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From Construction to Operation: A Public Service Ecosystem Framework for Urban Rail Transit's Economic Impact

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Abstract

Urban rail transit (URT) is becoming an important component of a modern city's transportation infrastructure, which greatly improves the overall efficiency of urban mobility. However, it remains unclear whether URT systems stimulate economic growth through agglomeration effects or inadvertently hinder productivity through fiscal crowding-out effects. To address the question, we analyzed panel data from 26 Chinese cities from 2007 to 2020 through the theory of public service ecosystems (PSE) to interpret the effects of URT construction and operation on the economy from the dual perspectives of value creation and value destruction. We found that URT construction follows the law of diminishing marginal returns, whereas operational efficiency is positively associated with economic growth. Furthermore, URT construction usually exhibits stronger economic benefits in the central and western regions of China, whereas the optimization of operational efficiency is more effective in the eastern regions. Our findings offer phase-specific strategies for policymakers: prioritizing network expansion for emerging URT systems and formulating service innovation roadmaps for mature systems.

Keywords: urban rail transit; economic growth; public service ecosystem; regional heterogeneity; infrastructure governance



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1. Introduction

Urban rail transit (URT), including metro, light rail, and maglev systems, constitutes a strategic public transportation infrastructure that redefines urban spatial economies through mobility transformation [1,2]. Moreover, URT development embodies a critical public value proposition: reconciling economic agglomeration with equitable accessibility in rapidly urbanizing societies [3]. While URT investments are typically deemed to be growth catalysts by governments around the world, their economic returns are still not accurately assessed. Neoclassical proponents assert that labor market expansion will lead to multiplier effects [4], whereas public choice theorists warn of diminishing returns from fiscal overcommitment [5]. These theories are contradictory for two reasons: (1) inadequate theoretical frameworks capturing URT's phased impacts and (2) insufficient attention to spatial heterogeneity in networked infrastructure governance [6,7].

Traditional economic frameworks, particularly Input-Output Analysis (IOA) and the Neoclassical Growth Model (NGM), evaluate URT's economic impacts by quantifying direct investment and construction costs [8–13]. Since its introduction by Leontief in 1936, IOA has been widely used to reveal structural relationships between inter-industry inputs and outputs, playing a critical role in national and regional economic planning [14]. In

the public transportation sector, IOA models are often employed to quantify the economic multiplier effects of investments. For instance, Lee et al. employed IOA to show that high-speed rail construction in Sejong City, South Korea, significantly boosted industrial output, employment, and income, noting that the method is also applicable to URT and other transport infrastructure investments. Ji et al. found that transport infrastructure investment had a positive impact on China's GDP growth during 2016–2018 [9]. Roland-Holst further demonstrated that infrastructure investment exhibits a strong structural Keynesian multiplier effect, promoting the growth of products and services along supply chains [15]. Similar IOA-based analyses also include evaluations of the employment effects of the California high-speed rail project [13].

However, traditional IOA has several inherent limitations. First, it assumes linear and fixed inter-industry relationships within public transportation systems over time, overlooking economies of scale and nonlinear effects [13,16]. Moreover, the applicability of input-output (IO) models depends heavily on data completeness [17]. In newly planned cities or developing countries, detailed regional IO tables are often unavailable. Researchers typically rely on indirect derivations or proxy assumptions, such as scaling national IO tables to regional levels. This approach inevitably introduces uncertainty and error [18]. For example, in Sejong City, researchers constructed a regional IO table using a four-step method and derived regional data from the national IO table. While methodologically reasonable, the precision of the results remains limited [13].

The Neoclassical Growth Model (NGM) is used to evaluate the long-term effects of capital, labor, and technological changes on economic growth from a macroeconomic perspective [19]. For instance, Yao et al. use the NGM to find that high-speed rail investment significantly promotes urban economic growth and accelerates regional economic convergence in China [20]. Yet, its assumptions of perfect competition and rational behavior limit its ability to capture regional heterogeneity and differences in industrial structure. Other methods, such as Cost-Benefit Analysis (CBA), are used *ex ante* to evaluate transport investments. CBA assesses feasibility by comparing expected benefits with total costs, such as maintenance and operation of URT [18,21]. Because all factors in CBA are expressed in monetary terms, it helps reduce the risk of major decision errors in large-scale transport investments. Nevertheless, fully monetizing intangible benefits is almost impossible, and benefit calculations remain subjective depending on location-specific and time-specific conversion factors [18].

