

Article

Do New Light Rail Stations Enhance Property Values in Mature Cities? Evidence from UK Cities

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Abstract

With the growing focus on sustainable development, light rail transit (LRT) systems are increasingly viewed as key drivers of low-carbon mobility and spatial equity. However, as urban spatial structures become more stable, it remains unclear whether LRT systems can still enhance quality of life, property values and contribute to inclusive urban regeneration. This study explores Manchester, Sheffield, and Nottingham, three UK cities with recent LRT development experience, as case studies. Using LRT constructed or expanded between 1995 and 2019 as a quasi-natural experiment, a difference-in-differences (DID) model is applied to estimate the causal impact of LRT expansion on property prices. The results indicate that LRT construction can lead to a 4.44% to 8.29% increase in nearby property values, with a lagged effect observed after implementation. The impact is more pronounced in areas with well-developed bus networks and in lower-income areas. Further mechanism analysis suggests that the effect is indirectly driven by improved accessibility and enhanced convenience of access to local amenities.

Keywords: light rail transit; property values; difference-in-differences; sustainable urban development; quasi-natural experiment; MSOA



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1. Introduction

Sustainability and social inclusion have increasingly become central concerns in urban land-use and transport planning [1]. The United Nations Sustainable Development Goals (SDGs) [2] emphasise the importance of building resilient and sustainable communities and infrastructure, fostering industrial innovation, and promoting sustainable development. Among these, urban transportation infrastructure, particularly light rail transit (LRT) systems, plays a pivotal role in improving air quality [3], reducing greenhouse gas emissions [4], alongside driving urban regeneration and economic revitalisation. As a catalyst for spatial restructuring, the planning and development of LRT systems are closely linked to land value dynamics [5,6].

Over the past few decades, governments and planners have increasingly justified LRT investments not merely based on improving mobility, but also for their broader economic, social, and environmental benefits [7,8]. For example, cities such as New York in the United States and Calgary in Canada [9,10], as well as Greater Kuala Lumpur in Malaysia and Seoul in South Korea [11,12], have witnessed rising property values and rental prices following the expansion of their LRT systems. From the perspective of transit-oriented development (TOD), these projects not only generate economic benefits for residents and nearby communities, but also improve living conditions, stimulate commercial activities,

and enhance urban livability [10,13]. These international experiences demonstrate that LRT systems not only improve urban accessibility but also play an essential role in advancing the achievement of the SDGs.

In this global context, it remains uncertain whether continued public transport investment can still generate inclusive economic benefits and mitigate spatial inequality in mature urban settings. In a highly urbanised and mature economy like the United Kingdom, light rail is not only a solution to reduce congestion but also a strategic instrument to promote regional renewal and optimise land use patterns [14]. In addition to these economic and spatial benefits, LRT is also promoted in policy discourse to support environmental sustainability and equitable urban access [15], further justifying its continued expansion in mature cities.

More specifically, the UK, as a historically growing and densely urbanised country, gives a valuable background to examine whether modern transport interventions can rebuild developed urban structures and reshape land markets. The British railway system originated during the 19th-Century railway revolution. The proliferation of steam locomotives during the Industrial Revolution led to the rapid expansion of a nationwide network. After the nationalisation of the railway system in 1948, the UK rail network experienced a period of contraction and aging [16]. However, by the 1990s, the UK began to shift towards light rail systems as a more cost-effective transportation solution for urban areas [8]. The completion of Manchester Metrolink in 1992 marked the re-emergence of modern light rail. By converting existing rail lines and integrating urban transit, Metrolink became the first modern LRT system in the UK [17]. Subsequently, cities like Birmingham (2003) and Nottingham (2004) adopted similar systems, forming regionally coordinated solutions [18]. Today, the UK has seven LRT networks serving major cities such as Manchester and Nottingham. Building on its long-standing tradition of infrastructure planning, the UK also promotes integrated mobility and land development through policy frameworks such as the National Model Design Code [19], which requires local authorities to improve accessibility, land-use mix, and land value enhancement in planning.

While the broader impacts of LRT systems can be observed through changes in urban structure and regional regeneration, variations in surrounding property values, as one of the main channels through which TOD generates economic benefits for residents and nearby communities, more directly reflect their market and economic impacts [10]. The significance of examining property prices lies in the fact that fluctuations in real estate values are often regarded as market responses to improvements in accessibility, provision of amenities, and the enhancement of regional vitality [12]. On the one hand, rising property prices can be interpreted as a positive signal indicating that rail transit is fostering regional or urban attractiveness [20]. Some scholars argue that increasing house prices may reduce income inequality, leading to improved outcomes in the social and economic pillars of sustainability [21]. On the other hand, others regard it as an indirect indicator of urban gentrification [22]. Therefore, examining whether and how rail transit influences property prices is not only relevant for assessing the economic returns on infrastructure investments, but also for balancing spatial equity and broader sustainability policy objectives in urban development.

Despite the growing body of research on the economic effects of rail transit, however, several critical research gaps remain. First, most existing studies are limited to single-city or single transport intervention (e.g., study of Kelana Jaya Line LRT system and Seoul Metro Line 9) [12,23] analyses or urban areas with specific spatial and institutional background. This limitation undermines the generalisability and comparative validity of cross-city analyses. Second, most existing studies focus on short-term effects [10,12], with limited exploration of whether these impacts persist or diminish after adjustments in land markets and urban structures.

While existing studies provide valuable insights into transit-induced land value changes, the long-term and cross-city evidence remains insufficient. In mature economies such as the United Kingdom where urban structures and land markets are already well established, it remains unclear whether new or expanded LRT systems can still reshape property markets and support sustainable urban regeneration.

To address these knowledge gaps, this study focuses on three key research questions:

- (1) To what extent do new or expanded LRT systems influence surrounding property values in mature urban contexts such as the UK?
- (2) Through which mechanisms do LRT investments foster sustainable and inclusive urban regeneration?
- (3) How do these impacts vary across societies with different socio-economic and infrastructural characteristics?

To verify whether LRT systems still possess such transformative potential in mature urban areas and to address the temporal and spatial limitations of previous studies, this research adopts a comparative multi-city approach to assess how light rail development influences property values. The UK offers an ideal empirical context, with consistent institutional frameworks and available data on transport and property values. This study selects three representative cities, Manchester, Sheffield, and Nottingham, that have new or extended LRT systems in recent years. These cities not only share common experience with light rail development, but also exhibit diverse policy settings, spatial configurations, and planning strategies so that can make them fit for comparative analysis of heterogeneous LRT impacts.

Building on this rationale, this study treats the construction and expansion of LRT systems between 1995 and 2019 as a quasi-natural experiment and employ a difference-in-differences (DID) approach to quantify the causal relationship between LRT interventions and surrounding property values.

The research contributes to transport research in two main ways. Firstly, it introduces the use of MSOAs as a finer spatial unit of analysis for land transaction values, allowing a more granular and detailed examination of the impacts of LRT on urban spatial structure. Previous studies largely focused on city-level effects [24,25] or on spatial proximity to rail infrastructure [5,26], lacking detailed analysis at finer spatial scales. This approach overcomes the limitations of coarse geographic units, like administrative boundaries, and provides a new path for understanding the linear relationship between transit infrastructure and localised land markets.

Second, the study deepens understanding of LRT-related economic externalities in the UK. While earlier research has shed light on LRT effects, much of it focuses on London or projects from the early 2000s [5,27]. Analyses of newer or extended LRT systems in other regions have received little attention. By evaluating multiple cities with post-1995 LRT investments, this study offers systematic evidence on long-term property value impacts and reveals heterogeneous outcomes across urban contexts. The findings also provide empirical insights for policymakers how transit investments influence property markets and reflect spatial and economic transformations across diverse urban environments.

2. Literature Review

2.1. Previous Research

This section reviews the existing empirical evidence on how LRT systems influence sustainable urban development, and land and property values across different contexts, summarising global findings to identify key research gaps.

The economic impact of transportation infrastructure on land value is a central topic in urban economics and transport planning [28]. Land value is largely determined by accessibility, and rail transit increases land premiums by reducing commuting costs and

enhancing locational advantages [29]. If people are willing to pay for transport convenience, quality schools, and liveable neighbourhoods, then the value of these amenities should be capitalised into land values. When accessibility advantages are recognised and capitalised by the market, such value appreciation is eventually reflected in the prices of residential or commercial properties [30].

