active Living (DrAL), specializes in connecting built environments with public health. Her pioneering work in active living research has been crucial for developing theoretical frameworks, focusing on high-risk populations, and translating research into actionable tools for policy and design. Leading 25 funded projects totaling nearly $15 million, she's authored over 100 publications and delivered 300 presentations. Her accolades include awards from the Council of Educators in Landscape Architecture, APHA, and ASLA, and her work influences global urban planning and health-oriented design projects.

Dr. Wei Li, Associate Professor of Urban Planning at Texas A&M University, is recognized for advancing smart mobility in small communities. With over 40 peer-reviewed publications and $3.9 million in NSF and NIH funding, his research connects technological innovation with community needs. As founder of the ENDEAVR Institute, he drives smart-city tech in underserved areas. His teaching has impacted over 300 students across fields, and he has served on more than 110 graduate committees. Dr. Li's achievements have earned him multiple awards, including the prestigious Smart 50 Award.