The Impact of Urban Rail Transit on Urban Boundary Expansion: Evidence from Changzhou's Metro Launch

Zhenyuan Pan

Beijing Normal–Hong Kong Baptist University (BNBU)

Faculty of Business and Management (FBM), BBA (Hons) in Applied Economics

Working Paper – Dec 2025

Table of Contents

Abstract

We study how urban rail transit affects urban spatial expansion by exploiting Changzhou's 2019 metro opening as a quasi-natural experiment. Using a two-way fixed-effects difference-in-differences design on panel data for Changzhou and comparable cities from 2007 to 2023, we estimate that the metro increased Changzhou's built-up area by roughly 330–340 square kilometers relative to the counterfactual without a metro. Event-study estimates, placebo tests, and robustness checks support the identifying parallel-trends assumption. To capture inter-city linkages, we estimate spatial econometric models and test for spillovers in built-up area across nearby cities. We then conduct mediation analysis, informed by the Alonso–Muth–Mills framework, to assess whether changes in population density transmit the effect of rail transit to the urban boundary. The results indicate that the metro opening accelerated outward boundary expansion partly by lowering population density, with the density channel accounting for about one-third of the total treatment effect. Overall, the evidence shows that rail transit infrastructure can reshape urban form in medium-sized Chinese cities and highlights the need to coordinate rail investment with land-use regulation when using transit to manage urban growth.

1. Introduction

1.1. Background

Over the past few decades, China's rapid urbanization has led to substantial growth in both urban population and built-up land (Li et al., 2024; Song et al., 2021). The national urbanization rate increased from roughly 36% in 2000 to about 64% by 2020 based on official statistics (Guo et al., 2023), and urban built-up areas expanded markedly, reflecting the outward movement of city boundaries as rural land was converted to urban uses (Song et al., 2021; Tian et al., 2025). This expansion has generated economic opportunities but also costs in terms of farmland loss, traffic congestion, and environmental pressures (Pu et al., 2023; Tian et al., 2025; Zheng & Kahn, 2013). In this context, Chinese planners have increasingly relied on urban rail transit (metros and light rail systems) as a key instrument for managing urban growth and promoting more sustainable, transit-oriented development. Rail transit has been promoted as a way to provide high-capacity mobility while guiding urban form toward denser, transit-oriented corridors and reducing car dependence and peripheral expansion (Cervero, 2008; Pan & Zhang, 2008; Zhang, 2020; Xu et al., 2017). By the end of 2020, 45 cities in China, ranging from megacities to medium-sized cities, had opened metro systems, with nearly 8,000 km of track in operation (Guo et al., 2023), consistent with a nationwide policy emphasis on transit-oriented urbanization and national programs such as the “Transit Metropolis” initiative and related planning guidelines for development around rail lines (Jiang et al., 2013; Xu et al., 2017; Zhang, 2020). Changzhou, a prefecture-level city of over five million residents in Jiangsu province, provides a representative case of this policy approach: the city opened its first metro line in 2019 to expand public transport capacity and guide subsequent urban development. Yet despite the scale and policy prominence of such investments, the causal impact of introducing urban rail transit on a city’s spatial expansion, measured by changes in built-up area, remains empirically underexplored, especially for medium-sized Chinese cities such as Changzhou.

1.2. Research Questions

This study asks whether the 2019 opening of Changzhou's urban rail transit system causally affected the city's built-up area and, conditional on a nonzero effect, whether the change reflects containment or acceleration of urban sprawl. We use this episode to study how introducing metro rail in a medium-sized developing city shapes its spatial development trajectory. This inquiry speaks to the literature on urban form and transport, in which many studies of Chinese cities examine economic and other urban development effects of rail or station-area land values and ridership (e.g., Zhang, 2020; Guo et al., 2023) but devote relatively little attention to urban boundary expansion as an explicit outcome. Changzhou's experience therefore provides a useful case for understanding how new metro systems may influence urbanization patterns in similar Chinese cities that are adopting rail transit to pursue more orderly growth.

1.3. Contributions & Objectives

This paper investigates how the 2019 opening of Changzhou's metro altered the city's urban boundary and makes three main contributions. First, it adds evidence from a medium-sized Chinese city to a literature that has focused largely on megacities, thereby clarifying whether rail transit in second-tier cities curbs or amplifies urban sprawl. In contrast to studies that emphasize economic output, ridership, or land values around individual stations, this paper treats the expansion of the built-up area as the central outcome and links it to a clearly dated rail transit shock. Using panel data for Changzhou and a matched group of comparable cities from 2007 to 2023, we implement a difference-in-differences design, complemented by event-study specifications, that treats the metro opening as a quasi-natural experiment. Second, we quantify the causal effect of rail transit on urban spatial form: the preferred estimates imply that the metro increased Changzhou's built-up area by about 330 square kilometers relative to the no-metro counterfactual, and that this effect is robust to alternative controls and placebo tests. Third, we combine spatial econometric models and mediation analysis to unpack mechanisms. We examine potential spatial spillovers to neighboring Jiangsu cities and show that roughly one-third of the metro's effect on urban area operates through a reduction in population density, consistent with monocentric city theory and the hypothesized density channel. Together, these results highlight the conditions under which rail transit in medium-sized Chinese cities serves as a tool for growth management rather than simply a facilitator of outward expansion. They also provide a basis for policy design that integrates metro investment with land-use regulation and complementary instruments such as urban growth boundaries and transit-oriented development zoning.