In property value research, the determinants of real estate value are typically categorised into three groups: physical attributes, accessibility, and environmental characteristics. The combined value of these features constitutes the total value of a property. Among these, transportation accessibility, particularly rail accessibility, has gained increasing attention from scholars [31]. As economies grow and rail systems become more widespread globally, more scholars in different regions have followed this research area. For example, Cervero & Landis (1993) [32] compared office submarkets near transit stations in Washington, D.C., and Atlanta with those in highway-oriented areas, and found that offices near stations had slightly higher rents than their competitors. Tan et al., (2019) [33] drew similar conclusions in their study of Wuhan, China, noting not only a rise in property prices near stations but also population growth and land-use redevelopment in those areas. Transit generally exhibits a positive capitalisation effect on land and property values near stations, with the effect diminishing as distance increases [31]. More recently, Zhang (2023) [34] differentiated between land and property value in the context of Australia's Gold Coast light rail system, revealing that public transport investments could positively impact property value while having a negative effect on land value. Differences in urban maturity, planning context, and data scale often lead to mixed or insignificant results across regions, indicating that the relationship between rail transit and land value remains context-dependent. Nevertheless, recent global events such as the COVID-19 pandemic have altered travel behaviors and challenged the traditional relationship between public transport and housing prices. Several studies [35,36] have shown that the impact of metro accessibility on housing prices slightly declined during the pandemic, mainly due to travel restrictions and the widespread adoption of remote working. However, in the long term, as urban activities recover and travel demand increases, transport accessibility continues to be regarded as an important determinant shaping the spatial distribution of real estate markets.

2.2. UK Context

In the UK, most studies on light rail focus on projects developed in the early 2000s. Song et al. (2019) [5], for instance, examined the Docklands Light Railway (DLR) in London and found that residential properties within the station areas experienced premiums of 0.352% and 0.093% per 100 metres of proximity to the southeast and north branches, respectively. This finding aligns with Gibbons & Machin (2005) [27], who showed that the impact of London's underground system on property prices was even greater than many traditionally important amenities such as schools or parks. However, earlier research on the Tyne and Wear Metro [37] showed inconsistent results that some lines were associated with rising prices, while others showed declines. In a short-term study, Du & Mulley (2007) [38] found no significant price increase associated with the system's extension [28]. These studies reveal clear heterogeneity in both spatial and temporal dimensions. Yet, as British cities become more mature, existing studies tend to rely on static frameworks, often overlooking the long-term dynamics of urban development. However, these positive effects are not universal.

Nevertheless, recent global events such as the COVID-19 pandemic have altered travel behaviour and challenged the traditional relationship between public transport and housing prices. Several studies [35,36] have shown that the impact of metro accessibility on housing prices slightly declined during the pandemic, mainly due to travel restrictions and

the widespread adoption of remote working. However, in the long term, as urban activities recover and travel demand increases, transport accessibility continues to be regarded as an important determinant shaping the spatial distribution of real estate markets.

Differences in urban maturity, planning context, and data scale often lead to mixed or insignificant results across regions, indicating that the relationship between rail transit and land value remains context dependent.

2.3. Methodological Development

Various analytical strategies have been employed to examine the impact of public transport on land prices.

2.3.1. Hedonic Pricing Framework (HPM)

Early studies often relied on the hedonic pricing framework (HPM), which incorporates econometric techniques such as ordinary least squares or fixed effects models to estimate how different attributes influence property prices. HPM assumes that property prices are determined by the combination of features that provide utility to users, and that changes in these features or their quantities can alter the property's value. Many scholars have used this model to study the relationship between rail infrastructure and property value. It is particularly useful for capturing both market-based characteristics like plot size and non-market attributes such as transport accessibility [39,40]. Some argue, however, that HPM suffers from endogeneity issues, sample selection bias, and typically relies on limited observational data [41]. However, its inability to account for spatial dependence and endogeneity has led scholars to adopt spatial econometric techniques.

2.3.2. Geographically Weighted Regression (GWR)

With the advancement of spatial analysis techniques, scholars have increasingly recognised the importance of spatial heterogeneity in assessing the impacts of transport infrastructure. This has led to the adoption of spatial econometric models, such as Geographically Weighted Regression (GWR) to capture location-specific effects and spatial spillovers [26,42,43]. GWR not only helps identify local variations in land value caused by transport accessibility but also enables the visualisation of regression coefficients through spatial distribution maps, offering decision makers tools for specific policy design. Traditional GWR focuses, however, only on spatial variation, overlooking temporal dynamics. Yet, as B. Huang et al. (2010) [44] emphasise, improvements in local amenities and infrastructure often lead to long-term effects that develop gradually. While GWR captures spatial heterogeneity effectively, it cannot isolate causal impacts over time, prompting the use of quasi-experimental approaches.

2.3.3. Quasi-Experimental Methods

In recent years, quasi-experimental methods have become increasingly prominent in regional and urban economics. The Difference-in-Differences (DID) model is among the most widely used approaches [23,25,45]. DID estimates the causal impact of an exogenous intervention by comparing pre- and post-treatment outcomes between a treatment group (affected areas) and a control group (unaffected areas). Under the parallel trends assumption, DID can control for time-invariant unobserved factors as well as common time shocks affecting all units, thereby mitigating endogeneity concerns to some extent [25,46]. Unlike conventional approaches such as HPM or GWR, which primarily focus on correlation analysis or spatial heterogeneity, DID provides a more robust framework for causal inference, though its identification still depends on key assumptions and appropriate robustness checks.

In summary, existing research largely focuses on city-level effects, with limited attention to finer scale market heterogeneity or underlying mechanisms. In the UK, empirical

evidence on the long-term effects of newly built or extended light rail systems over the past two decades remains sparse. The capitalisation effects of rail transport often display complex spatiotemporal patterns that vary across regions and contexts. Future research needs to integrate causal inference with spatial analytical approaches to fully uncover the mechanisms behind transport's impact on land and property values.

2.4. Theoretical Analysis

The positive impact of rail transport on property values can be theoretically explained through three key mechanisms: improved accessibility, spatial spillovers, and land-use intensification. The influence of transportation infrastructure on land value is rooted in classical location theory [47], which argues that transport accessibility increases land value by reducing commuting costs and enhancing the attractiveness of a given area. Urban land users make residential location decisions by weighing commuting costs against land rent and are willing to pay higher rents for better accessibility. Therefore, improvements in accessibility reduce travel costs and expand employment options, thereby increasing an area's overall appeal and contributing to land value appreciation.

In addition, accessibility theory also underpins the concept of spatial spillovers from infrastructure [48]. This theory posits that the degree of connectivity between a given location and other important functional areas within the city, such as workplaces, commercial zones, and schools, enhances its value and makes it more attractive to residents and businesses. The introduction of railway infrastructure not only improves local population mobility but also encourages the clustering of commercial facilities such as restaurants, retail outlets, and leisure spaces along the infrastructure corridor. Given the influence of service accessibility on residential location decisions, increased infrastructure density improves the appeal of residential plots and raises residents' willingness to pay, indirectly contributing to property value growth.

Under the model of Transit-Oriented Development (TOD), urban planning promotes the high-density integration of residential, commercial, and office functions around public transport (transit) stations. Numerous studies on TOD [49,50] have confirmed that transit improvements positively affect property values. Moreover, the lifestyle enabled by TOD has been particularly attractive to certain demographic groups such as child-free couples, young people, and immigrants [51]. Thus, improvements in transit systems and the concentration of commercial and service amenities reinforce each other, enhancing neighbourhood desirability, improving residents' quality of life, and further boosting property values.

Based on the above theoretical framework, this study anticipates that the expansion of light rail systems will have a significantly positive effect on local land and housing values. This effect is expected to operate through three interrelated mechanisms: (1) improved accessibility enhances the spatial attractiveness of the area; (2) increased attractiveness promotes the agglomeration of commercial and residential-related POIs; and (3) under TOD planning, integrated land-use around transit hubs increases residents' willingness to pay, while the concentration of POIs strengthens consumer appeal. Together, these mechanisms suggest that light rail expansion not only improves regional accessibility, but also raises the spatial clustering of amenities, ultimately leading to increased property values in surrounding areas.

This study employs a DID research framework to identify the causal effects of light rail expansion on housing prices and to reveal the heterogeneous impacts across different socioeconomic and spatial contexts. It provides new empirical evidence and theoretical insights for understanding how transport investments in multiple cities drive urban regeneration and exert long-term influences on land values.

3. Methodology

3.1. Research Objects

In this study, the districts traversed by the Manchester Metrolink, Sheffield Supertram, and Nottingham Express Transit, light rail systems with new or expanded LRT lines between 1995 and 2019, were selected as the objects of analysis (Table 1). Land transaction data and eco-social factor data for these districts was collected and mathematical modelling undertaken to examine the extent to which LRT routes have influenced changes in land values in the surrounding areas.

Table 1. Research Area.

