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Time-dependent associations between accessibility to tram stops, proximity to tram tracks, and property prices: From construction to operation

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ABSTRACT

Research on how accessibility to tram stops and proximity to tram tracks affect property prices has been limited. Additionally, the time-dependent effects of the tram system and its effects at different price levels remain underexplored. This study fills these gaps by analyzing the relationship between Chengdu Tram Line 2 and nearby property prices. Using a before-and-after treatment-control design and a dataset of 33,150 property transactions over six years, it applies multilevel hedonic price, difference-in-differences (DID), and quantile regression models to investigate the association between accessibility to tram stops, proximity to tram tracks, and property prices during various phases (e.g., construction and operation phases). Our findings are listed below. First, the positive influence of accessibility to tram stops only becomes significant during the operation phase. Specifically, property prices within 800 m of tram stops are 1.4 % higher than those farther away. Second, price penalties induced by proximity to tram tracks persist throughout the construction and operation phases. Third, the impact of accessibility to tram stops varies significantly across different price levels. Specifically, buyers of low-priced properties are more willing to pay a premium for accessibility to tram stops, whereas purchasers of high-end properties prefer greater distances from tram tracks to avoid nuisances. The results highlight the time-dependent accessibility benefits and negative externalities linked to tram services. Finally, policy implications, such as measures to alleviate the disturbances caused by tram tracks, are discussed.

1. Introduction

The widespread use of private cars is evident in many countries. While cars provide convenience for personal travel, they also contribute to numerous social and environmental challenges, such as air pollution, traffic congestion, and accidents. These issues present ongoing difficulties for policymakers and urban planners (Ewing & Cervero, 2010). To combat the rising number of car trips and reduce carbon emissions in line with global sustainable development goals (SDGs), many cities and regions are promoting the development of transit systems (Ou et al., 2024; Zhou et al., 2024; Phusakulkajorn et al., 2023; Peng, Fu, Wu, Dai, & Yang, 2025). This focus on transit is increasingly important as decarbonization efforts gain momentum.

Trams, also known as streetcars or trolleys, are rail-based transit modes that operate on tracks embedded in roadways. With a long history of service, trams effectively complement the metro and bus networks of many cities. As a public resource, trams are particularly well-suited for densely populated urban areas, offering substantial economic and social advantages (Prud'homme, Koning, & Kopp, 2011; Wang, Wu, Yao, & Tan, 2023). These benefits include: (1) connecting different parts of the city to enhance mobility and reduce commute times; (2) utilizing clean energy for operations to limit environmental impacts (Kenworthy, 2008); and (3) being less expensive and requiring less land compared to metro systems—trams typically cost one-third of the investment per kilometer. Furthermore, tram networks may stimulate local economies along their routes, improve residents' quality of life, and promote social equity. Currently, tram systems are operated in 310 cities across 50 countries and regions, with a total mileage of 17,073.22 km. These systems are predominantly found in European countries, which account for 75.4 % of the global mileage. Key countries include Germany

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(3562.67 km), Russia (2640.70 km), Ukraine (1388.70 km), France (927.06 km), Poland (977.50 km), and Romania (579.80 km) (Han et al., 2023). Additionally, tram systems can be found in several Asian countries, such as China (646.64 km) and Japan (269.81 km), (Han et al., 2023).

Like many other forms of transit, trams offer residents convenient stop-to-stop services (Yang et al., 2019; Yang et al., 2020). In theory, buyers are willing to pay a premium for properties located near tram stops. Although the effect of accessibility to heavy rail transit (e.g., commuter rail and metro) and bus-based transit (e.g., conventional bus services and bus rapid transit (BRT)) on property values has been extensively explored (Andersson et al., 2010; Debrezion et al., 2007; Efthymiou & Antoniou, 2013; Gupta, Van Nieuwerburgh, & Kontokosta, 2022; Yan, Zhang, & Yang, 2024), research on the effects of accessibility to tram stops (tram accessibility) on property prices (or values) is relatively limited (Chwiałkowski & Zydroń, 2022). Furthermore, proximity to tram tracks can result in negative externalities. Residents living near tram lines may experience nuisances such as noise pollution, unattractive landscapes, and obstruction of railroad tracks. The impact of negative externalities of transit on property prices, including issues related to noises (Baldassare et al., 1979; Diao, Li, Sing, & Zhan, 2023), crime near transit facilities (Bowes & Ihlanfeldt, 2001; Plano, 1993), and sight obstruction (Portnov et al., 2009), are well-documented in various global contexts. However, research on how proximity to tram tracks affects property prices has been limited. In summary, there has been a notable gap in research examining the effects of accessibility to tram stops and proximity to tram tracks on property values in neighborhoods.

The impact of transit on property prices is likely to vary across time (Cao & Lou, 2018; Golub et al., 2012; Trojanek & Gluszak, 2018) and price level (Mathur, 2020; Yang et al., 2020). This raises important questions regarding (1) the timing of tram-related impacts on nearby property values and (2) the extent of these impacts at different price levels. On the one hand, this study aims to explore the timing of price premiums and penalties, addressing questions such as, "When do the price effects of trams occur? Are tram-induced disamenities present after operation?" On the other hand, this study focuses on how accessibility to tram stops and proximity to tram tracks affect properties across various price levels, investigating whether the tram system influences low-priced (low-end) and high-priced (high-end) properties differently. Gaining a deeper understanding of these dynamics can assist transportation planning departments in conducting benefit-cost analyses and determining the optimal timing for value capture (Mulley & Tsai, 2016). Furthermore, these insights can serve as a valuable reference for buyers at different economic levels, enabling them to make informed decisions.