2. Conceptual Background and Hypotheses

2.1. Urban Rail Transit

Urban rail transit is a high capacity, fixed guideway mode of urban public transport that lowers generalized commuting costs and provides safe, reliable and energy efficient service; its system performance is usually evaluated using indicators such as on time arrival, capacity utilisation and energy and infrastructure efficiency (Pan et al., 2018). A large empirical literature on urban rail transit in China and elsewhere mainly studies engineering and operational performance and a set of local economic externalities, for example land price appreciation and employment concentration. By contrast, relatively few studies view rail transit as embedded in a broader political economic and spatial system in which planning and operations are tied to local public finance, land management and urban governance.

This conceptual simplification appears in at least two ways. First, in many empirical models of urban outcomes, transport infrastructure enters only as a static control variable, such as subway line density or station coverage, which makes it difficult to identify the dynamic policy effects and spatial heterogeneity of metro investment (Zheng & Kahn, 2013; Guo et al., 2023). Second, standard urban economic theory emphasises that transportation costs shape urban structure (Alonso, 1964), but existing work provides limited empirical evidence on the specific channels through which rail transit affects urban form, including delayed adjustments in land markets and strategic behaviour among developers. In the Chinese context, Cervero and Dai (2014) argue that rail transit often functions as a policy tool linked to land finance, which complicates direct comparison with Western transit oriented development practice. Urban rail transit therefore constitutes a core element of transit oriented development (TOD) and offers a natural conceptual framework for analysing the link between metro investment and changes in city boundaries (Calthorpe, 1993).

2.2. Urban Boundaries

Urban boundaries are a central concept for understanding how rail transit influences spatial urban expansion. Recent work has shifted from treating the urban boundary as a fixed administrative line to viewing it as a functional and data driven construct. Tian et al. (2025) use a multiscale framework for China to analyze the relationship between urban expansion and ecosystem services, which highlights differences between administrative units and cross administrative urban agglomerations and shows that rigid administrative boundaries can contribute to resource misallocation and fragmentation of ecosystem services. At the global scale, Li et al. (2024) construct the GloPPRUA dataset by combining several population datasets with joint thresholds for population density and settlement size, providing a harmonized urban boundary measure that is not tied to national administrative definitions. Dong et al. (2024) argue that geolocated mobile phone records, together with computational methods, can be used to delineate functional urban areas in a dynamic way that reflects actual patterns of population presence and movement. Taken together, these studies demonstrate that operational definitions of urban boundaries span administrative, density based, and functional approaches, but they also reveal two gaps that are directly relevant for this paper. First, these perspectives are rarely integrated within a single empirical framework that links administrative, ecological, and functional dimensions of urban space. Second, most of the existing work treats transportation infrastructure as a background condition when defining urban boundaries rather than analyzing how investments such as urban rail transit causally reshape the urban footprint. Building on this literature, this paper uses the expansion of the built up area as an explicit measure of the urban boundary and exploits the opening of Changzhou's metro as a quasi natural experiment to study boundary expansion and its mechanisms in small and medium sized Chinese cities.

2.3. Urban Rail Transit and Urban Boundary Expansion

2.3.1. Transit-Oriented Development (TOD) Theory

The transit oriented development (TOD) framework conceptualises urban rail transit as a key instrument for shaping compact and sustainable urban form, particularly by influencing the location and intensity of development relative to city boundaries. Its core idea is that high density, mixed use development around rail stations can support a more compact urban structure and limit low density expansion at the fringe (Calthorpe, 1993). From this perspective, TOD provides a natural theoretical basis for analysing how metro investment may contain or redirect urban boundary expansion.

2.3.2. TOD in the Chinese Context

In China, TOD ideas have been localized through the national "Transit Metropolis" strategy, and by 2020, 45 cities had opened urban rail systems with more than 8,000 kilometres of track (Guo et al., 2023). Whereas in the United States TOD is primarily used to channel development to station areas and reduce extensive sprawl at the urban edge (Cervero, 2008), Chinese practice places greater emphasis on strengthening the urban core while also accommodating planned expansion at the periphery (Xu et al., 2017). Evidence from large cities such as Shanghai shows that new metro lines attract higher density development in accessible locations and redistribute growth inward or along transit corridors (Pan & Zhang, 2008). New metro cities such as Changzhou adopt similar strategies, using rail transit to organise both boundary expansion and nodal intensification around stations. This approach is intended to promote infill and higher land use intensity near transit nodes, even though in practice it may coincide with continued outward growth of the built up area. These patterns reflect the way China's land finance and government led planning link rail investment to land development, with urban rail transit often functioning as a policy tool connected to land finance (Zhang, 2020).

In this institutional context, different transport infrastructures have distinct impacts on urban form. Highways tend to accelerate suburbanization and decentralization of Chinese cities, whereas the effects of urban rail transit are more nuanced and can simultaneously support decentralization of some activities and the vitality of central areas (Baum-Snow et al., 2017). On the one hand, transit investment can foster more compact growth by concentrating development near stations, consistent with the TOD principle of node focused development. On the other hand, rapid transit improves accessibility and allows residents and firms to commute over longer distances, which can encourage additional expansion at the urban fringe. Global evidence further indicates that building a subway does not automatically raise overall city population (Gonzalez-Navarro & Turner, 2018), which suggests that rail transit may primarily reallocate where urban growth takes place within and across cities rather than increasing aggregate growth.