Light Rail System	Local Authority District
Manchester Metrolink	Manchester, Rochdale, Oldham, Tameside, Stockport, Trafford, Salford, Bury.
Sheffield Supertram	Sheffield, Rotherham
Nottingham Express Transit	City of Nottingham, Ashfield, Gedling, Broxtowe, Rushcliffe.

The Manchester Metrolink, the city's light rail system, has undergone a series of phased expansions since its initial opening in 1992, gradually developing into an extensive network serving the wider metropolitan area. Phase 1 (1992) established connections between the city centre and Altrincham as well as Bury [52]. Phase 2 (1999–2000) extended the system to Eccles. Between 2011 and 2014, the network further expanded to Oldham, Rochdale, East Didsbury, and Manchester Airport and divide to phase 3a and 3b [53]. The completion of the Second City Crossing in 2017 enhanced capacity and city-centre connectivity, followed by the opening of the Trafford Park Line in 2020, which marked the most recent major extension [52,54,55].

The Sheffield light rail system, Supertram, was inaugurated in 1994, with a total length of approximately 29 km and more than 50 stops, radiating east, west and north from the city centre. In 2018, a Tram-Train service was introduced to connect the city centre with Rotherham, marking the first light rail–railway hybrid operation in the UK [56,57].

The Nottingham Express Transit (NET) commenced operation in 2004 with an initial network of approximately 14 km. In 2015, Phase Two was completed, adding two new lines linking the university, the Queen's Medical Centre, Beeston and Clifton, which expanded the system to over 32 km with nearly 50 stops [58,59].

The three cities' light rail systems share notable commonalities in both their development trajectories and functional roles. First, they are all major regional centres in the UK, where light rail construction was initiated during the 1990s and early 2000s, with further extensions over the past decade. Second, they are in close geographic proximity, all within the metropolitan areas of northern and central England and can be regarded as typical post-industrial cities. Consequently, their transport development paths and socio-economic structures render them broadly comparable, providing representative cases for examining the socio-economic impacts of light rail transit (see Figure 1).

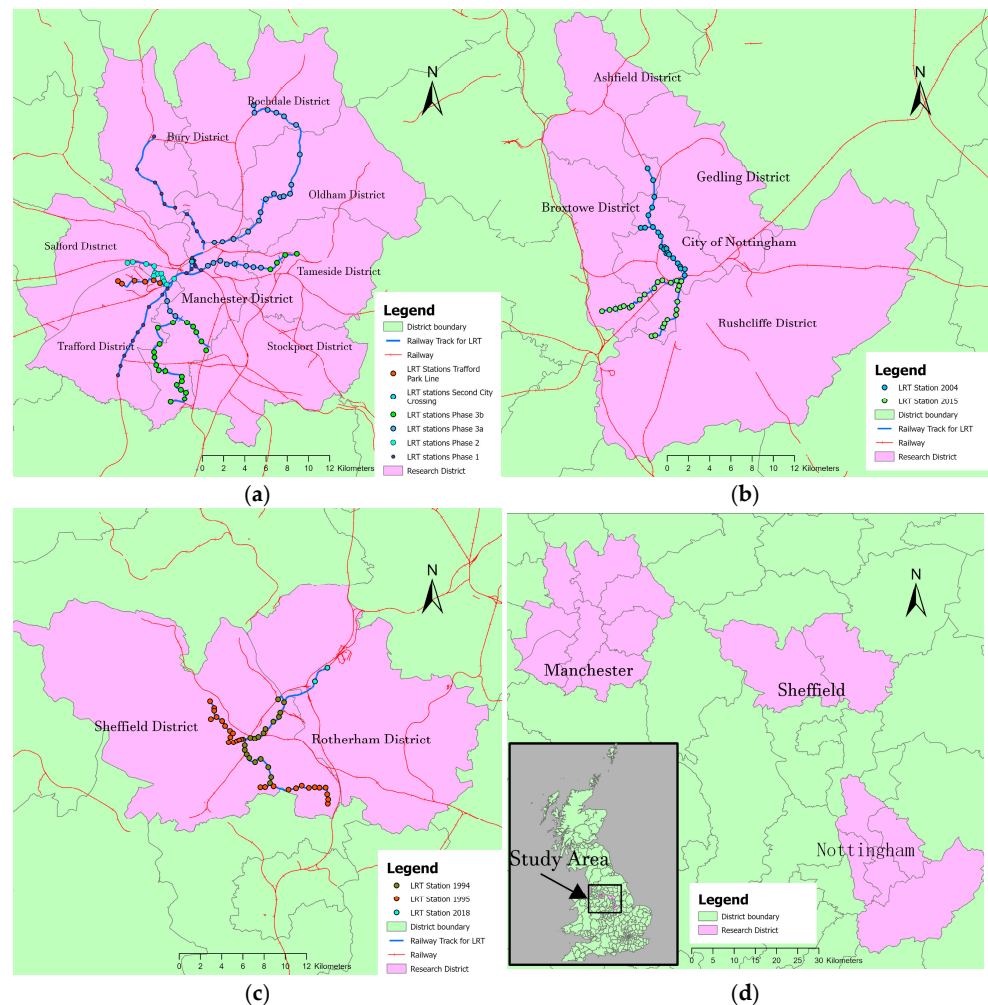


Figure 1. Study areas: (a) Manchester, (b) Nottingham, (c) Sheffield, and (d) UK Location map.

3.2. Research Design

In the DID design, this study treats the construction of light rail stations as an exogenous shock and uses the logarithmic average housing price within each MSOA as the dependent variable. Specifically, MSOA (Middle Layer Super Output Area) is a commonly used spatial analytical unit in the United Kingdom and has been widely applied in area-level empirical studies on housing prices and real estate markets [60,61].

As shown in Figure 2, The key treatment indicator is whether the area has been served by a newly opened light rail station. A 500-m buffer was created around each station opened during the period of interest, a distance commonly used to define the area of influence [62]. MSOAs that exhibited substantial spatial overlaps with the 500-m buffer were classified as the treatment group, while MSOAs entirely located outside the buffer were defined as the control group. This classification ensures spatial proximity and socioeconomic comparability between treatment and control areas.

In the DID design, the treatment group includes only the newly constructed or expanded stations, while the original stations that considered as already treated, are excluded from the analysis to avoid confounding effects. In addition, MSOAs with only a very small portion of their area intersecting with the buffer zone were not classified as treatment, in order to ensure a more rigorous identification of treatment effects.

Subsequently, a set of control variables for the analysis was identified based on a review of the relevant literature (see Section 3.2: Research Data). This identification strategy aims to compare housing market performance before and after the establishment of LRT

stations between MSOAs located near stations (treatment group) and those farther away (control group).

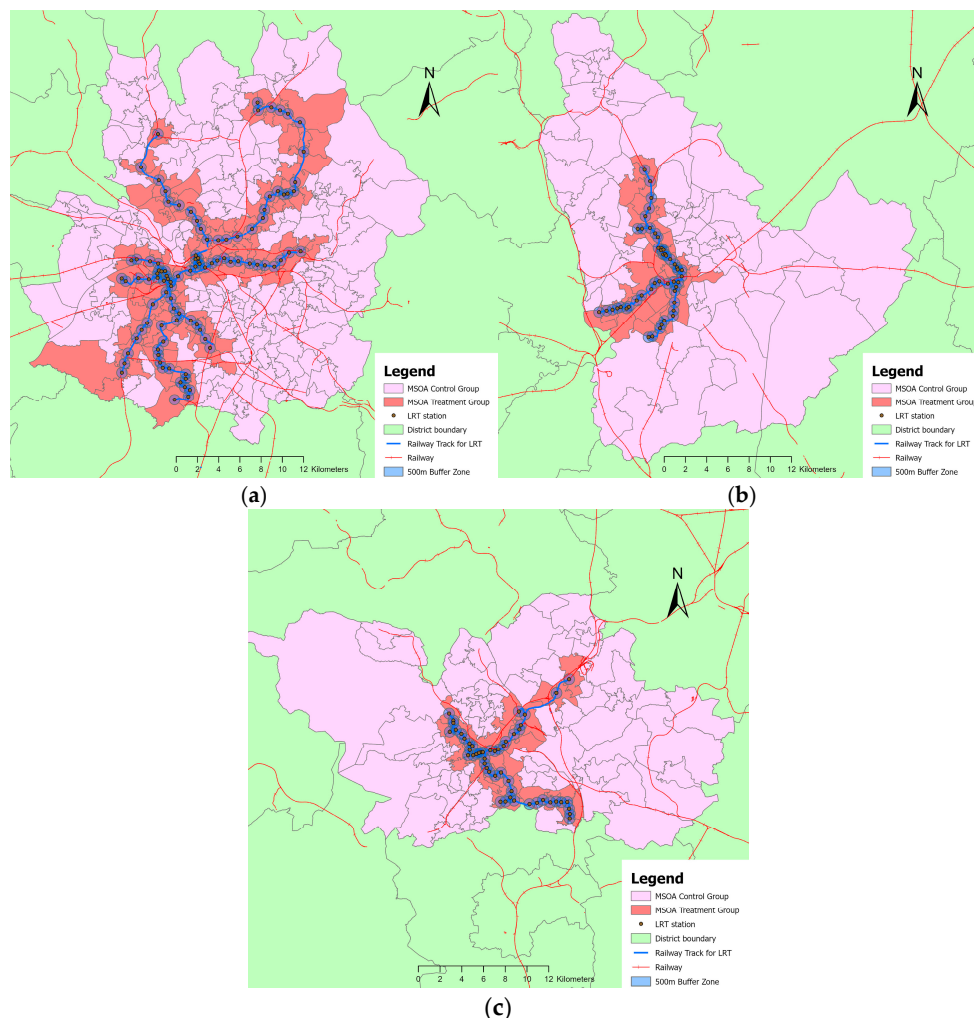


Figure 2. Treatment and control group delineation: (a) Manchester; (b) Nottingham; (c) Sheffield.