To address these issues, this study analyzes 33,150 property transactions over six years, using a cascade of multilevel hedonic price and difference-in-differences (DID) models. The focus is on the relationship between accessibility to tram stops, proximity to tram tracks, and property prices during different phases (construction and operation), with the first tram line in Chengdu (a national central city in southwest China) as a case study. Additionally, quantile regression models are employed to assess how the impact of trams on property prices varies, revealing that low-priced properties respond to the tram system differently from high-priced ones.

This study makes four significant contributions. First, it focuses on a transit mode that has received limited scholarly attention compared to rail transit, BRT, and conventional bus services. Second, it jointly examines the effects of accessibility to tram stops and proximity to tram tracks (two tram-related variables) on property prices. Third, it investigates the magnitude of the effects of two tram-related variables on property prices across different phases. Lastly, it tests the heterogeneity of the effects on property prices across various price quantiles. This study finds that low-priced homeowners are more willing to pay for properties near tram stops but less willing to pay for locations far from tram tracks, underscoring the varying preferences among various economic groups.

The remainder of this paper is organized as follows: Section 2 introduces Chengdu and its Tram Line 2. Section 3 outlines the data. Section 4 details the methodology applied. Section 5 presents the results. Finally, Section 6 summarizes the findings, discusses policy implications, and outlines future research directions.

2. Chengdu tram line 2 at a glance

Chengdu, the capital of Sichuan Province in southwestern China (Fig. 1), is a vibrant city at the sub-provincial level with a permanent population of 21.40 million (2023 data). In 2023, the city achieved a remarkable annual gross domestic product (GDP) of 2.20 trillion yuan (ranking among the top nine cities on the Chinese mainland), solidifying its status as a key economic hub in southwestern China. It also stands out as a center for education and research, home to numerous respected universities, research institutes, and science parks. Known for fostering technological innovation, Chengdu hosts many tech companies. Additionally, it has a history spanning over 2000 years.

As of the end of 2023, Chengdu Tram Line 2 was the only tram line operating in Chengdu and southwest China and one of the longest line in the country (Hou et al., 2023). This Y-shaped tram line combines trunk and feeder services and employs off-board fare payment. Serving as a complementary transit option, Chengdu Tram Line 2 strategically intersects with four metro lines (Metro Lines 2, 4, 6, and 9) and Chengdu–Dujiangyan Intercity Railway. This integration creates an efficient urban rail transit network that connects two traditional central districts of Chengdu (i.e., Qingyang and Jinniu Districts) with suburban areas such as Pidu District and High-Tech West District (Fig. 1).

Chengdu Tram Line 2 features a dedicated track located in the center of the road (Fig. 2). It has an average travel speed of 23.5 km per hour. The fare for a complete journey is 2 yuan, considerably lower than the metro fare. The minimum headway is 6.75 min. This blend of affordability and convenience makes Chengdu Tram Line 2 an essential transit choice for residents along its established lines. Table 1 presents the performance metrics for Chengdu Tram Line 2 in 2023.

Fig. 3 provides a detailed timeline illustrating the development of Chengdu Tram Line 2. In September 2015, the Chengdu Municipal Development and Reform Commission approved the Chengdu Tram Line 2 project. Construction began in April 2016. The first segment opened to the public in December 2018. After one year of trial service, the entire line became fully operational. By examining different phases, this study provides insights into the evolving relationship between the development of the tram system and the local property market, highlighting the broader implications of this major urban initiative.

3. Data

In recent years, real estate platforms like Lianjia, Beike, and Anjuke have become prominent in China, offering reliable real estate transaction data. These platforms now serve as key resources for real estate research. We collected real estate transaction data from the website of the Lianjia real estate agency (cd.lianjia.com) covering January 2015 to February 2021. Our dataset includes not only transaction prices but also various property attributes (or characteristics), such as type, floor area, geographic coordinates, building height, and decoration status.

We conducted a series of preprocessing steps on the real estate data. First, we focused exclusively on "ordinary residential" properties, excluding types like "villa" and "business apartment." Then, we used Geographic Information System (GIS) tools to calculate each property's linear distance to tram stops and excluded properties outside a 3 km buffer from tram tracks, thereby filtering out properties marginally influenced by the tram system. This distance threshold is consistent with established studies (Chu et al., 2021). To minimize potential interference from metro stations, we also excluded properties within 800 m of these stations. After the above steps, we compiled a robust dataset of 33,150 real estate transactions from January 2015 to February 2021,