Overall, traditional economic analysis methods have been widely applied in research on transportation infrastructure. However, empirical studies focusing specifically on URT remain limited and reveal several methodological limitations in evaluating its economic impacts [2,21]. First, these studies tend to adopt a producer-centric perspective, paying limited attention to consumers as another key stakeholder in the URT system [22]. Second, empirical studies often focus on construction-phase impacts, overlooking the potential long-term economic benefits arising from the operational phase [22]. Third, these methods rely on static assumptions or homogenizing simplifications, such as assuming constant returns to scale or the assumption of uniform technology and capital returns, and thus overlook differences across cities or regions [13,23]. Fourth, traditional methods generally rely on linear assumptions, such as fixed IO coefficients, while neglecting market adjustments and nonlinear economic effects [11]. These shortcomings highlight the need for more comprehensive and systematic theoretical frameworks to explain the interactions between URT and regional economies.

The Public Service Ecosystem (PSE) theory provides a dynamic, multi-actor perspective for mechanism analysis. It emphasizes how value creation and value destruction emerge through resource flows and interactions at different stages [24]. Value creation

refers to the positive outcomes generated through collaboration and interaction among multi-actors, such as enhanced industrial development, employment growth, land appreciation, improved labor market efficiency, and business agglomeration. In contrast, value destruction refers to the reduction or loss of value caused by conflicts, coordination failures, or mismanagement among actors, which can manifest as fiscal pressures, resource waste, or public dissatisfaction [25,26]. During the construction phase, URT investment can stimulate industrial development, increase employment, and drive land appreciation, thereby creating value, but it may also generate fiscal pressures and environmental burdens, leading to value destruction. In the operational phase, enhanced mobility can improve labor market efficiency and promote business agglomeration, creating further value, whereas distorted fares or inefficient services can result in resource waste and public dissatisfaction, constituting value destruction [27]. This lifecycle perspective provides a solid theoretical foundation for detailed empirical studies on the economic effects of URT.

Unlike the traditional goods-dominant logic, which emphasizes the product itself as the core of value creation and regards the producer as the primary creator of value, the PSE theory centers on public service logic, emphasizing that value is co-created by consumers and producers during the process of use, with consumers acting as “co-creators” of value [28,29]. Traditional theories and methods, by focusing on the producer’s perspective, have largely concentrated on the construction phase of URT, overlooking the long-term economic and social benefits arising from the operational phase. In contrast, the PSE framework highlights the critical role of consumers in value creation and emphasizes the inseparability of the construction and operational stages, thereby incorporating URT into a lifecycle perspective [28]. This comprehensive theoretical approach reveals both the industrial expansion and investment-driven effects of the construction phase and systematically assesses the operational phase’s impacts on resource flow and economic resilience, providing a clearer framework for understanding URT’s economic value. At the same time, this process also includes the potential for value destruction [25].

Based on this theoretical framework, we developed models to assess the impact of URT systems on urban economic growth, including construction-stage models from the provider perspective and use-stage models from the user perspective [30]. We regard urban economic growth as an outcome of value creation, whereas an economic downturn reflects value destruction. To address the limitations of traditional economic analyses, which rely on static or linear assumptions and often overlook region-specific differences, we applied the Fixed Effects Threshold (FET) model and the Individual Fixed Effects (IFE) model. The FET model identifies nonlinear threshold effects during the capital-intensive construction phase, distinguishing investment levels that generate value creation from those that entail value destruction risks [31]. The IFE model, applied primarily to the operational phase, captures unobserved individual and regional heterogeneity, allowing for a more accurate estimation of URT’s operational impacts across cities compared with conventional models [32]. Together, these models enable a detailed assessment of how URT construction and operation stages affect urban economic outcomes.