MSOAs (Middle Layer Super Output Areas) are one of the official statistical and spatial units used in the UK census, and this spatial boundary is adopted to ensure consistency and comparability in spatial analysis and to facilitate alignment with official datasets.

The main regression Formula (1) used in this study is specified as follows:

$$Y_{it} = \alpha + \beta \cdot DID_{it} + \gamma_t + \delta_i + X_{it} \cdot \theta + \epsilon_{it} \quad (1)$$

In this equation, Y_{it} represents the average housing price of $MSOA_{it}$ in $Year_{it}$; $DID_{it} = Treat_{it} \times Post_{it}$, where $Treat_{it}$ is a treatment group dummy variable (equal to 1 if the MSOA intercepted within the buffer zone, and 0 otherwise), and $Post_{it}$ is a post-treatment dummy variable indicating the years after the opening of the light rail. X_{it} is a vector of control variables. δ_i captures MSOA fixed effects, controlling for time-invariant unobserved heterogeneity across spatial units, while γ_t represents year fixed effects, accounting for temporal shocks common to all units. ϵ_{it} is the error term.

To further enhance the credibility and interpretability of the main findings, a series of extended analyses were conducted. First, a mechanism analysis was performed by introducing Point of Interest (POI) variables to investigate whether light rail drives up housing prices through enhanced local functional accessibility. For robustness checks, clustered

standard errors were computed, the sample timeframe adjusted, and a Propensity Score Matching-Difference-in-Differences (PSM-DID) approach employed to control for potential biases. Furthermore, a placebo test was conducted to validate the causal interpretation of the results. Finally, heterogeneity analyses were carried out by stratifying the sample across three dimensions (county-level, socioeconomic profiles, and bus connectivity levels) to reveal spatial variations and social difference in the effects of LRT expansion.

3.3. Research Data

The data used in this study cover a wide range of geographic and socioeconomic information within the study area. Specifically, property transaction data are obtained from the HM Land Registry's Paid Price data [63], which includes all registered property transactions from 1995 to 2019. The dataset contains key variables such as transaction price, tenure type, and geographic location. Although the transaction data provide precise geographic locations and sale prices, we choose to aggregate prices at the MSOA level rather than modelling individual transactions. This decision reflects both data limitations. Detailed property attributes in the Paid Price data are not systematically recorded. It also reflects methodological considerations, as difference-in-differences models are typically implemented at the area level to ensure comparability between treatment and control groups.

Demographic information is derived from aggregate data from the 2001 and 2011 national Census conducted by the UK Office for National Statistics (ONS). These data were accessed via the NOMIS [64] website and include socioeconomic indicators such as population structure, employment status, and housing characteristics. Point of Interest (POI) data were extracted from the Ordnance Survey [65], covering the period from 2014 to 2019. The dataset includes the geographic coordinates of commercial facilities and public service locations. In addition, this study utilises data from OpenStreetMap [66] to obtain the distribution of bus stops in 2011, including information on stop names and geographic coordinates. All datasets were georeferenced and processed using ArcGIS Pro 3.1.0 to ensure spatial consistency and temporal continuity across multiple data sources.

The Middle Layer Super Output Area (MSOA) was introduced in the UK in 2001 as one of the official geographic units for statistical and spatial data analysis. It enables researchers to divide cities into smaller areas to examine subtle changes at the sub-urban level. For this study, the MSOA 2021 was chosen as the study area. Although the MSOA area has changed slightly between 2001 and 2011, the study areas were converted by the 'MSOA (2001 or 2011) to MSOA (2011 or 2021) to Local Authority District (2022) Exact Fit Lookup' [67,68] provided by the ONS to match earlier MSOAs to their corresponding MSOA 2021 units. This approach ensures that the study area remains consistent across all years, thereby improving the spatial comparability and consistency of the dataset.

Table 2 provides definitions of the variables used in this study. The control variables were selected based on a review of relevant research [23,34,50], referencing variables with similar attributes commonly used in studies conducted within the UK context.

Before modelling, data is cleaned to address spatial and temporal inconsistencies. First, transactions with missing geolocation or price information are excluded. Secondly, to mitigate potential estimation bias from small sample sizes, MSOAs with fewer than 19 transactions across the entire study period (1995–2019) were removed. This threshold was determined based on the 5th percentile of the transaction count distribution, ensuring sufficient statistical power for DID estimation [69].

Table 2. Description of Variables.

Dependent variable	
lnaverage_price	Logarithm of the average house price in the MSOA21
Core variables	
DID	$Treat_{\{i\}} \times Post_{\{t\}}$
Control variables	
p_under16	Population under 16 years old
p_aged16to64	Population between 16 and 64
p_65yearsandover	Population aged 65 and over
EcoActive	Number of economically active population (excluding full-time students) in employment
p_education	Population of education establishments (including Halls of residence)
p_health	Population of medical and care establishments
p_level4qualifications	Number of people with Level 4 education or above
Car_or_van	The number of cars and vans
Average_rooms	Average rooms per household
populationdensity	Population density per unit area
Mediator variable	
EatDrink	Eating and drinking POI count
Retail	Food, drink and multi-item retail POI count
HomeOfficeLeisure	Household, office, leisure, and garden POI count
PropertyServices	Property and development services POI count

4. Exploratory Results

4.1. Baseline Regression

Table 3 reports the baseline regression results. Model (1) presents the basic specification without control variables, accounting only for year fixed effects and MSOA fixed effects. Model (2) builds upon this by incorporating additional socioeconomic control variables, including age structure, educational level, employment composition, housing conditions. Although all explanatory variables have been estimated, the discussion below concentrates on the core variables that directly relate to the study's main hypotheses, to maintain focus and clarity.

The results of Model (1) show that LRT station construction has a significant positive impact on housing prices within the treatment group. This result indicates that, following the opening of LRT, the average housing prices in the treatment groups increased by approximately 8.29% compared to the control group significantly. After adding the control variables in Model (2), the estimate increasing degree slightly decreases to 4.44%, and remains highly significant. These results suggest that the positive impact of LRT on property prices remains robust after accounting for potential confounding factors. Overall, LRT construction leads to a statistically and economically significant price increase of about 4.44–8.29%. The difference between the two models likely reflects concurrent urban development and demographic changes, and the results of Model (2) more accurately capture the true capitalization effect of LRT improvements by including these factors in the estimation.

Table 3. The result of Baseline regression.

	(1)	(2)
Variables	lnaverage_price	lnaverage_price
DID	0.0829 *** (6.68)	0.0444 *** (3.69)
p_under16		0.0043 (0.08)
p_aged16to64		0.0761 (0.73)
p_65yearsandover		−0.1672 *** (−6.54)
EcoActive		0.2363 *** (3.30)
p_education		−0.0302 (−1.63)
p_health		0.0050 (0.30)
p_level4qualifications		0.0506 *** (4.35)
Car_or_van		−0.0372 ** (−2.34)
Average_rooms		−0.0188 * (−1.78)
populationdensity		−0.0007 *** (−2.74)
Constant	11.5147 *** (5534.94)	10.3331 *** (23.32)
Observations	9934	9934
R-squared	0.938	0.941
Year	YES	YES
MSOA21	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Parallel Trend Test

To validate the key parallel trends assumption of the DID model, this study adopts an event study approach. This involves plotting the trends in property prices for the treatment and control groups over several years before and after the construction of LRT stations and estimating different years specific treatment effects relative to the reference year.