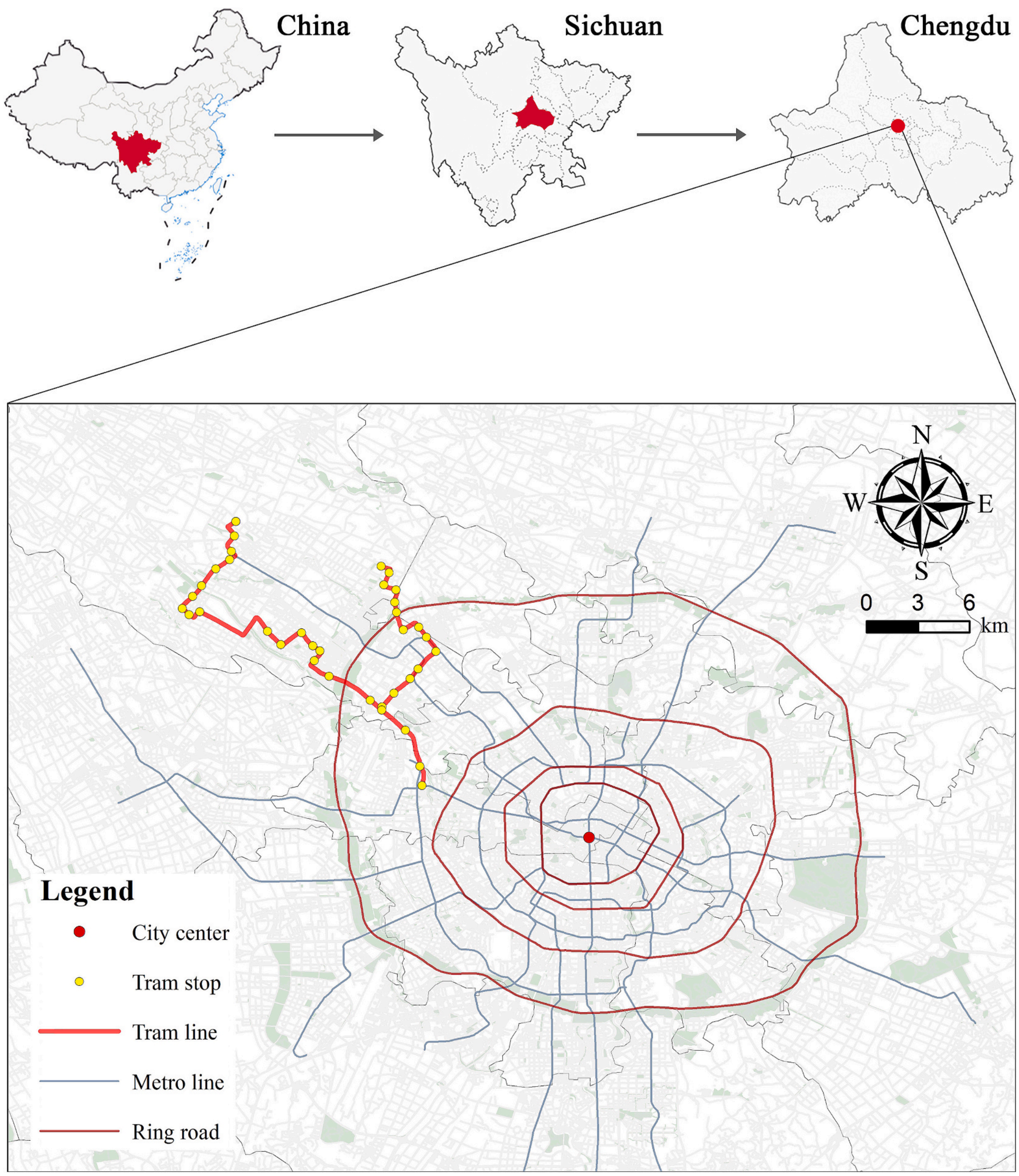

Fig. 1. Location of Chengdu and its Tram Line 2.

providing a strong foundation for further analysis. Fig. 4 illustrates the spatial distribution of these samples.

This study aims to examine how accessibility to tram stops and proximity to tram tracks influence property prices. To enable detailed analysis, we introduced several dummy variables. First, we defined properties within 800 m of tram stops or those within 1000 m of tram tracks as the treatment group, while properties beyond these distances served as the control group. We hypothesized that properties near tram stops have higher values due to accessibility benefits, while those closer to tram tracks could experience nuisance-related price penalties. Additionally, we included several time dummy variables to represent two distinct periods—the tram system's construction and operation phases—and their interaction with the treatment group.

Given the six-year span of real estate transaction data, we adjusted each transaction price based on the Chinese Consumer Price Index (CPI) to account for inflation, following the literature. This adjustment allows us to use the inflation-neutral real estate price as our dependent variable. Independent variables are grouped into control and explanatory variables, with attributes like floor area, building height, and decoration status serving as controls. Table 2 provides a comprehensive overview of all variables, including descriptive and statistical information, establishing a foundational understanding of the dataset used in our analysis.

The main explanatory variables, Stop_800 and Track_1000, assess accessibility to tram stops and proximity to tram tracks, respectively. Moreover, the analysis covers three periods: the pre-construction phase (January 2015 to March 2016), the construction phase (April 2016 to December 2018 for the first opening section, or April 2016 to December 2019 for the rest of the line), and the operation phase (January 2019 or 2020 onward). Two dummy variables are, therefore, created to represent the construction and operation phases. To capture fixed year-quarter effects, we included 25 time dummy variables for each quarter from 2015Q1 to 2021Q1.

4. Methodology

4.1. Hedonic price model

The hedonic price model serves as a powerful and widely employed

Fig. 2. Snapshot of Chengdu Tram Line 2.

method in the realm of economics to assess the value of a product or service based on its inherent attributes (Espinet Rius et al., 2022). This model operates on the premise that the overall value of a product can be deconstructed into the values associated with its attributes. That is to say, rooted in the principle that a product's price is determined by the attributes it possesses, the hedonic price model dissects the various attributes of a product to understand how each component contributes to its overall market value. At its core, the term "hedonic" originates from the Greek word "hēdonē," which means pleasure. The hedonic price model endeavors to quantify the pleasure or utility derived from a

Table 1.
Performance measures of Chengdu Tram Line 2 in 2023.

Performance measures	Value
Annual ridership	12.72 million
Maximum daily ridership	63,100
Operational mileage	39.3 km
Number of tram stops	47
Minimum headway	6.75 min
Maximum travel speed	70 km/h
Average travel speed	23.5 km/h
Traction energy consumption	0.77 kWh/vehicle-km
Track gauge	1435 mm

product's various attributes. In doing so, it deconstructs the product into its constituent features, assigning values to each feature based on their impact on desirability.