Against this background, we first consider potential spatial spillovers from Changzhou's metro opening to neighboring cities. If the new metro attracts population and development from nearby cities, the resulting reallocation of growth may slow urban boundary expansion in surrounding Jiangsu cities. This reasoning leads to the following hypothesis.

Hypothesis 1 (H1). Changzhou's metro opening in 2019 generates a negative spatial spillover, whereby built up area expansion in Changzhou is associated with slower urban boundary expansion in geographically proximate Jiangsu cities.

We then turn to the local effect of metro construction on Changzhou itself. Existing empirical studies on urban rail transit focus mainly on economic outcomes in first tier cities and provide relatively little evidence on medium sized cities (Xu et al., 2017). Moreover, Western TOD theory does not fully capture the policy driven nature of rail oriented development under China's land finance regime. This study uses Changzhou as a case and exploits the 2019 metro opening as a quasi natural experiment to estimate the causal impact of urban rail transit on built up area expansion using a difference in differences design. In this way, the analysis contributes evidence on a policy tool type TOD model in a medium sized Chinese city and addresses the lack of empirical work on how metro construction affects urban boundaries outside megacities.

Hypothesis 2 (H2). The 2019 metro opening in Changzhou increased the built up area of Changzhou relative to comparable cities without metro service.

2.4. Population Density as a Mediating Mechanism

2.4.1. Monocentric City (Alonso–Muth–Mills) Model

The Alonso-Muth-Mills (AMM) model formalizes a monocentric city in which all employment is located in a central business district and households choose residential locations along a one-dimensional urban corridor (Alonso, 1964; Mills, 1967). At distance d from the CBD, households face commuting cost *kd* and land rent *R*(*d*); with income *w* and consumption c as the numeraire good, the budget constraint is:

$$R(d)=R_0-kd \tag{1}$$

Spatial equilibrium requires that utility be equal across locations. This condition implies a bid rent function.

$$\mathrm{w=c+R(d)+kd} \tag{2}$$

Where R_0 is central land rent and the parameter *k* is the unit commuting cost. Land rent therefore declines linearly with distance, and a lower *k* flattens the rent gradient.

In open city versions of the model, the urban boundary *b* is determined by the point at which urban land rent equals the opportunity cost of land for agricultural use. Let r_a denote agricultural land rent and *c* housing construction cost per unit of land. The boundary condition is

$$R(d)=R_0-kd \tag{3}$$

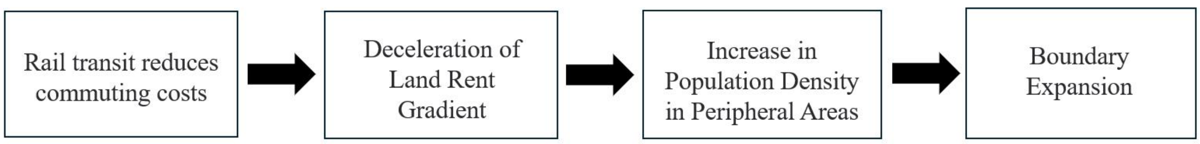
which yields the city radius

$$R(b)=r_a q+c \tag{4}$$

Equations (2)–(4) show that a reduction in commuting cost *k* increases the equilibrium city radius *b* and thus expands the built-up area. At the same time, lower commuting costs raise the optimal land consumption per household, which reduces population density at a given distance from the CBD. These comparative statics provide the theoretical basis for viewing population density as an endogenous channel through which transport infrastructure affects the urban boundary.

Figure 1 illustrates this mechanism pathway.

Figure 1
Mechanism Pathway Linking Rail Transit and Urban Boundary Expansion



2.4.2. Mechanism Pathway

The core mechanism in this paper is that urban rail transit alters commuting costs and accessibility, which in turn changes population density and ultimately the extent of the built-up area. When new rail lines reduce travel costs to the CBD, households and developers have incentives to locate farther from the center and to choose larger residential lots, leading to lower average density and a more dispersed urban footprint. In many Chinese cities, peripheral rail transit has been associated with intensified residential development at the urban fringe, consistent with this pattern (Zhang, 2020). Therefore, we develop the following hypothesis.

Hypothesis 3 (H3). Population density positively mediates the impacts of urban rail transit on urban boundaries.

2.5. Industrial Structure and Secondary Industry Share

Urban expansion in China is strongly shaped by the spatial distribution of secondary industry. Manufacturing and other secondary activities typically demand land intensive facilities such as factory buildings, warehousing, and logistics space, often in single storey configurations with low floor area ratios, which generate low density industrial land use. Under tight land supply and high land prices in core urban areas, these activities tend to move toward the urban fringe and convert previously undeveloped land into industrial use. This process directly enlarges the built up area and indirectly contributes to job housing separation and suburbanization (Song et al., 2021).

Evidence from case studies further supports these mechanisms. In Haikou, Pu et al. (2023) document that urban development boundaries and expansion potential depend on the configuration of urban land uses, including industrial land, and conclude that flexible, policy driven development boundaries must trade off industrial demand against ecological security (Pu et al., 2023). For the Pearl River Delta, Jiang et al. (2024) find that population agglomeration enhances economic development through increased market demand and that cities with a larger secondary industry base are more likely to display mutually reinforcing growth of industry and population, which is consistent with stronger pressures for outward spatial expansion (Jiang et al., 2024).