By proposing a PSE framework, this study aims to resolve the longstanding theoretical debate on URT’s economic impacts. We have three objectives: (1) to establish a multi-stage analytical framework to comprehensively analyze the role of URT in economic development, providing new theoretical support and research approaches for studying the relationship between public infrastructure and regional economy; (2) to quantify the nonlinear lifecycle impacts of URT through a dual-model approach, distinguishing threshold effects during capital-intensive construction phases from operational spillovers in service utilization; (3) to uncover regionally divergent policy pathways by comparing the economic mechanisms dominating China’s eastern and central-western regions, as well as those in

first-tier and second-tier cities, thereby informing spatially adaptive infrastructure governance strategies.

2. Literature Review

2.1. URT and Economic Growth

The relationship between infrastructure and economic growth remains contested. Although early studies reported a positive correlation, they were often constrained by issues such as endogeneity and reverse causality. Calderón and Servén addressed these challenges using the System Generalized Method of Moments (GMM) estimator and found that both the quantity and quality of infrastructure significantly contribute to economic growth [33]. Romano et al. employed a staggered difference-in-differences (DID) approach to study Brazil's Federal Highway Concession Program and found that improved transport accessibility increased municipal tax revenue [34]. However, other studies, including the meta-analysis by Elburz et al., have produced mixed or inconclusive results [35]. More recently, Govinda analyzed data from 87 countries between 1992 and 2017, focusing on transport, electricity, and telecommunications infrastructure [36,37]. The findings suggest that short-term effects are generally limited and that transport infrastructure may even have negative impacts in the short run. In the long term, the elasticity of GDP with respect to infrastructure ranges from 0.09 to 0.1 [37]. These effects vary across countries and regions, with substantial academic disagreement over the impact of transport infrastructure on economic performance in East Asia. Among infrastructure types, transportation infrastructure is distinctive and controversial due to its potential short-term negative impacts and significant regional variation in effects. Due to its high costs and controversial economic impacts, URT provides a valuable case for exploring the complex relationship between transport infrastructure and economic growth [11,38].

It has long been debated whether URT robustly boosts economic growth or simply burdens public budgets. Some scholars, using quantitative models, emphasize URT's capacity to expand labor markets and improve productivity through accessibility gains [39,40]. In developed countries, URT has been particularly promoted as a catalyst for broad development agendas, including urban regeneration and revitalization [40]. For example, Knowles et al. demonstrated that investment in modern light rail systems in the UK and globally can stimulate new economic growth by alleviating significant transport constraints [41]. In contrast, other scholars, using a case-study method, warn of the risks derived from over-investment. For instance, Gómez-Ibáñez documented that light rail projects in San Diego, Buffalo, and Portland incurred debt-to-revenue ratios exceeding 150%, reflecting systemic fiscal hazards [42]. This issue is more acute in developing economies, where research remains limited.

The institutional characteristics of China determine the uniqueness of URT financing. Unlike Europe and the United States, which focus on ridership recovery, China's URT financing relies on the land value capture mechanism, resulting in spatially stratified outcomes. Specifically, URT promotes the appreciation of land values along its routes, thereby generating fiscal revenue through land transfers [43]. For example, in Shenzhen, the city has implemented a Transit-Oriented Development (TOD) model that promotes efficient land use and commercial development around transit stations, simultaneously boosting the operational efficiency of URT by over 10% [44,45]. In contrast, URT companies in central-western cities generally yield low benefits after the completion of URT construction. Some of them even operate at a loss and carry heavy debt burdens [46,47]. However, prevailing studies treat these regional disparities as exogenous variables, while underestimating the endogenous PSE mechanism through which URT's economic lifecycle is dynamically mediated.