In the realm of real estate economics and valuation, the hedonic price model stands as a fundamental tool and cornerstone (An et al., 2024; Tsai, 2024). It provides a robust framework for appraising the worth of residential and commercial properties. It untangles the intricacies embedded in property pricing, elucidating that the value of a property is a composite of its various attributes, such as gross floor area, age, and regional accessibility. By dissecting the multifaceted attributes contributing to the perceived value of a property, the hedonic approach equips researchers, policymakers, and market participants with a nuanced understanding of real estate dynamics. Its versatility and analytical depth make it indispensable for unraveling the complex relationships between property attributes and market values. In this study, the hedonic price model emerges as a valuable instrument, adept at elucidating how the presence of a tram system influences property prices in the surrounding area.

Typically estimated through regression analysis, the hedonic price model designates the value of a property as the dependent variable (i.e., response or predicted variable), while its various attributes serve as independent variables (i.e., predictors), offering a quantitative understanding of their respective impacts. The coefficients of these independent variables signify the impact of each attribute on the overall value of the property. The hedonic price model has three basic forms (Yang et al., 2023), as outlined below.

Linear model:

$$\mathrm{P_i} = \beta_0 + \sum_{n=1}^{N} \beta_n \mathrm{X_{in}} + \varepsilon_i$$

Semi-log model:

$$\mathrm{LnP_i} = \beta_0 + \sum_{n=1}^{N} \beta_n \mathrm{X_{in}} + \varepsilon_i$$

Double-log model:

$$\mathrm{LnP_i} = \beta_0 + \sum_{n=1}^{N} \beta_n \mathrm{LnX_{in}} + \varepsilon_i$$

where P_i represents the transaction price of property i, β_0 denotes a constant term, X_{in} signifies the n-th hedonic variable for property i, β_n is the coefficient of the n-th hedonic variable (X_{in}), N is the number of hedonic variables, and ε_i is the error term.

In the conventional hedonic price model, predictors are considered at a single level. However, in China, properties are often grouped or nested within gated communities (or residential districts). It is, therefore, imperative to adopt the multilevel hedonic price model, as outlined below.

Multilevel linear model:

$$\mathrm{P_{ij}} = \beta_0 + \sum_{n=1}^{N} \beta_n \mathrm{X_{ijn}} + \mu_j + \varepsilon_{ij}$$

Multilevel semi-log model:

$$\mathrm{LnP_{ij}} = \beta_0 + \sum_{n=1}^{N} \beta_n \mathrm{X_{ijn}} + \mu_j + \varepsilon_{ij}$$

Multilevel double-log model:

$$\mathrm{LnP_{ij}} = \beta_0 + \sum_{n=1}^{N} \beta_n \mathrm{LnX_{ijn}} + \mu_j + \varepsilon_{ij}$$

where P_{ij} is the price of property i in residential district j, β_0 represents a constant term, X_{ijn} signifies the n-th hedonic variable, β_n stands for the coefficient of the n-th hedonic variable, N represents the number of hedonic variables, μ_j is the random intercept, and ε_{ij} is the error term.

4.2. DID model

The DID model is a statistical technique widely used in econometrics and social sciences to estimate causal effects in observational studies (Cao & Lou, 2018; Liang, Yu, Zhang, Lu, & Yang, 2023). It addresses the challenge of identifying causal relationships when randomization is impossible, such as in the case of policy changes or interventions. The fundamental idea behind DID is to compare the changes in outcomes over time between a treatment group that experiences a policy change and a control group that does not. By considering the differences in outcomes between the two groups before and after treatment, the DID model aims to isolate the causal impact of treatment from other confounders. An assumption of the DID model is the parallel trends assumption. If it holds, deviations from parallel trends after treatment can be attributed to the causal effect of treatment.

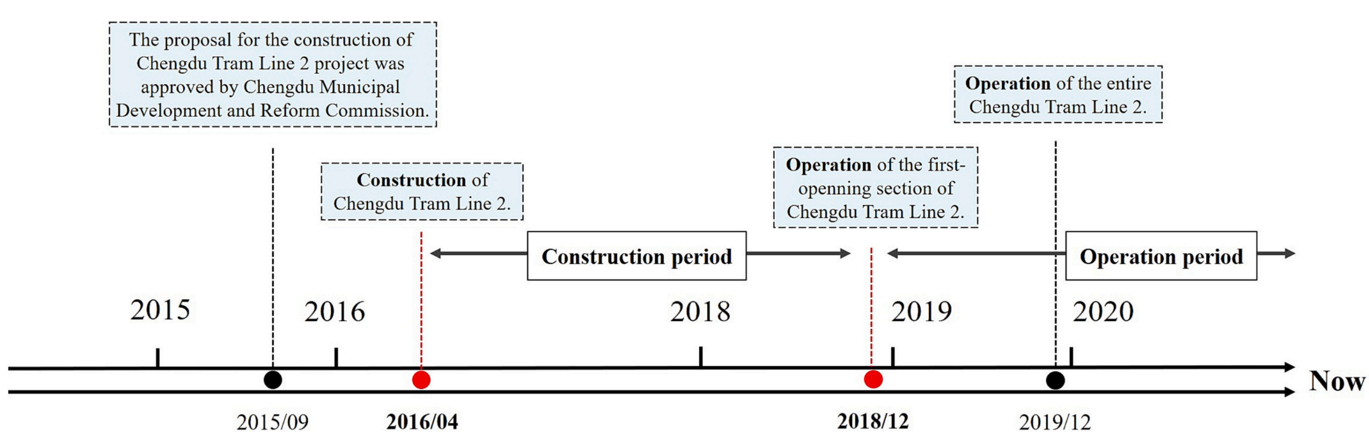

Fig. 3. The timeline of the development of Chengdu Tram Line 2.