Because of these mechanisms, the secondary industry share is a key confounder when estimating the impact of urban rail transit on urban boundary expansion. Cities that receive a new metro line may at the same time undergo industrial upgrading or deindustrialization that changes land demand independently of transit policy. To isolate the causal effect of urban rail transit on built up area growth in our difference in differences framework, we therefore control for the secondary industry share in all empirical specifications. At the same time, the above mechanisms imply a structural relationship between industrial structure and urban boundary dynamics, which motivates the following hypothesis.

Hypothesis 4 (H4). Ceteris paribus, cities with a higher secondary industry share experience faster urban boundary expansion than otherwise similar cities with a lower secondary industry share.

3. Data and Empirical Strategy

3.1. Data Sources and Sample Selection

The empirical analysis is based on a city-level panel from 2007 to 2023 constructed from the China City Statistical Yearbook (National Bureau of Statistics), which reports population, economic aggregates, and urban development indicators for Chinese prefecture-level cities. Information on urban boundaries is complemented with detailed built-up area statistics from local statistical yearbooks, allowing us to construct a consistent measure of urban land area over time. The sample defines Changzhou as the treated city, where the first metro line started operation in September 2019, and includes ten control cities that are comparable to Changzhou before the treatment. We select these control cities using a Euclidean distance matching procedure that computes the distance between Changzhou and every other city based on key 2018 socio-economic characteristics, including population (in millions) and built-up area (square kilometers). The ten cities with the smallest distances form the control group, yielding an eleven-city balanced panel for the difference-in-differences analysis.

3.2. Variable Definitions

Table 1
Correlation Matrix of Key Variables

Variable	1	2	3	4	5	6	7
1. Urban Build Up Area	1						
2. Year	0.056	1					
3. Treat1	0.215	0	1				
4. Time	0.033	0.721	0	1			
5. Treatpost	0.267	0.143	0.462	0.198	1		
6. SecondIndus	-0.169	-0.530	0.111	-0.441	0.002	1	
7. POPdensity	-0.114	0.017	0.146	0.028	-0.037	0.072	1

Our outcome variable is the urban boundary, operationalized as the built-up area of each city in square kilometers. In the DID framework, treatment status is represented by two indicator variables. The first is a city-specific treatment dummy, treat_i, which equals 1 for Changzhou and 0 for each control city. The second is a post indicator, time_t, which equals 1 for years from 2020 to 2023 and 0 for years prior to the metro opening. As a key control, we include the share of secondary industry in GDP (SecondIndus) to capture cross-city differences in the demand for land-intensive industrial uses that may influence urban expansion. For the mediation analysis, we define population density as population per square kilometer and treat it as a potential mediator that transmits the effect of rail transit on built-up area, consistent with the theoretical mechanism in Section 3.4 where reduced commuting costs lead to lower density and a larger urban footprint.

3.3. Empirical Methods

3.3.1. Difference-in-Differences Approach

We estimate the effect of Changzhou's metro opening on urban boundary expansion using a difference-in-differences (DID) design based on city-level panel data from 2007 to 2023. The treatment group consists of Changzhou, and the control group consists of cities that are ex ante similar to Changzhou in socio-economic characteristics. The DID estimator compares changes in built-up area after the 2019 metro opening between the treatment and control cities and attributes any differential change to the metro introduction under a parallel-trends assumption (Angrist & Pischke, 2009).

Our baseline specification is:

$$\text{Urban Build Up Area}_i=\beta_0+\beta_1\text{treat}_i+\beta_2\text{time}_t+\beta_3(\text{treat}*\ \text{post})+\gamma_X+\epsilon_i \qquad (5)$$

Urban Build Up Area_{it} denotes the built-up area of city i in year t. The indicator $treat_i$ equals 1 for Changzhou and 0 for all other cities, and $time_t$ equals 1 for years 2020 and later and 0 otherwise. X_{it} is a vector of time-varying controls, including population, GDP, and the secondary-industry share. μ_i and λ_t capture time-invariant city characteristics and common shocks in each year, respectively, and ε_{it} is the idiosyncratic error term. The interaction coefficient β_3 is interpreted as the average treatment effect on the treated, that is, the change in Changzhou's built-up area after 2019 relative to the counterfactual evolution of the control cities.

3.3.2. Constructing the Control Group (Euclidean Distance Matching

Before estimating equation (5), we construct a comparison group of cities using a Euclidean distance criterion based on pre-treatment socio-economic indicators. Let $X_i=(X_i1,\ldots,X_in)$ denote a vector of built-up area, measures of transportation infrastructure, average income, and other core development indicators measured in 2018. For each candidate city j, we compute its Euclidean distance from Changzhou as:

$$D_{ij}=\sqrt{\sum_{k=1}^{n}(X_{ik}-X_{jk})^2} \tag{6}$$

Each city is treated as a point in an n-dimensional space, where each coordinate corresponds to one of the socio-economic variables in X. Cities with smaller values of D_{ij} are more similar to Changzhou in their pre-metro characteristics and are therefore selected as control cities. This selection rule yields a control group that closely matches Changzhou in demographic, economic, and spatial conditions prior to treatment and thereby improves the credibility of the DID design.