Despite growing scholarly interest, empirical studies remain relatively scarce, and several practical limitations persist. First, the scope of the research is limited. Most studies focus on first-tier cities or a small number of sample cities, neglecting the development experiences of second- and third-tier cities and lacking broad regional comparisons. Second, studies are scarce and often rely on a narrow set of indicators [23,48]. Research on transportation infrastructure has primarily focused on high-speed rail or highways, leaving URT understudied. Existing studies often focus on housing prices or land values, with relatively few systematic analyses of broader economic effects. Third, a systematic theoretical framework is often lacking. Many studies remain at the correlational level, identifying only statistical relationships or trends between URT and economic growth, without solid theoretical support [11]. Fourth, some newer methods, such as DID, although offering improvements in causal identification, assume parallel trends and treat URT as a one-time event, making it difficult to capture the gradual, long-term economic effects arising during both construction and operation [49,50]. This limits their ability to explain how URT's construction and operational stages jointly influence urban economic outcomes.

To address the issues outlined above, this study compiles panel data on URT construction and operation for 26 Chinese cities over the period 2007–2020. The analysis centers on the relationship between URT construction and operation and per capita GDP. By applying the PSE framework, we further elucidate how URT influences economic outcomes through the dual mechanisms of value creation and value destruction, capturing both its promoting and inhibiting effects [25]. This approach not only provides a solid theoretical foundation for assessing the economic impacts of URT but also offers conceptual guidance for understanding how other transport infrastructure may affect regional economic performance.

2.2. Value Creation in Public Service Ecosystems

The concept of value is arguably elusive, as it stems from its different conceptualizations as 'value-in-exchange' and 'value-in-use' [51]. In the industrial era, traditional thinking on value was primarily shaped by goods-dominant logic (G-D logic), which emphasized value-in-exchange, viewing value as embedded in goods and determined by producers. In contrast, service-dominant logic (S-D logic) argues that value does not exist prior to use and experience. Instead, it emphasizes value-in-use and value-in-context, meaning that value is uniquely determined by users [51]. Value creation refers to the process through which customers and producers actively create value during use, through interaction [52]. In recent years, an increasing number of scholars have referred to it as "value co-creation" to emphasize the collaborative role of consumers and producers in the value creation process. Value is activated and transferred to users through goods and other service-related resources [53]. This requires a fundamental shift in thinking, urging organizations to redefine the very nature of value.

In 2013, Osborne et al. introduced S-D logic into the field of public management, proposing the concept of public service-dominant logic (PSDL) and public service logic (PSL). In 2016, they further developed this into the PSE framework, which systematically builds on PSL [28,30,54]. The framework highlights a dynamic, multi-level network of interactions among governments, citizens, organizations, and other stakeholders, where public value is co-created by both service providers and users. More importantly, the PSE theoretical framework emphasizes that value co-creation is a dynamic process and that value co-destruction may occur when public services are mismanaged [55–57].

Currently, only a few scholars have paid attention to the application of public service ecosystem theory in public infrastructure. However, we recognize that this theoretical framework holds practical significance for analyzing the relationship between transporta-

tion infrastructure development and regional economy. This framework emphasizes the role of public service users as co-creators of value, providing an important theoretical basis for this study to consider the operational phase of URT when examining its economic impact. According to the PSE framework, we clearly distinguish two value creation stages for URT: the production stage (infrastructure development) and the usage stage (service operation) [58,59]. This paper analyzes URT's impact on the regional economy from the perspective of value-in-use rather than value-in-exchange. Infrastructure investments like URT may have limited short-term financial returns but offer significant long-term benefits by improving efficiency, protecting the environment, and encouraging economic clustering. However, it should be noted that if these stages fail to align with public needs, value destruction may occur, such as fiscal strain [60]. The theoretical framework is shown in Figure 1.