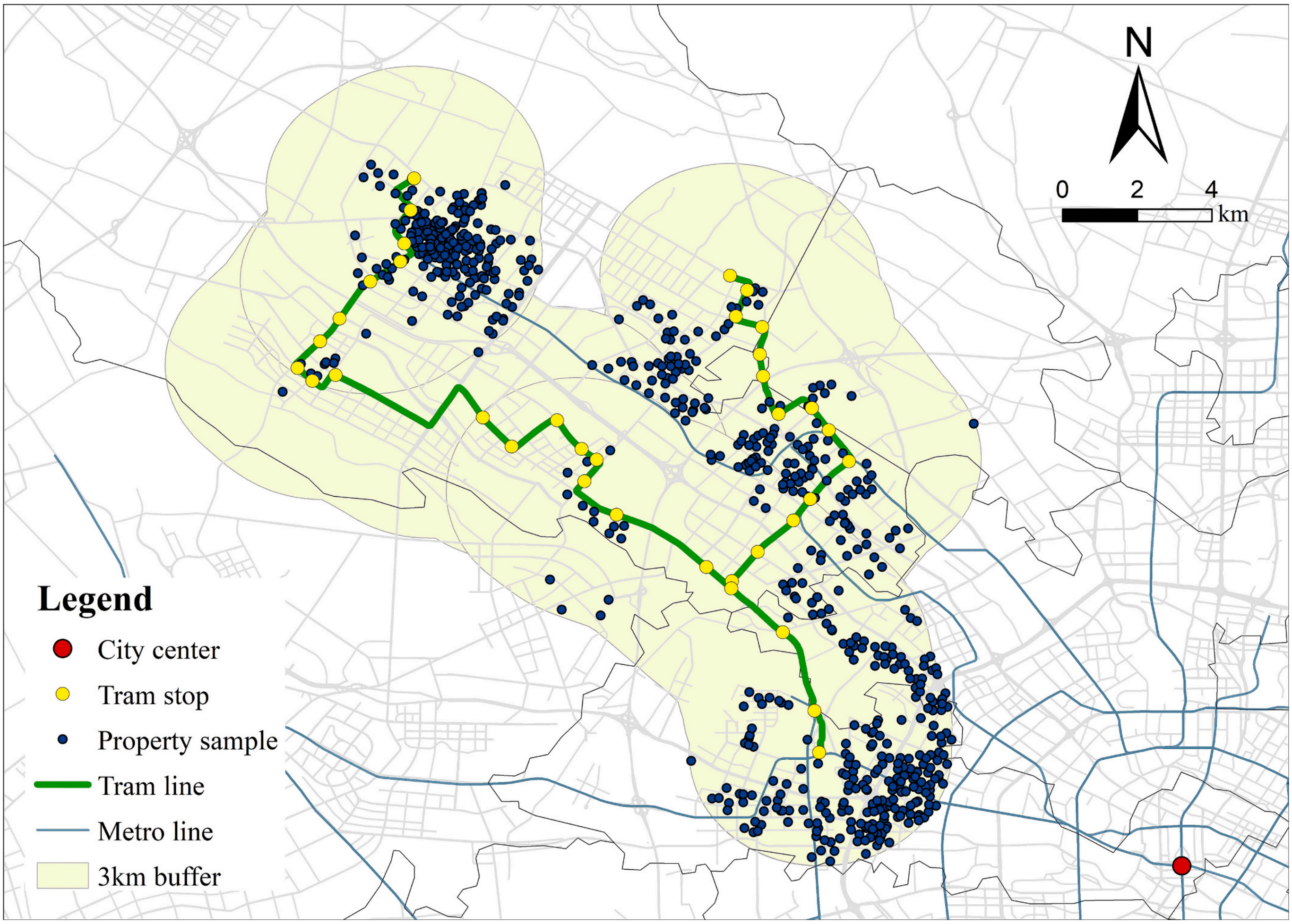

Fig. 4. The spatial distribution of property samples.

To implement the DID model, researchers typically collect data on both the treatment and control groups before and after treatment. The difference in outcomes between the treatment and control groups is calculated before treatment (pretreatment period) and after treatment (post-treatment period). The DID estimator is then obtained. It provides an unbiased assessment of the causal effect of treatment under the parallel trends assumption, offering researchers a valuable tool for causal inference in observational studies.

4.3. Quantile regression model

Quantile regression, an extension of conventional linear regression, offers a nuanced perspective on modeling relationships between variables by focusing on different percentiles of the dependent variable. While conventional linear regression examines the mean or expected value of the dependent variable, quantile regression enables an enhanced understanding of the conditional distribution and captures variations across the entire spectrum. In quantile regression, the emphasis shifts from predicting the average or central tendency to analyzing the conditional quantiles of the dependent variable. This is particularly valuable when dealing with datasets that exhibit heteroscedasticity or asymmetry, situations where conventional linear regression may fall short. By estimating the coefficients at various quantiles, quantile regression provides a more robust characterization of the relationship between the predictors and different segments of the dependent variable's distribution. A distinct advantage of quantile regression is its ability to accommodate outliers and extreme values. Conventional linear regression models are highly sensitive to these influential points, potentially skewing the results. Quantile regression, however, offers a better approach by considering the spread of the dependent variable at different quantiles, making it especially suitable for datasets with non-normal distributions. In summary, quantile regression offers a flexible and insightful framework for analyzing the conditional distribution of the dependent variable. By embracing a broader perspective that considers various quantiles, this approach improves the analytical toolkit, particularly when faced with complex datasets that exhibit various patterns and attributes.