Specifically, a series of lead and lag dummy variables of the treatment were included to examine whether property prices in treatment and control areas followed similar trends before the opening of LRT stations. Within this framework, the year immediately preceding the station opening is defined as the reference period, and the estimated coefficients represent property value changes relative to this baseline. The dynamic effects are estimated within a time window covering five years before and ten years after the opening, while testing whether the coefficients for the pre- and post-treatment years differ significantly.

The Figure 3 below displays the results of the parallel trends test. The solid line represents the estimated coefficients, while the dashed lines represent the 95% confidence intervals. The estimates for the pre-treatment period ($t = -5$ to $t = -1$) are all close to zero and statistically insignificant, indicating that the treatment and control groups followed similar price trends prior to the intervention. After treatment, the estimated coefficients

show a general upward trend, with statistically significant effects emerging between $t = 6$ and $t = 9$. This result suggests that the opening of LRT station had a delayed but sustained and cumulative positive impact on housing prices within the treatment MSOA.

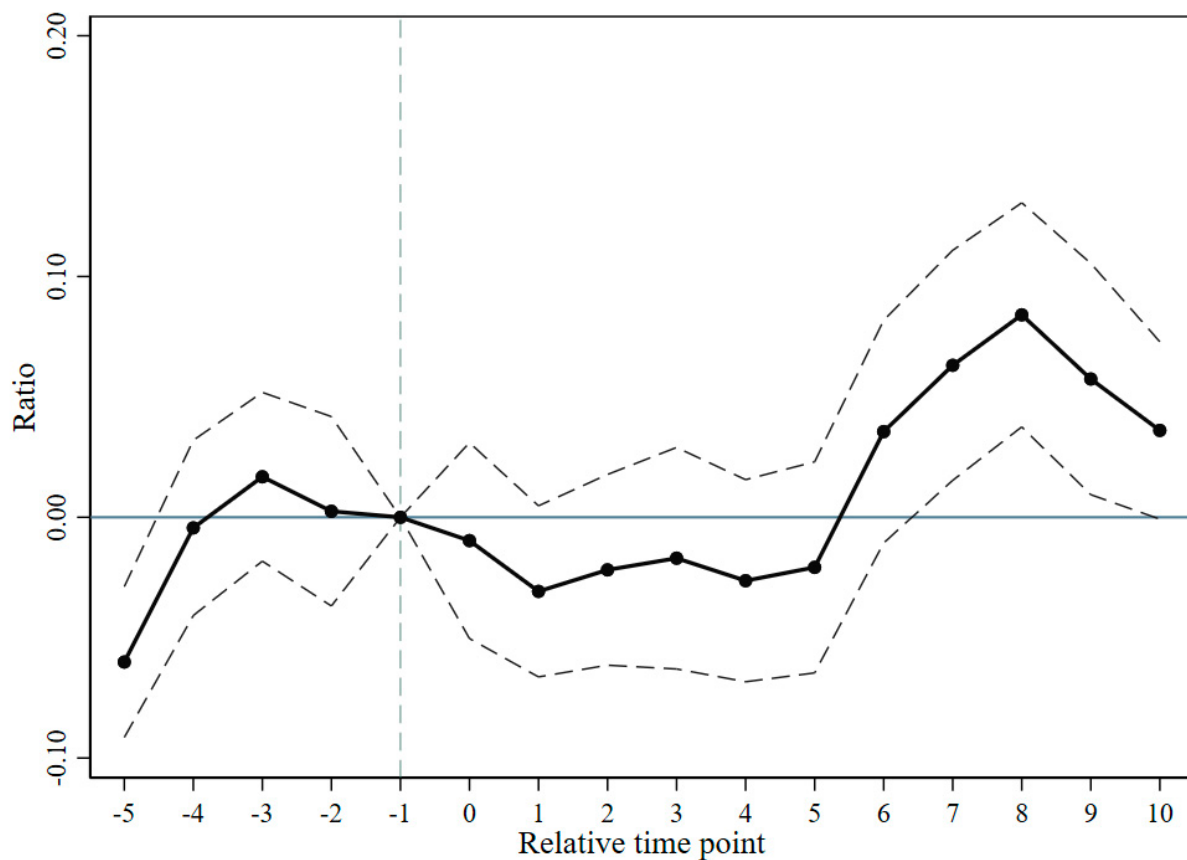


Figure 3. Parallel trend test.

Overall, the results provide strong support for the validity of the parallel trends assumption and suggest a lagged effect. This result shows that the effect of LRT on property values is not immediate but takes several years to play out.

4.3. Robustness Test

To strengthen the credibility of the main regression results, this study implements a series of robustness checks.

Firstly, Model (1) addresses potential intra-cluster correlation in the panel data by clustering standard errors at the MSOA level to obtain robust inference. The core specification remains the same as the baseline DID model, while additionally applying cluster-robust standard errors at the MSOA level to account for potential intra-cluster correlation in repeated observations within each spatial unit. This adjustment allows for arbitrary serial correlation within each MSOA over time, thereby producing consistent standard errors [70].

Secondly, Model (2) restricts the sample period to observations from 2001. This allows testing of the stability of the results under a different sample window. The main reason for selecting this period is that the MSOA statistical geography was officially introduced in the UK in 2001 and was subsequently standardised in later censuses. Limiting the sample to post-2001 ensures that the spatial units used in the analysis are consistent in terms of boundary and data completeness. Therefore, this way helps prevent potential bias that might arise from inconsistencies or redefinitions in earlier MSOA boundaries.

Third, Model (3) conducts a robustness check using a difference-in-differences (DID) model combined with propensity score matching (PSM-DID) to improve the comparability of pre-treatment characteristics between the treatment and control groups and to more reliably identify causal effects in observational data.

Finally, following the approach of Z. Wang et al. (2022) [71] and Dagestani et al. (2023) [72], a placebo test is conducted to further examine whether the observed effects may be driven by random factors or unobserved variables. The core idea of the placebo test is to construct pseudo-treatment groups and conduct repeated simulations to assess whether the estimated effects arise from the actual intervention rather than from random variation or other systematic influences.

Table 4 presents the regression results under three different robustness check strategies, aiming to assess whether the estimated impact of LRT on property prices is sensitive to model specification.

Model (1) serves as the baseline specification. It controls MSOA and year fixed effects, and clusters standard errors at the MSOA level to address potential intra-area correlation in the error terms. For example, housing prices in certain areas may be influenced by unobserved long-term locational advantages, urban planning preferences, or socioeconomic inertia, which could lead to serial correlation within those areas over time. The results show that the estimated rate of increase is almost 4.4%, which is statistically significant at the 1% level. It indicates that the opening of LRT significantly increases housing prices within the buffer zone and the effect is robust because this model shows a similar result to the original baseline model.

Model (2) restricts the sample period to post-2001 observations to avoid possible interference from early rail projects and to ensure consistency in MSOA boundaries and census data, as MSOAs were formally standardised in 2001. The result in this model also remains 4.41% increasing in property prices, closely aligning with the baseline model and confirming the stability of the results across different time windows. The post-2001 sample helps to exclude potential interference from earlier LRT developments while ensuring consistency in MSOA boundaries, thus providing initial robustness evidence. Nonetheless, incorporating additional time windows in future analyses would further strengthen the reliability of the findings.

Model (3) applies a PSM-DID approach. By matching MSOAs with similar propensity scores, this method improves the comparability between treatment and control units in terms of observable characteristics. The covariates mentioned earlier are used for matching, and each treated unit is matched to four control units using nearest-neighbour matching (1:4 ratio). After matching, all covariates were well balanced ($|\text{bias}| < 10\%$), indicating satisfactory matching quality (see Appendix A for detailed balance statistics). The result estimates a 5.05% increase, and once again confirms the robustness of the main effect and enhances the credibility of the findings.

Finally, this study conducted a placebo test to further determine whether the observed effect was driven by random factors or unobserved variables. Keeping the sample structure unchanged, we randomly select the same number of MSOAs as in the actual treatment group to construct a “pseudo-treatment group.” Then, this test will repeat 500 random assignments, with each iteration involving a DID regression. Based on these results, the researcher will record the estimated coefficients and corresponding p -values from each run and print a distribution plot of the estimated coefficient to compare with the true treatment effect.

The result (Figure 4) shows that the coefficients from the placebo tests are approximately normally distributed and centred around zero, with values significantly deviating from the actual DID estimate. This suggests that the true estimated effect is unlikely to be the result of random assignments. These findings effectively rule out the possibility of

spurious effects driven by random variation and further confirm the robustness of the main regression results.

Table 4. Robust t-statistics in parentheses for Robustness Test.