3.3.3. Spatial Econometric Models

Urban expansion in one city may generate spatial spillovers through migration, land and housing markets, or policy coordination with neighbouring cities. To allow for such spatial dependence, we re estimate the baseline difference in differences specification using two standard spatial panel models, the Spatial Lag Model (SLM) and the Spatial Error Model (SEM) (Anselin, 1988). The dependent variable is *Urban Build Up Area*$_i$, and the treatment indicator $treat_i$, the post period indicator $time_t$, and the control $vectorX_it$ are defined as in equation (5). The spatial weight matrix W is a row normalised first order contiguity matrix based on shared borders between cities, with $w_ij = 1$ if cities i and j are adjacent and $w_ij = 0$ otherwise.

$$\begin{cases} Urban\ Build\ Up\ Area_i = \beta_0 + \beta_1 treat_i + \beta_2 time_t + \beta_3 (treat *\ post) \\ \qquad \rho WBuild\_Up\_Area\_i\_t + \gamma_X + \epsilon_i \end{cases} \tag{7}$$

where ρ captures the extent to which changes in built up area in neighbouring cities feed back into the built up area of *cityi*. The SEM instead attributes spatial dependence to unobserved shocks:

$$\begin{cases} Urban\ Build\ Up\ Area\ i = \beta_0 + \beta_1 treat_i + \beta_2 time_t \\ + \beta_3 (treat *\ post) + \rho WBuild\_Up\_Area\_i\_t + \gamma_X + \epsilon_i \\ \qquad U_{it} = \mu W u_{it} + \epsilon_{it} \end{cases} \tag{8}$$

so that μ measures spatial correlation in the error term. Comparing the DID coefficient β_3 across the baseline model, the SLM and the SEM provides a diagnostic for whether ignoring spatial dependence materially biases the estimated impact of the metro opening on urban expansion.

3.3.4. Mediation Analysis

We next examine whether changes in population density constitute a mechanism through which urban rail transit affects urban expansion. In the Alonso Muth Mills monocentric city model, lower commuting costs flatten the bid rent gradient, induce households to choose larger lots at greater distances from the central business district, and thereby expand the urban boundary (Alonso, 1964; Mills, 1967). In our setting, this mechanism implies that the metro should reduce population density in the treated city while population density should be negatively associated with the built up area.

Let $PopDensity_{it}$ denote population per square kilometre. The first step of the mediation analysis estimates the effect of the metro on this mediator:Estimate the treatment effect on population density:

$$PopDensity\ it{=}\alpha_0{+}\alpha_1 treat_i{+}\alpha_2 time_t{+}\alpha_3(treat{*}\ \ post){+}\gamma_X{+}\epsilon_i \qquad (9)$$

Using the same set of controls and fixed effects as in the baseline DID regression. The second step augments the outcome equation with $PopDensity_{it}$:

$$Urban\ Build\ Up\ Area_i{=}\beta_0{+}\beta_1 treat_i{+}\beta_2 time_t{+}\beta_3(treat{*}\ \ post)$$

$$+\beta_4 POPdensity\_it{+}\gamma_X{+}\epsilon_i \qquad (10)$$

A negative estimate of α_3 combined with a negative estimate of β_4 indicates that the metro expands the built up area partly by lowering population density. We compute the product $\alpha_3{\times}\beta_4$ as the indirect effect and use the Sobel test statistic to assess whether this indirect effect is statistically different from zero (Sobel, 1982).

4. Empirical Results

4.1. Baseline Difference-in-Differences Results

Table 2 reports the difference-in-differences (DID) estimates of the metro's effect on urban area expansion. All specifications are estimated with city and year fixed effects. In column (1), which excludes additional control variables, the coefficient on the treatment interaction treatpost is 329.6 with a t statistic of 15.92 ($p < 0.001$). This estimate implies that, following the 2019 opening of Changzhou's urban rail transit, the city's built-up area increased by about 330 square kilometers more than that of the control cities. When the secondary-industry share (SecondIndus) is added as a control in column (2), the estimated coefficient on treatpost remains very similar at 336.1 with a t statistic of 12.73, which indicates that the main treatment effect is robust to controlling for differences in industrial structure. The coefficient on SecondIndus is −160.3 with t = −0.55, so it is not statistically different from zero; we therefore treat the negative sign only as suggestive and note that it is consistent with the mechanism explored later in the mediation analysis. The intercept represents the average pre-treatment urban area implied by the model.

Table 2
Difference-in-Differences Regression Results for Urban Area Expansion
(reghdfe with year fixed and city fixed)

	(1) Urban area_~sq.km	(2) Urban area_~sq.km
treatpost	329.6***	336.1***
	(15.92)	(12.73)
SecondIndus		-160.3
		(-0.55)
_cons	428.7***	505.5**
	(2346.30)	(3.63)
N	340	340

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

4.2. Spatial Econometric Results

To account for spatial dependence in urban expansion, we estimate spatial panel models using a contiguity-based weight matrix, following standard spatial econometric approaches (Anselin, 1988; Elhorst, 2014). Table 3 presents the binary spatial weight matrix W for Jiangsu cities, where each element equals 1 if two cities share a common border and 0 otherwise. This matrix is used to construct both the spatial lag and spatial error specifications.