The interpretation of quantile regression coefficients is intuitive. For example, the coefficient estimated at the median quantile reflects the typical relationship between the predictor and the dependent variable, while the coefficients at other quantiles reveal this relationship varies across the distribution. This adaptability makes quantile regression a valuable tool in fields such as finance, economics, and epidemiology, where understanding the impact of predictors at different points of a distribution is crucial.

The formula for the quantile regression model can be expressed as follows:

$$P_i = \beta_{0q} + \sum_{n=1}^{N} \beta_{nq} X_{in} + \varepsilon_i$$

where β_{0q} represents a constant term, β_{nq} is the coefficient of the n-th variable associated with the q-th quantile, and other variables retain their previously defined meanings.

The model seeks to estimate the quantile-specific coefficients β_q by minimizing the following function:

Table 2.
Description and summary of the variables. ($N = 33{,}150$).

Variables	Description	Unit	Mean	Std. Dev
Dependent variable				
Price	Transaction price adjusted (or deflated) by CPI	10^4 yuan	101.1	56.64
Control variables				
Floor area	Gross floor area	m^2	88.93	28.42
Living room3+	1 if having 3 or more living rooms and 0 otherwise		0.003	–
Bedroom3	1 for a property with 3 bedrooms and 0 otherwise		0.433	–
Bedroom4+	1 for a property with 4 or more bedrooms and 0 otherwise		0.077	–
Intermediate floor	1 for a property on the intermediate floor and 0 otherwise		0.370	–
High floor	1 for a property on the high floor and 0 otherwise		0.347	–
Building height	The total floor of the building		22.24	8.35
Elevator	1 if equipped with elevators and 0 otherwise		0.920	–
Decoration	1 if finely decorated and 0 otherwise		0.339	–
Explanatory variables				
Stop_800	1 for a property located within 800 m of tram stops and 0 otherwise		0.151	–
Track_1000	1 for a property located within 1000 m of tram tracks and 0 otherwise		0.223	–
Construction	1 for a property transacted during the construction phase and 0 otherwise		0.403	
Operation	1 for a property transacted during the operation period and 0 otherwise		0.289	

$$\widehat{\beta}_q = \operatorname{argmin}\left[\sum_{\varepsilon_i \geq 0} q\varepsilon_i - \sum_{\varepsilon_i < 0} (1-q)\varepsilon_i\right]$$

Different quantiles correspond to different coefficient and constant-term estimates. Therefore, the quantile regression model allows for a flexible examination of the conditional distribution of the dependent variable, providing information on the impact of the predictors at different points of the distribution. This feature makes it a valuable tool in scenarios where conventional mean-based regression approaches may not capture the full complexity of the relationship between variables.

5. Results

5.1. *Hedonic price modeling: revealing the time-invariant price effects of the tram system*

After evaluating alternative basic functional forms, including linear and semi-log models, we chose a double-log model for our analysis. This model demonstrated superior performance, as indicated by its higher adjusted R^2 and lower AIC and BIC values, effectively capturing the patterns in the data. In this double-log model, dummy variables are retained in their original form. To track property price trends over time, we incorporated 24 time dummies (using 2015Q1 as the baseline), enhancing the model's precision.

Table 3 presents the results of multilevel double-log models. Model 1 provides a baseline analysis, focusing solely on control variables without considering the tram system's influence. Building on this, Model 2 incorporates the two main variables of interest—Stop_800 and Track_1000—to assess the tram system's impact on property prices. In this sub-section, we did not distinguish between the three development phases (pre-construction, construction, and operation), aiming to understand the overall, time-invariant effects of the tram system on property values.

Table 3.
Hedonic modeling results to test the time-invariant effects of the tram system.

Variables	Model 1		Model 2		
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	VIF
Floor area	0.963***	246.41	0.963***	246.38	1.91
Living room3+	0.079***	6.51	0.079***	6.50	1.03
Bedroom3	0.051***	26.77	0.051***	26.76	1.64
Bedroom4+	0.062***	17.88	0.062***	17.87	1.64
Intermediate floor	0.006***	3.76	0.006***	3.75	1.46
High floor	0.001	0.90	0.001	0.90	1.46
Building height	0.003	0.70	0.003	0.71	2.22
Elevator	0.063***	9.83	0.064***	9.88	2.11
Decoration	0.069***	45.57	0.069***	45.56	1.23
Stop_800	–	–	−0.018	−0.32	2.66
Track_1000	–	–	−0.251***	−4.84	2.70
Time dummies	Yes		Yes		–
Constant	−0.658***	−23.26	−0.568***	−19.26	–
Random effects					
Variance (Residential district)	Estimate	95 % confidence interval	Estimate	95 % confidence interval	
	0.193	[0.172, 0.218]	0.166	[0.147, 0.187]	
Performance statistics					
AIC	−47,698.84		−47,761.09		
BIC	−47,396.12		−47,441.56		

Note: *** Significant at the 1 % level. ** Significant at the 5 % level. * Significant at the 10 % level.

The results from Model 1 illustrate the impact of control variables on property prices. Nearly all control variables are significant at the 1 % level, and their coefficient signs and magnitudes align with our expectations. Moreover, the *z*-statistic for Floor area (246.41) is particularly noteworthy, highlighting its crucial role as the most significant factor affecting property prices. Additionally, having more living rooms and bedrooms positively influences property values. The presence of an elevator is linked to a 6.3 % increase in property value, indicating its importance in price determination. Furthermore, properties located on intermediate floors tend to command higher prices than those on lower or higher floors, consistent with findings in the Chengdu property market literature (Yang et al., 2022; Yang et al., 2023). Lastly, the height of the building shows a weak association with property prices.