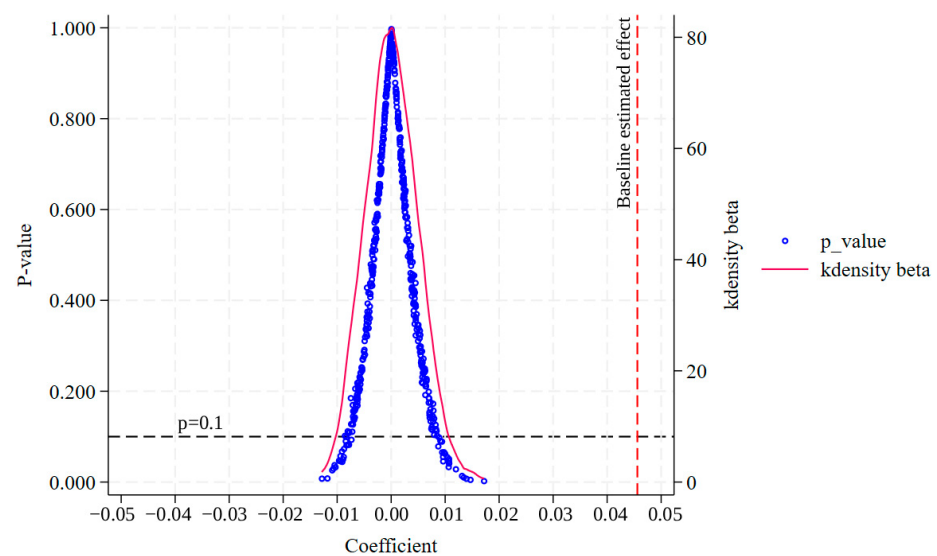
	(1)	(2)	(3)
Variables	lnaverage_price	lnaverage_price	lnaverage_price
DID	0.0444 *** (2.67)	0.0441 *** (3.29)	0.0505 *** (4.19)
p_under16	0.0043 (0.06)	−0.0631 (−1.18)	0.0349 (0.71)
p_aged16to64	0.0761 (0.61)	0.0976 (0.92)	0.0080 (0.08)
p_65yearsandover	−0.1672 *** (−4.25)	−0.1421 *** (−5.40)	−0.1622 *** (−6.64)
EcoActive	0.2363 ** (2.31)	0.1806 ** (2.43)	0.2664 *** (3.82)
p_education	−0.0302 (−0.96)	−0.0481 ** (−2.54)	−0.0037 (−0.20)
p_health	0.0050 (0.19)	0.0062 (0.35)	−0.0103 (−0.59)
p_level4qualifications	0.0506 *** (2.71)	0.0427 *** (3.60)	0.0363 *** (3.12)
Car_or_van	−0.0372 (−1.63)	−0.0132 (−0.82)	−0.0422 *** (−2.67)
Average_rooms	−0.0188 (−1.29)	−0.0256 ** (−2.37)	−0.0137 (−1.36)
populationdensity	−0.0007 ** (−2.23)	−0.0009 *** (−3.24)	−0.0007 *** (−2.70)
Constant	10.3331 *** (16.99)	11.1456 *** (24.78)	10.4480 *** (27.61)
Observations	9934	7348	9663
R-squared	0.941	0.905	0.942
Year	YES	YES	YES
MSOA21	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$.

To further test the robustness of the DID estimation results, the approach of Peng and Tian [73] was followed, redefining the control group to mitigate potential spatial spillover effects that might exist. Specifically, MSOAs located outside the 500-m buffer zone but directly adjacent to treated areas were excluded from the control sample to ensure greater spatial independence between groups. The results (see Table 5) show that the direction and statistical significance of the estimated coefficients remain consistent with the baseline estimates, indicating that the main findings are robust to alternative control group definitions and not affected by spatial contamination. Specifically, the estimated coefficients remain significant and close in magnitude to those in the baseline regression (0.0829 in Model (1) and 0.0444 in Model (2), see Table 3).

Table 5. Robustness check of redefining control group by excluding adjacent MSOAs.

	(1)	(2)
Variables	lnaverage_price	lnaverage_price
DID	0.0857 *** (6.73)	0.0458 *** (3.67)
p_under16		−0.0569 (−0.90)
p_aged16to64		0.0566 (0.50)
p_65yearsandover		−0.1652 *** (−5.35)
EcoActive		0.2601 *** (3.45)
p_education		−0.0906 *** (−3.65)
p_health		0.0311 (1.51)
p_level4qualifications		0.0941 *** (5.96)
Car_or_van		−0.0559 *** (−2.66)
Average_rooms		−0.0351 ** (−2.46)
populationdensity		−0.0013 *** (−3.90)
Constant	11.4953 *** (3987.50)	10.8569 *** (21.46)
Observations	6554	6554
R-squared	0.937	0.941
Year	YES	YES
MSOA21	YES	YES

*** $p < 0.01$, ** $p < 0.05$.**Figure 4.** The result of placebo test.

4.4. Mechanism Analysis

To further explore the mechanisms through which LRT affects land values, this study introduces the number of local POIs as mediating variables. The aim is to examine whether improved accessibility leads to enhanced service provision and functional diversity, thereby increasing the attractiveness and value of land. The hypothesis is that the opening of LRT systems improves regional accessibility, which in turn attracts more commercial and public service establishments, reflected in rising densities of commercial and public POIs. These new facilities enhance residents' preferences for the area, stimulate housing demand, and ultimately raise local property prices.

Table 6 reports the difference-in-differences (DID) regression results using the density of four types of POIs as dependent variables: (1) eating and drinking; (2) food, drink, and multi-item retail; (3) household, office, leisure, and garden; and (4) property and development services.

The selection of these four POI categories is based on two considerations:

1. Eating and retail related establishments represent high-frequency consumer demands closely tied to population density and transit accessibility. The construction of LRT may enhance the vibrancy and accessibility of these facilities, thereby unlocking commercial potential along the transit corridor.
2. Household or leisure-related, and property development services reflect the overall functional completeness and environmental appeal of an area. These types of POIs not only contribute to daily convenience but also significantly affect residents' perception of the quality of the community environment and liveability. Functional POIs influence residents' perceptions of neighbourhood quality, which may in turn affect housing demand and contribute to property value increases in station areas. At the same time, previous studies have incorporated appropriate proportions of commercial, office, recreational, and service land uses into land use mix indices, which have been widely applied in property value research [74].

The analysis of the spatial distribution and density of such POIs allows for an effective evaluation of LRT's indirect impact on housing market appeal. They provide insight into the transmission mechanisms through which transit improvements influence property values.

The regression results show that LRT construction has a significant positive effect on most types of POIs, with estimates robust at the 1% significance level. In Model (1), the number of eating and drinking POIs increased by 10.61%. Model (2) shows an 9.23% increase in food, drink, and multi-item retail POIs. However, the results in Model (3) are not statistically significant, suggesting that LRT has a weaker effect on household, office, leisure, and garden-related facilities. Finally, Model (4) further reveals that LRT significantly increases the density of property and development services POIs by 10.79%, indicating a notable clustering of infrastructure-related service industries around station areas. These findings provide preliminary evidence that LRT systems indirectly drive-up housing prices via a mechanism channel rooted in heightened regional attractiveness, achieved through the intensification of service provision density for daily living and the amplification of commercial accessibility.

Table 6. Robust t-statistics in parentheses of Mechanism analysis.

	(1)	(2)	(3)	(4)
Variables	EatDrink	Retail	HomeOfficeLeisure	PropertyServices
DID	0.1063 *** (4.36)	0.0923 *** (4.48)	0.0256 (0.92)	0.1079 *** (3.91)
p_under16	−0.2043 * (−1.82)	0.1903 ** (2.40)	−0.0828 (−0.81)	0.1911 (1.59)
p_aged16to64	1.1645 *** (6.02)	0.7717 *** (5.95)	0.7416 *** (4.63)	0.9814 *** (5.32)
p_65yearsandover	−0.4789 *** (−7.68)	−0.7861 *** (−16.09)	−0.4418 *** (−6.48)	−0.4847 *** (−7.15)
EcoActive	−0.5685 *** (−4.19)	−0.4097 *** (−4.33)	−0.3378 *** (−2.95)	−0.4342 *** (−3.58)
p_education	−0.0358 (−0.99)	0.0241 (0.76)	−0.2125*** (−5.37)	0.0038 (0.08)
p_health	0.1394 *** (3.75)	0.0558 ** (1.97)	0.1155 *** (2.97)	−0.1146 *** (−2.83)
p_level4qualifications	0.1667 *** (6.57)	0.0406 * (1.95)	0.2543 *** (9.92)	0.2234 *** (7.20)
Car_or_van	−0.1884 *** (−4.85)	−0.0944 *** (−3.25)	−0.0766 ** (−2.17)	−0.0112 (−0.28)
Average_rooms	−0.0592 ** (−2.21)	−0.0503 ** (−2.53)	−0.0429 * (−1.71)	0.0789*** (2.84)
populationdensity	−0.0008 (−1.31)	−0.0008 * (−1.83)	−0.0015 *** (−2.74)	0.0014 ** (2.11)
Constant	0.1350 (0.13)	1.6211 ** (2.27)	0.2767 (0.30)	−3.7699 *** (−3.62)
Observations	9934	9934	9934	9934
R-squared	0.926	0.934	0.906	0.755
Year	YES	YES	YES	YES
MSOA21	YES	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5. Heterogeneity Analysis

To further examine the heterogeneous effects of light rail transit (LRT) on land values and explore potential underlying mechanisms, this study conducts subgroup analyses based on three dimensions: Regional level variation, public transport accessibility, and socio-economic status. Specifically, the socio-economic indicator is counted by the proportion of population in social grades AB (higher and intermediate managerial, administrative, and professional occupations), as derived from the 2001 Census data. Finally, bus stop location is obtained from OpenStreetMap, based on 2011 data.