Table 3

Binary Adjacency Matrix of Cities in Jiangsu Province

	Nanjing	Nantong	Suqian	Changzhou	Xuzhou	Yangzhou	Wuxi	Taizhou	Huai'an	Yancheng	Suzhou	Lianyungang	Zhenjiang
Nanjing	0	0	0	1	0	1	0	0	0	0	0	0	1
Nantong	0	0	0	0	0	0	0	1	0	1	1	0	0
Suqian	0	0	0	0	1	0	0	0	1	0	0	1	0
Changzhou	0	0	0	0	0	0	1	0	0	0	0	0	1
Xuzhou	0	0	1	0	0	0	0	0	0	0	0	1	0
Yangzhou	0	0	0	0	0	0	0	1	1	0	0	0	1
Wuxi	0	0	0	1	0	0	0	0	0	0	1	0	0
Taizhou	0	1	0	0	0	1	0	0	0	1	0	0	0
Huai'an	0	0	0	0	0	0	1	0	0	1	0	0	0
Yancheng	0	1	0	0	0	0	1	0	1	0	0	0	0
Suzhou	0	1	0	0	0	0	1	0	0	1	0	0	0
Lianyungang	0	0	1	0	1	0	0	0	0	0	1	0	0
Zhenjiang	1	0	0	1	0	1	0	0	0	0	0	0	0

Notes: This table presents the first-order contiguity matrix for 13 prefecture-level cities in Jiangsu Province, China. Entry wij = 1 indicates that city i and city j share a common border; wij = 0 otherwise.

Table 4 reports the corresponding regression results for ln(Urban Area). In column (1), the benchmark model without spatial terms shows that population growth (ln_population) has a strongly positive association with built-up area (coefficient = 2.146, $p < 0.01$), so the elasticity of built-up area with respect to population is about 2.15. GDP (ln_gdp) enters with a negative and statistically significant coefficient (coefficient = -0.253, $p < 0.01$), suggesting that, conditional on population, higher GDP is associated with more intensive land use and a slower outward expansion of the urban boundary.

Column (2) reports the spatial lag model (SLM). The estimated spatial lag coefficient on W_{js} s001is -0.114, which is negative in sign but not statistically different from zero at conventional levels. This pattern is consistent with the hypothesis that the introduction of rail transit in Changzhou could dampen neighboring cities' boundary expansion through population reallocation, yet the absence of statistical significance implies that the data do not provide reliable evidence of such a spillover effect. We therefore do not attach strong economic interpretation to this coefficient. In the context of open-city style urban models where migration responses help equalize utilities across locations (Alonso, 1964; Mills, 1967; Roback, 1982), one might expect some negative spillovers. However, frictions in population mobility and institutional constraints in the Chinese context likely attenuate these effects, which is consistent with the statistically insignificant spatial lag estimate.

Table 4
Spatial Panel Regression Results for ln_Urban Area

VARIABLES	(1) ln_Urban Area	(2) W_js_s001	(3) sigma_e
ln_gdp	-0.253***		
	(0.0970)		
ln_population	2.146***		
	(0.314)		
ln_Urban Area		-0.114	
		(0.0694)	
Constant			0.197***
			(0.0156)
Observations	85	85	85
Number of groups	5	5	5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column (3) reports the spatial error model (SEM). The estimated standard deviation of the spatial error component, sigma_e, is 0.197 and significant at the 1 percent level, which indicates residual spatial correlation in unobserved determinants of urban expansion after controlling for observed covariates. This residual correlation is consistent with SEM interpretations in the spatial econometrics literature (Anselin, 1988; Elhorst, 2014) and is plausibly related to factors such as cross-city coordination of land policies or large-scale infrastructure investment that are not explicitly modeled but exhibit spatial clustering. Their influence is captured through the error process rather than through a spatial lag of the dependent variable.

4.3. Mediation Results

Table 5 reports the regressions underlying the mediation analysis. Column (2) shows that the coefficient on the treat*time interaction in the population density equation is -1,096 with a standard error of 307.3, implying that the metro opening significantly reduced population density in Changzhou relative to the control cities. Column (1) indicates a negative association between population density and urban area: the coefficient on population density is -0.112 with a standard error of 0.00686, so lower density is associated with a larger built up area. Taken together, these two coefficients imply an indirect effect of urban rail transit operating through population density, given by:

$$\textit{Indirect Effect} = a \times b = (-1{,}096) \times (-0.112) \approx 122.8$$

Using the Sobel test (Sobel, 1982), the corresponding z statistic is:

$$Z = \frac{(-1{,}096)^2 * \ (0.00686)^2}{\sqrt{(-0.112)^2 * \ (307.3)^2 * \quad (-1{,}096)(-0.112)}} = \frac{122.752}{\sqrt{1{,}241.01}} \approx 3.48$$

and the two sided p-value is approximately 0.0005, which confirms that the mediated effect is statistically different from zero. Comparing this estimate with the baseline difference in differences estimate of the total effect in Table 2, 336.1, suggests that about 36 percent of the metro's impact on built up area operates through changes in population density. This is consistent with the mechanism in which improved rail accessibility lowers commuting costs, enables residents to relocate toward the urban fringe, reduces average density, and thereby expands the urban boundary.