In comparison to Model 1, Model 2 demonstrates lower AIC and BIC values, indicating its higher quality for our data. Notably, the variable Stop_800 is statistically insignificant, suggesting that accessibility to tram stops is too weak to decisively influence property prices. In contrast, the coefficient of Track_1000 is negative and significant at the 1 % level, indicating that properties within 1 km of tram tracks tend to have lower prices than those located further away. This observation aligns with existing literature highlighting the negative externalities associated with transit (Ahlfeldt et al., 2019; Chica-Olmo et al., 2019; Diao, Li, Sing, & Zhan, 2023). We suspected that the negative impact of living near tram tracks stems from (1) unattractive landscapes along the tram line, (2) disrupted street connectivity, and (3) noise pollution generated during tram operations.

5.2. DID modeling: presenting the time-dependent price effects of the tram system

To capture the time-dependent effects of the tram system on property prices, we introduced interaction terms between two time dummies representing the construction and operation phases and the tram-related variables into Model 2 and developed a DID model. The Construction and Operation dummies are not directly included in the DID model because they are nearly linear combinations of the quarterly dummies. Table 4 presents the DID modeling results.

A key focus is the performance of the interaction terms. Both Stop_800 and Stop_800 × Construction are statistically insignificant. The statistical insignificance of the interaction term Stop_800 × Construction can be attributed to two main factors. First, there are no anticipation effects prior to the tram's opening. Second, any potential anticipation effects could be negated by substantial disturbances experienced during the construction phase, such as noise and air pollution. Moreover, the interaction term Stop_800 × Operation is statistically significant, with a positive coefficient of 0.014. This observation indicates that the impact of accessibility to tram stops becomes significant only during the operation phase. Specifically, property prices within 800 m of tram stops increased by 1.4 % following the start of tram operations. This finding provides strong evidence that the commencement of tram operations positively influences the prices of nearby properties, highlighting the tram system's positive effect on local property values.

The interaction terms Track_1000 × Construction and Track_1000 × Operation are both significant at the 1 % level, with similar negative coefficients of −0.016 and −0.017, respectively. This result underscores the nuisances of living near tram tracks. During the construction phase, traffic control at the site can disrupt residents' daily travel, while environmental pollution (e.g., air and noise pollution) from construction activities may significantly influence homebuyers' property choices. Once the tram is operational, the ongoing presence of tram tracks and unattractive surroundings further detracts from the quality of life for nearby residents, prompting them to prefer homes further away from tram tracks. Overall, these factors illustrate the complex challenges associated with tram-related activities, from temporary inconveniences during construction to lasting noise and landscape issues during operations. Such challenges can have a significant impact on the property preferences and choices of potential residents in the area.

Table 4.
DID modeling results to test the time-dependent price effects of the tram system.

Variables	DID model	
	Coefficient	z-statistic
Floor area	0.963***	246.50
Living room3+	0.079***	6.51
Bedroom3	0.051***	26.74
Bedroom4+	0.062***	17.89
Intermediate floor	0.006***	3.76
High floor	0.001	0.88
Building height	0.003	0.68
Elevator	0.064***	9.87
Decoration	0.069***	45.60
Stop_800	−0.022	−0.39
Track_1000	−0.240***	−4.60
Stop_800 × Construction	−0.007	−0.93
Stop_800 × Operation	0.014*	1.93
Track_1000 × Construction	−0.016***	−2.60
Track_1000 × Operation	−0.017***	−2.70
Time dummies	Yes	
Constant	−0.570***	−19.30
Random effects		
Variance(Residential district)	Estimate	95 % confidence interval
	0.166	[0.147, 0.187]
Performance statistics		
AIC	−47,790.88	
BIC	−47,437.71	

Note: *** Significant at the 1 % level. ** Significant at the 5 % level. * Significant at the 10 % level.

5.3. Quantile regression: comparing the effects of the tram system across the distribution of prices

We developed a series of quantile regression models to assess the impacts of accessibility to tram stops and proximity to tram tracks on property prices across the distribution of prices, with the results detailed in Table 5. This quantile regression analysis reveals differences across various quartiles, highlighting the nuanced effects of the tram system.

The tram accessibility variable is statistically significant at the 1 % level in all models. It has a positive price effect for low-priced properties (at the 0.05 and 0.10 quantiles) and a negative effect for high-priced properties (at the 0.50, 0.90, and 0.95 quantiles). These findings suggest that tram accessibility positively influences the prices of low-priced properties, as buyers in lower income brackets are more likely to seek homes near tram stops for added convenience. In contrast, its negative correlation with high-priced properties indicates that wealthier residents, who generally have more transportation options, tend to choose homes farther from tram stops to avoid potential disturbances.

Additionally, Track_1000 shows a negative relationship with prices for high-priced properties while having minimal impact on low-priced properties. High-priced properties within 1 km of tram tracks sell at a discount of 7.8 % to 12.3 % compared to those farther away, suggesting that buyers of high-priced properties prefer to live at a distance from tram tracks to avoid potential disturbances. In contrast, residents in lower income brackets seem less affected by such factors. This analysis provides valuable insights into the differing considerations affecting property choices across economic strata regarding tram accessibility and proximity to tram tracks.

6. Conclusions

The implementation of transit systems is essential for achieving sustainable development in response to growing traffic pressures and worsening environmental conditions (Bao, Ou, Chen, & Wang, 2022; Wu, Yao, & Wang, 2023; He et al., 2022). While trams are widely used, limited research has focused on their effects on property prices—particularly regarding how the timing of tram accessibility and proximity to tram tracks impacts these prices, as well as how these effects differ across different property price levels. This study develops a series of multilevel hedonic price, DID, and quantile regression models to analyze the influence of tram accessibility and proximity to tram tracks on property prices in Chengdu, China. We incorporated two time dummies (i.e., Construction and Operation) to capture the time-dependent effects on property prices. Additionally, we examined how these effects vary across different property price levels.