First, the sample is divided by region, based on the MSOA's administrative affiliation, into three groups: Greater Manchester (Model 1), Nottinghamshire (Model 2), and South Yorkshire (Model 3). Separate regressions are then conducted to estimate the impact of LRT on housing prices in each region. As shown in Table 7, the effect of LRT on property prices is most significant in South Yorkshire, and notably higher than in the other two counties. This difference suggests varying regional responses to LRT development, potentially due to differences in economic activity, urban scale, and infrastructure capacity. Despite the variation in effect size, all three counties exhibit a generally positive impact, indicating that LRT expansion consistently contributes to increases in property values across different regional backgrounds.

It is necessary to note that the relatively higher estimated effect observed in South Yorkshire (0.736) may be partly attributed to the spatial distribution of newly extended light rail stations. As shown in Figure 1 (see Section 3.1), the Sheffield Supertram was extended to the Rotherham area in 2018, passing through several former industrial corridors where baseline property values were relatively low prior to the expansion. In December 2017, before the extension, the average house price was £129,500 in Rotherham and £156,746 in

Sheffield, compared with £243,582 for England as a whole [75]. In contrast, the Metrolink Trafford Park Line in Trafford was completed in 2020, where the average house price had already reached £273,604 in the same year. Following the extension, accessibility between these Sheffield districts, the city centre, and major employment areas improved significantly, leading to a greater proportional increase in property values compared with Manchester and Nottingham.

Second, Table 8 presents the results of groups analysis based on socioeconomic status, measured by the proportion of residents in social grade AB. MSOAs with an AB population share equal to or above the sample mean are classified as high-income areas, while those below the mean are classified as lower-income areas. Separate regressions are then performed for each group.

The results show that the positive impact of LRT on housing prices is more pronounced in low-income areas. Within these areas, property values experienced a statistically significant increase following the building of LRT. This finding suggests that the effectiveness of transit investments varies by socioeconomic context. One possible explanation is that residents in lower-income areas are more reliant on the improved accessibility provided by light rail and thus respond more strongly to transit enhancements and this leads to a greater impact on property prices.

Finally, MSOAs are divided into two groups based on bus stop density. If the bus stop density in an MSOA is equal to or above the sample mean, it is classified as the high bus network coverage group (Group 1); otherwise, it is classified as the low bus network coverage group (Group 2). Separate regressions are then conducted for each subgroup.

The results (Table 9) gest a potential synergy between the light rail system and existing bus networks. In areas with dense bus stops, residents may have a higher dependence on public transport in their daily lives and are thus more sensitive to improvements in accessibility. The introduction of new light rail lines therefore provides an additional accessibility enhancement, which is particularly attractive to potential homebuyers and contributes to property price premiums in these areas.

These findings highlight the importance of considering local background both in terms of socioeconomic composition and other transit infrastructure when evaluating the impacts of rail investments on property values.

Table 7. Robust t-statistics in parentheses in regional-level.

	(1)	(2)	(3)
Variables	lnaverage_price	lnaverage_price	lnaverage_price
DID	0.0360 *** (2.76)	0.0322 (1.64)	0.7360 * (1.76)
p_under16	0.1894 *** (2.59)	−0.0306 (−0.42)	−0.2294 ** (−2.19)
p_aged16to64	−0.0685 (−0.47)	−0.0846 (−0.38)	0.1466 (1.13)
p_65yearsandover	−0.2242 *** (−4.33)	−0.0623 * (−1.84)	0.0442 (0.82)
EcoActive	0.2615 *** (3.04)	0.1175 (0.63)	0.2710 * (1.75)
p_education	−0.0348 (−1.28)	0.0098 (0.20)	0.0572 (1.50)
p_health	−0.0238 (−1.08)	0.1159 ** (2.58)	−0.0383 (−0.95)
p_level4qualifications	0.0462 *** (3.17)	−0.0210 (−0.35)	0.0624 ** (2.25)

Table 7. Cont.

Variables	lnaverage_price	lnaverage_price	lnaverage_price
Car_or_van	−0.0062 (−0.27)	−0.1235 *** (−3.41)	−0.0952 ** (−2.23)
Average_rooms	−0.0900 (−1.62)	0.0280 (0.90)	−0.0241 (−1.54)
populationdensity	−0.0011 ** (−2.15)	−0.0003 (−0.58)	−0.0007 ** (−1.97)
Constant	10.7646 *** (10.99)	12.2501 *** (29.55)	9.6576 *** (10.56)
Observations	5902	1711	2321
R-squared	0.938	0.957	0.950
Year	YES	YES	YES
MSOA21	YES	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8. Robust t-statistics in parentheses in socioeconomic status.

	(1)	(2)
Variables	lnaverage_price	lnaverage_price
DID	0.0128 (0.79)	0.0608 *** (3.41)
p_under16	−0.1018 (−1.49)	0.1355 ** (2.08)
p_aged16to64	0.0418 (0.34)	−0.0181 (−0.13)
p_65yearsandover	−0.1690 *** (−4.23)	−0.1183 *** (−3.33)
EcoActive	0.2304 *** (2.64)	0.4563 *** (3.96)
p_education	−0.0435 * (−1.74)	−0.0304 (−1.02)
p_health	0.0874 *** (4.02)	−0.0854 *** (−3.24)
p_level4qualifications	0.0519 *** (3.76)	0.0518 *** (2.66)
Car_or_van	−0.0759 *** (−3.66)	0.0285 (1.04)
Average_rooms	−0.0192 (−1.52)	−0.0327 (−1.57)
populationdensity	−0.0006 (−1.52)	−0.0013 *** (−3.21)
Constant	11.5889 *** (18.85)	7.9106 *** (14.20)
Observations	4963	4971
R-squared	0.945	0.916
Year	YES	YES
MSOA21	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Robust t-statistics in parentheses for bus stop density.

	(1)	(2)
Variables	lnaverage_price	lnaverage_price
DID	0.1193 *** (5.07)	0.0089 (0.74)
p_under16	0.0652 (1.03)	−0.0631 (−0.79)
p_aged16to64	−0.2713 * (−1.94)	0.2211 (1.62)
p_65yearsandover	−0.1453 *** (−4.58)	−0.1389 *** (−3.30)
EcoActive	0.3574 *** (3.14)	0.2575 *** (2.98)
p_education	−0.0847 *** (−2.83)	0.0178 (0.77)
p_health	0.0439 * (1.72)	−0.0292 (−1.32)
p_level4qualifications	0.0725 *** (3.92)	0.0283 ** (2.00)
Car_or_van	−0.0265 (−1.03)	−0.0501 ** (−2.42)
Average_rooms	−0.0178 (−1.02)	−0.0050 (−0.44)
populationdensity	−0.0007 * (−1.81)	−0.0007 * (−1.87)
Constant	11.4964 *** (23.81)	9.3911 *** (12.40)
Observations	4872	5062
R-squared	0.938	0.946
Year	YES	YES
MSOA21	YES	YES

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion

This section revisits the three research questions by synthesising the empirical findings and situating them within the broader literature on transit-induced land value changes. Specifically, the first research question examined whether the construction and expansion of LRT systems increase nearby property values; the second explored the underlying mechanisms through which accessibility improvements shape land market responses; and the third assessed how these effects vary across different socioeconomic and spatial contexts. Consistent with previous studies [31–33], the findings from this study confirm that accessibility improvements brought by light rail are capitalised into land and property values. By adopting a multi-city and long-term framework, this study further reveals spatial heterogeneity in mature urban contexts, highlighting that continued transit investment supports urban regeneration and more balanced accessibility. The baseline regression results indicate that LRT construction significantly increases property prices within the treatment areas by approximately 4.44–8.29%. This positive effect remains robust even after controlling for a wide range of socioeconomic variables. Compared with previous studies, Diao et al. (2017) [46] reported that the opening of Singapore’s Circle Line increased nearby housing values by about 8.6%, while a global meta-analysis by Zhang & Yen (2020) [76] found that mature Bus Rapid Transit (BRT) systems typically raise surrounding land and property values by around 4.3%. Taken together, these comparisons suggest that LRT

expansion in the UK continues to demonstrate the substantial economic significance of rail-based accessibility improvements.