Table 5
Regression Results with Interaction Effects on Urban Area and Population Density

	(1)	(2)
VARIABLES	Urban area_~sq.km	Population density_~per sq.km
Population density_~per sq.km	-0.112***	
	(0.00686)	
1.treat1	381.3***	719.8***
	(25.66)	(205.5)
1.time	174.9***	84.50
	(21.61)	(183.1)
0b.treat1#0b.time	0	0
	(0)	(0)
1.treat1#1.time	213.0***	-1,096***
	(42.11)	(307.3)
SecondIndus	192.7**	2,935***
	(92.96)	(718.9)
Constant	349.2***	1,199***
	(43.09)	(340.0)
Observations	340	360
R-squared	0.891	0.529

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient on the treat*time interaction in column (1) of Table 5, which measures the direct effect of urban rail transit on urban area after controlling for population density, is 213.0 and remains highly significant. Its magnitude is smaller than the total effect of 336.1 from Table 2, indicating partial rather than full mediation: rail transit continues to expand the urban area directly, while an additional channel operates through the induced decline in density. The sum of the direct and indirect components, 213.0 + 122.8 = 335.8, is almost identical to the total DID effect of 336.1, which suggests that the mediation decomposition is internally consistent and that the results are robust to the inclusion of the mediating variable.

In addition, the direct effect of urban rail transit (treat*time) in the first column is 213.0, the coefficient is significant, and the magnitude is significantly reduced. This not only indicates that rail transit directly drives the expansion of the urban area, but also proves that population density is indeed a partial mediator.

Combined with the indirect effect (122.8), the total effect can be decomposed as:

$$\textit{Total effect} = \textit{Direct effect} + \textit{Indirect effect} = 213.0 + 122.8 = 335.8$$

This result is highly consistent with the total effect (336.1) in Table 1 without controlling the mediating variable, verifying the robustness of the model.

4.4. Robustness Checks

We assess the robustness of the difference-in-differences estimates using an event-study specification for pre-trends and a placebo DID regression. Figure 2 plots the estimated dynamic treatment effects. In the four pre-treatment periods (pre_5 to pre_2), all coefficients are close to zero and their 95% confidence intervals include zero, which suggests the absence of differential pre-treatment trends in urban area between Changzhou and the control cities. Table 6 formally tests this visual impression: a joint F-test of equality of the pre-treatment coefficients yields an F-statistic of 0.36 with a p-value of 0.8324, so we cannot reject the null that the pre-treatment effects are jointly zero at conventional significance levels. Taken together, the event-study plot and the joint test provide empirical support for the parallel-trends assumption required for causal interpretation of the DID estimates.

To verify that the main treatment effect is not driven by chance or omitted factors unrelated to the metro opening, we also estimate a placebo DID model in which a fictitious treatment indicator (fake_did) is randomly assigned. As reported in Table 7, the coefficient on fake_did is 82.07 with a standard error of 71.76 ($p > 0.1$), indicating no statistically significant effect when treatment status is randomly permuted. This placebo result implies that the sizable and significant effect found in the baseline specification does not arise from mechanical correlations in the data, which reinforces our conclusion that the opening of the rail transit system causally increased urban expansion in Changzhou.

Figure 2
Event Study Plot of Urban Effect Before and After Rail Transit Introduction

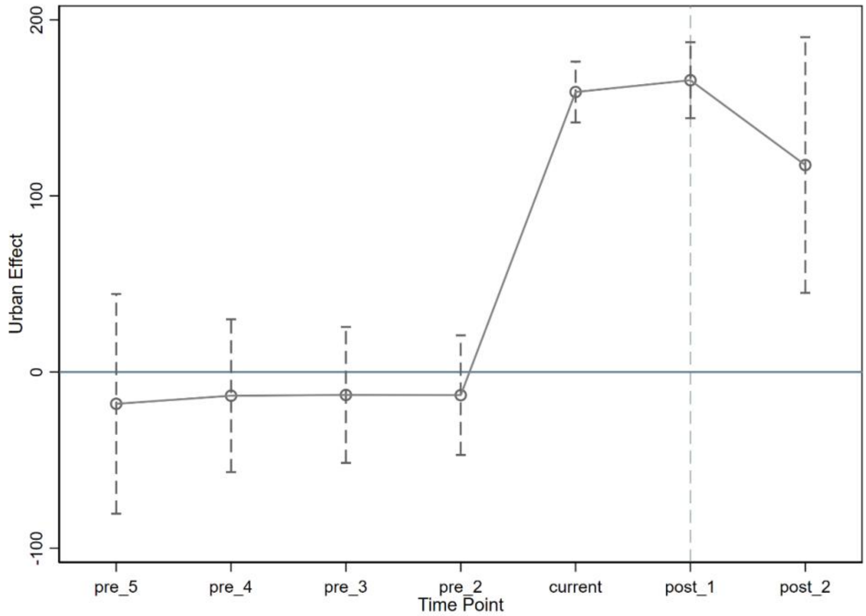


Table 6
Joint Test of Pre-Treatment Parallel Trends

Null Hypothesis	F-statistic	p-value
$Pre_{-5} = Pre_{-4} = Pre_{-3} = Pre_{-2} = 0$	0.36	0.832

Notes: This table reports the joint F-test for the null hypothesis that all pre-treatment coefficients are equal to zero. Failure to reject suggests the parallel trend assumption is satisfied.

Table 7
Placebo Test Using Fictitious Treatment Variable

	(1)
	Urban area_~sq.km
fake_did	82.07
	(71.76)
SecondIndus	-371.0
	(408.8)
_cons	758.3***
	(192.0)
N	476

Standard errors in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

5. Conclusion and Policy Implications

Our estimates show that the 2019 metro opening led to an increase of roughly several hundred square kilometers in Changzhou's built-up area and that about one third of this effect operates through a decline in population density, implying that new rail infrastructure can widen rather than contract the urban boundary in a medium-sized Chinese city. These findings yield three policy recommendations.