Using real estate transaction data spanning six years, we revealed key insights: (1) accessibility benefits only appear during the tram's operation phase; (2) proximity-related penalties persist across both construction and operation; and (3) tram impacts differ across property price levels. Specifically, low-priced property buyers are more willing to pay for tram accessibility, whereas high-priced property buyers tend to avoid proximity to tram tracks to minimize potential nuisances. These findings highlight the nuanced ways in which tram accessibility and proximity to tram tracks influence property preferences across economic strata.

In China, governments often prioritize rail transit (e.g., metro) projects to stimulate comprehensive urban development and use transit-oriented development (TOD) models (Wu et al., 2024). This approach has seen notable success in cities like Hong Kong and Shenzhen, where "heavy" transit systems such as metros predominate. However, the applicability of "light" transit systems such as trams and their potential

Table 5.
Quantile regression results to compare the effects of the tram system across the distribution of prices.

Variables	0.05 quantile		0.10 quantile		0.5 quantile (median)		0.90 quantile		0.95 quantile	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	t-statistic	Coefficient	*t*-statistic
Stop_800	0.019***	2.94	0.023**	2.38	−0.096***	−9.34	−0.176***	−14.31	−0.045**	−2.46
Track_1000	−0.014	−1.62	−0.047	−4.55	−0.078***	−8.64	−0.123***	−17.99	−0.114***	−12.43
Performance statistics										
Pseudo R^2	0.486		0.456		0.363		0.379		0.415	

Note: *** Significant at the 1 % level. ** Significant at the 5 % level. * Significant at the 10 % level. The control variables used remain consistent with those in Model 2.

to significantly boost land and property values remains uncertain. Our findings suggest that tram accessibility does enhance surrounding property values, but only after the tram system becomes operational. During the construction phase, the accessibility effect is minimal, with limited public interest in the forthcoming tram system.

Existing literature often suggests that "light" transit options, like trams and BRT, tend to have smaller impacts on nearby property values than heavy rail systems. Our study still identifies positive price effects of the tram system, signaling that the tram provides accessibility benefits to a broader population. We recommend a forward-looking policy approach to sustain tram system growth, involving careful consideration of land use policies, zoning, and investment strategies. By fostering sustainable and equitable development, policymakers can maximize the advantages of tram systems, ensuring that they are widely accessible and that communities are well-prepared for the transformations that accompany new transit infrastructure. Moreover, investments in rail-based transit, such as metro and tram systems, often entail substantial expenditures, making it insufficient to rely solely on direct revenues, such as passenger fares (ticket fees), to bridge the funding gap for construction and operation. Many Chinese cities, including Beijing, Hangzhou, Chongqing, and Chengdu, report annual net losses from rail transit operations, with only a few exceptions, such as Hong Kong. In addition to financial subsidies from the central government, local governments need to secure loans from banks to repay economic debts from rail-based transit. Developed countries in Europe and the United States often capture the benefits of rail transit through various taxation methods, including property tax, land tax, betterment tax, and value-added tax. However, in China, institutional differences have led the government to prioritize accessibility improvements over profitability in rail transit investments. While this approach enhances accessibility and often increases property values along transit routes, it also exacerbates fiscal deficits. To address this challenge, the introduction of policies and regulations that allow city governments to recover at least part of the infrastructure investment costs (value capture) is needed. Such measures could restructure the fiscal system and alleviate the financial burden on governments. Last, as revealed previously, given that the property value uplift from the tram system varies with time, city governments can use dynamic value capture measures.

This study identifies neighborhood disruptions and negative externalities associated with proximity to tram tracks, which may stem from noise pollution, reduced street connectivity, and visual impacts. To mitigate these issues, targeted interventions are proposed. Installing noise barriers and using materials that minimize wheel-rail noise can effectively address noise pollution (Diao, Li, Sing, & Zhan, 2023). Additionally, increasing the number of crossings and adding underground passages would improve connectivity, which eases pedestrian movement across tram lines. Finally, the tram's modest operating speed may deter some passengers, leading them to opt for alternative transport modes. Transport authorities should consider adjusting tram routes and speeds to enhance efficiency and increase the tram's appeal as a preferred transit option.

This study has some limitations. First, transit projects often encompass phases like network planning and construction approvals, which can also impact property prices. However, these earlier phases were not included here due to data limitations. Second, we analyzed heterogeneity in price level and time but not in spatial dimensions. Since Chengdu Tram Line 2 includes both trunk and feeder lines, potential variations in the impact of each line segment on property prices warrant further exploration for a more thorough understanding. Finally, we identified price penalties related to proximity to tram tracks. However, the modeling results do not allow us to ascertain the specific causes or sources of these price penalties (unattractive landscapes along the tram line? disrupted street connectivity? noise pollution generated during tram operations?). Further analysis is indispensable, provided that sufficient data and good research designs are available.

CRediT authorship contribution statement

Linchuan Yang: Writing – review & editing, Writing – original draft, Methodology, Conceptualization, Funding acquisition. **Senke Bi:** Writing – review & editing, Writing – original draft, Software, Investigation, Visualization. **Ya Zhao:** Writing – review & editing, Methodology. **Yuan Liang:** Methodology, Data curation, Writing – review & editing. **Ruoyu Wang:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization, Project administration.

Declaration of competing interest

None.

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Data availability

The authors do not have permission to share data.

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