The mechanism analysis provides suggestive evidence that LRT enhances local functional density and residential convenience by promoting the agglomeration of POIs, particularly eating and retail establishments. These functional improvements could increase the attractiveness of nearby neighbourhoods and contribute to observed increases in property values. This conclusion is consistent with previous studies [77,78], which also provide empirical evidence that transportation infrastructure exerts a significant effect on business locations, particularly retail and dining establishments. This reflects the core demand of light rail passengers and surrounding residents for daily consumption convenience and walkable lifestyle services. Nevertheless, the mechanism evidence presented here should be interpreted as suggestive rather than conclusive, as the study does not employ a formal mediation analysis framework.

The heterogeneity analysis shows that the price effect of LRT is not significant in areas with a higher proportion of high-income residents but is more pronounced in lower-income neighbourhoods. It figures out that potentially reflecting the greater reliance and willingness to pay among lower-income groups for improved accessibility. The results suggest that LRT expansion may contribute to sustainable urban development by enhancing equitable accessibility through providing greater locational advantages for lower-income groups who rely more heavily on public transport. However, these patterns also require caution against potential gentrification processes driven by residential relocation in areas experiencing rising property values. Research is ongoing by the authors to investigate the gentrification impacts of the light rail systems studied here.

The heterogeneity also observed across the three cities may reflect contextual differences in project timing and spatial configuration. For instance, the higher effect in South Yorkshire may relate to the 2018 Supertram extension to Rotherham, which ran through lower-value industrial areas, whereas in Greater Manchester, the 2020 Trafford Park Line expansion took place in already high-priced neighbourhoods. These findings suggest that variations in baseline market conditions and development stages may partly explain the inter-city differences in the magnitude of LRT impacts. Future research could incorporate more detailed city background or historical characteristics to further disentangle such contextual effects.

In addition, the spillover effect of LRT is stronger in areas with high bus stop density, implying a synergistic effect between the rail system and existing public transit infrastructure. Such multimodal integration appears to significantly enhance regional accessibility and housing demand. However, the magnitude of this positive impact may vary depending on local urban functions, planning policies, cultural factors, and geographic context that offer promising directions for future research.

Nevertheless, while this study focuses on long-term impacts, it does not cover the post-COVID-19 period. Prior research has shown that the implicit price of metro accessibility slightly declined during the pandemic, weakening the capitalisation effect of rail infrastructure development [79]. This temporary weakening mainly stemmed from reduced commuting demand and safety concerns associated with shared transport [35]. However, as cities recover and travel demand rebounds, accessibility is expected to remain a key driver of property market dynamics. Future research also should pay more attention to the land value impacts of LRT using post-pandemic period to examine whether a more fundamental change has occurred.

Moreover, the impacts of light rail transit on property values may not emerge immediately after the completion of new lines or stations. Therefore, part of the estimated effects in this study may reflect a cumulative process rather than an instantaneous response. Future

research could explicitly account for potential lag effects and long-term trends by employing dynamic or distributed lag models, thereby providing a more detailed understanding of the temporal evolution of transit-induced land value changes.

Although this study identifies the clustering of POIs as a key mediating mechanism, limitations in cross-sectional data prevented a deeper analysis of different POI subcategories—such as public infrastructure or leisure facilities—and their long-term effects. Future studies could incorporate more refined POI classifications and indicators of commercial vitality to better understand the long-term co-evolution between transit infrastructure and urban functional transformation. Additionally, a formal mediation analysis would reveal the links between POI clustering and price increases.

Finally, this study aggregates housing prices to the MSOA level to align with the area-level DID design and ensure comparability between treatment and control groups. It is acknowledged, however, that this aggregation inevitably reduces within-area variations, and future work could integrate micro-level data or apply spatial visualisation techniques with richer attributes to explore finer-grained heterogeneity.

6. Conclusions and Policy Suggestions

This study uses the cases of LRT expansion in multiple UK cities and applies a difference-in-differences approach to systematically evaluate the impact effects, mechanisms, and spatial heterogeneity of LRT station construction on property prices and sustainable development. The results show that the building of new LRT stations leads to an increase of approximately 4.44% to 8.29% in property prices within treatment MSOAs. This effect remains highly robust across different sample selections and model specifications. The analysis confirms that the positive capitalisation effects of LRT are largely mediated through improvements in local accessibility and functional agglomeration, which enhance the land-use vitality of station areas. This study echoes the SDGs, particularly Goal 11: Sustainable Cities and Communities, by examining how LRT expansion in mature urban environments promotes equitable accessibility and sustainable economic development.

Building on these findings, this study provides several policy implications for advancing equitable transit-oriented development (TOD) and sustainable land use planning. Policymakers should therefore prioritise investment in areas with limited public transit coverage and higher concentrations of disadvantaged populations, while remaining aware of potential gentrification pressures that may accompany property value growth. Equitable TOD strategies that balance accessibility gains with social inclusion, and potentially policies like rent controls, are essential for achieving sustainable and inclusive urban regeneration. In addition, planners are encouraged to better integrate public transport infrastructure with service-oriented land uses, such as retail and public amenities, to enhance the commercial appeal and functional capacity of station areas. This coordinated planning can help maximise the land value uplift and accelerate the return on transit investments.

Finally, given the increased impact on areas with good bus services, policies should promote the integrated development of multimodal transportation systems. Future LRT projects should therefore prioritise seamless integration through coordinated route planning, unified ticketing systems, and synchronised timetables to ensure smooth transfers between LRT and other public modes. LRT should particularly prioritise seamless integration with bus networks to improve the coherence and coverage efficiency of the overall transportation system.

The results of this study demonstrate the important role that LRT can play in the sustainable development of mature urban areas, providing benefits in the economic and social pillars of sustainability alongside the more obvious improvements in environmental aspects such as air quality and greenhouse gas emission. Investment in LRT can lead

to increased property prices and, in turn, reductions in economic inequality across post-industrial areas. This research adds to the body of evidence demonstrating the value of investment in sustainable public transport modes to address the UN SDGs.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Covariate balance before and after propensity score matching (PSM). Note: The table reports the mean, standardized bias, and variance ratio of covariates before (U) and after (M) matching. Matching quality is satisfactory, with all $|\text{bias}| < 10\%$ and variance ratios within the acceptable range.

Variables	Unmatched Mean			%bias	%reduct bias	t-Test		V(T)/ V(C)
	Matched	Treated	Control			t	p > t	
p_under16	U	7.1286	7.2652	−31.4		−13.42	0.000	3.62 *
	M	7.1568	7.1904	−7.7	75.3	−1.80	0.072	2.14 *
p_aged16to64	U	8.4585	8.4312	9.9		3.81	0.000	2.27 *
	M	8.4461	8.4661	−7.3	26.7	−1.64	0.101	1.46 *
p_65yearsandover	U	6.7786	6.9981	−46.2		−19.17	0.000	3.18 *
	M	6.8147	6.838	−4.9	89.4	−1.15	0.251	1.83 *
EcoActive	U	7.9438	8.0082	−17.6		−6.86	0.000	2.43 *
	M	7.9456	7.942	1.0	94.4	0.23	0.820	1.83 *
p_education	U	5.6396	5.5648	15.3		5.08	0.000	1.19 *
	M	5.6273	5.6261	0.2	98.4	0.06	0.954	1.20 *
p_health	U	6.0073	5.9508	15.1		5.31	0.000	1.53 *
	M	6.0089	6.0116	−0.7	95.3	−0.17	0.865	1.69 *
p_level4qualifications	U	6.9778	6.7766	31.4		10.14	0.000	1.03
	M	6.9488	6.9393	1.5	95.3	0.37	0.715	1.05
Car_or_van	U	7.9047	7.9608	−14.3		−4.83	0.000	1.27 *
	M	7.9203	7.9259	−1.4	90.0	−0.35	0.730	1.23 *
Average_rooms	U	5.0083	5.2453	−42.9		−14.53	0.000	1.30 *
	M	5.0514	5.0658	−2.6	9.39	−0.68	0.495	1.24 *
populationdensity	U	43.143	29.58	64.7		22.78	0.000	1.55 *
	M	42.015	41.882	0.6	99.0	0.14	0.890	0.91

* if variance ratio outside [0.89; 1.12] for U and [0.89; 1.12] for M.

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