First, rail transit should not be viewed as a stand-alone instrument for containing sprawl. In the absence of supportive land-use policies, improved accessibility may encourage low-density development at the urban fringe, as appears to have occurred in Changzhou. Consistent with transit-oriented development principles, urban rail investment needs to be coupled with measures such as higher allowable densities, mixed-use zoning, and housing incentives around stations so that growth is steered toward transit-served locations rather than dispersed to peripheral greenfield sites (Cervero, 2008).

Second, the outward pressure on the urban boundary highlighted by our results suggests a role for explicit growth management tools. Introducing urban growth boundaries or functionally similar development limits around new metro corridors can help protect farmland and ecological spaces while directing new construction toward designated urban zones, in line with evidence that development boundaries improve the balance between expansion and ecological security (Pu et al., 2023).

Third, transit expansion should be coordinated with the city's broader economic restructuring. Changes in industrial structure, employment locations, and housing demand can amplify or dampen the spatial effects of new rail lines, so integrating metro planning with industrial policy and land-use regulation is essential if rail investment is to support more compact and sustainable urban development in cities like Changzhou.

References

Alonso, W. (1964). Location and Land Use. Harvard University Press. https://doi.org/10.4159/harvard.9780674730854

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., & Zhang, Q. (2017). Roads, railroads, and decentralization of Chinese cities. *Review of Economics and Statistics, 99*(3), 435–448. https://doi.org/10.1162/REST_a_00656

Calthorpe, P. (1993). The next American metropolis: Ecology, community, and the American dream. Princeton Architectural Press.

Cervero, R. (2008). Effects of TOD on housing, parking, and travel. Transportation Research Board.

Combes, P.-P., Duranton, G., & Gobillon, L. (2019). The costs of agglomeration: House and land prices in French cities. Review of Economic Studies, 86(4), 1556–1589. https://doi.org/10.1093/restud/rdy045

Dong, L., Duarte, F., Duranton, G., Santi, P., Barthelemy, M., Batty, M., Bettencourt, L., Goodchild, M., Hack, G., Liu, Y., Pumain, D., Shi, W., Verbavatz, V., West, G. B., Yeh, A. G. O., & Ratti, C. (2024). Defining a city — delineating urban areas using cell-phone data. Nature Cities, 1(2), 117–125. https://doi.org/10.1038/s44284-023-00019-z

Gonzalez-Navarro, M., & Turner, M. A. (2018). Subways and urban growth: Evidence from Earth. *Journal of Economic Perspectives, 32*(3), 185–206. https://doi.org/10.1257/jep.32.3.185

Guo, X., Zhang, Q., Yin, Z., Li, Z., & Shao, C. (2023). Research on the impact of China's urban rail transit on economic growth: Based on PSM-DID model. *Frontiers in Environmental Science, 11*, 1082567. https://doi.org/10.3389/fenvs.2023.1082567

Jiang, P., Xu, C., Chen, J., & Chen, W. (2024). The impact of population agglomeration on economic development of the Pearl River Delta based on urban fixed effect model. Sustainable Development, 14(5), 88741. https://doi.org/10.12677/sd.2024.145157

Li, W., Zhang, Y., Li, M., & Long, Y. (2024). Rethinking the country-level percentage of population residing in urban area with a global harmonized urban definition. IScience, 27(6), 110125. https://doi.org/10.1016/j.isci.2024.110125

Mills, E. S. (1967). An Aggregative Model of Resource Allocation in a Metropolitan Area. The American Economic Review, 57(2), 197–210. http://www.jstor.org/stable/1821621

Pan, D., Zhao, L., Luo, Q., Zhang, C., & Chen, Z. (2018). Study on the performance improvement of urban rail transit system. Energy, 161, 1154–1171. https://doi.org/10.1016/j.energy.2018.07.067

Pan, H., & Zhang, M. (2008). Rail transit impacts on land use: Evidence from Shanghai, China. *Transportation Research Record: Journal of the Transportation Research Board, 2048*(1), 16–25. https://doi.org/10.3141/2048-03

Pu, L., Xia, Q., et al. (2023). Urban development boundary setting versus ecological security and internal urban demand: Evidence from Haikou, China. Land, 12(11), 1987. https://doi.org/10.3390/land12111987

Song, X., Feng, Q., Xia, F., Li, X., & Scheffran, J. (2021). Impacts of changing urban land-use structure on sustainable city growth in China: A population-density dynamics perspective. Habitat International, 107, 102296. https://doi.org/10.1016/j.habitatint.2020.102296

Tian, S., Wu, W., Chen, S., Li, Z., & Li, L. (2025). Socioeconomic factors behind the relationship between urban expansion and ecosystem services: a multiscale study in China. Landscape Ecology, 40(4). https://doi.org/10.1007/s10980-025-02098-w

Xu, W. A., Guthrie, A., Fan, Y., & Li, Y. (2017). Transit-oriented development: Literature review and evaluation of TOD potential across 50 Chinese cities. Journal of Transport and Land Use, 10(1). https://doi.org/10.5198/jtlu.2017.922

Zhang, M. (2020). Transit-oriented development in China: Policy and practice. *Transport Policy, 98*, 109–117. https://doi.org/10.1016/j.tranpol.2020.06.008

Zheng, S., & Kahn, M. E. (2013). China’s bullet trains facilitate market integration and mitigate the cost of megacity growth. Proceedings of the National Academy of Sciences, 110(14). https://doi.org/10.1073/pnas.1209247110