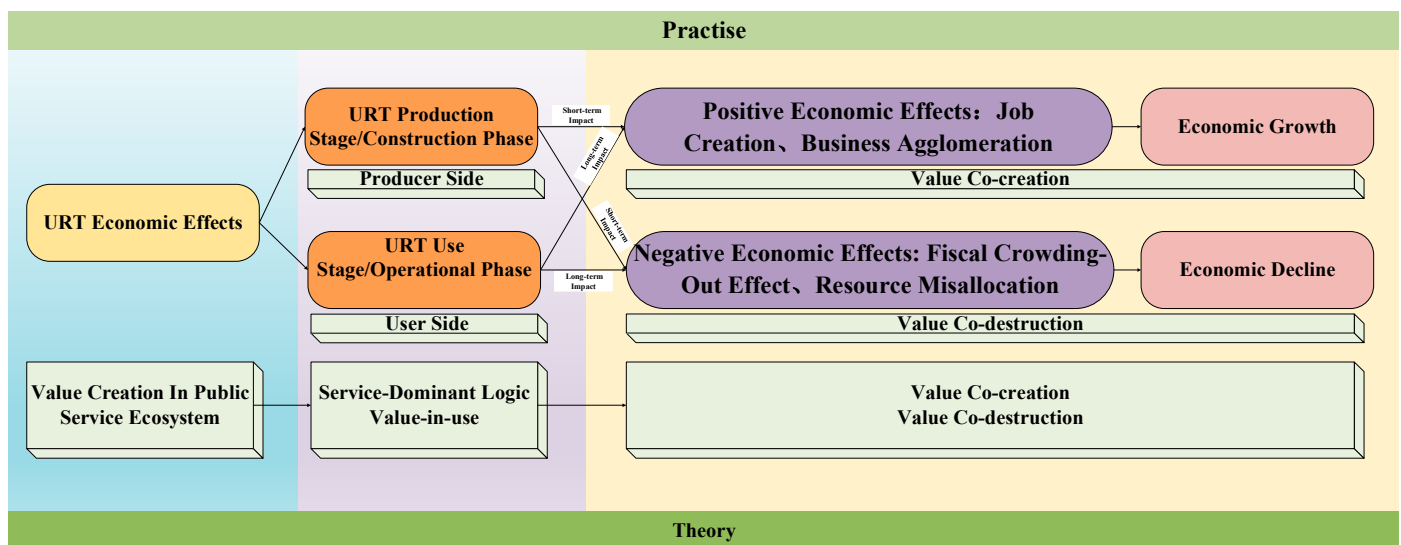


Figure 1. Theoretical framework.

3. Materials and Methods

3.1. Analytical and Technical Framework

Specifically, our study, based on the S-D logic of the PSE framework, emphasizes the joint role of producers and consumers in value creation [29,61]. Urban economic growth is regarded as the outcome of value creation, whereas economic downturn reflects value destruction. The construction-phase model is developed from the provider's perspective, while the operation-phase model is based on the user's perspective. In the construction phase, URT investment stimulates industrial development, employment growth, and land appreciation, thereby generating value and fostering economic growth [23]. At the same time, misaligned investment allocation or excessive debt accumulation may lead to value destruction and trigger economic decline [62]. In the operational phase, URT passenger flow intensity reflects system utilization efficiency and links service provision to economic outcomes. High passenger flow enhances labor mobility, supports agglomeration economies, and improves productivity, thereby creating additional value and driving economic growth [63]. Conversely, operational inefficiencies, such as underutilized routes or distorted pricing, may result in resource waste and public dissatisfaction, leading to value destruction and hindering economic development.

The PSE framework posits that value creation and value destruction are inherently embedded in a multi-level dynamic process spanning macro, meso, micro, and sub-micro levels, with interactions among these levels jointly shaping socioeconomic outcomes. Building on this theoretical foundation, this study selects control variables to capture the hierarchical

determinants of urban economic outcomes in a manner consistent with PSE logic [64,65]. At the macro level, government expenditure represents broad enabling conditions, such as fiscal capacity and public policy support, which can facilitate or constrain the potential of urban rail transit to generate public value. At the meso level, technological investment reflects innovation spillovers and absorptive capacity, mediating the translation of urban rail transit infrastructure into productivity gains and economic growth. At the micro level, human resources capture the effective utilization of labor mobility and skills, allowing the workforce to benefit from improved accessibility. At the sub-micro level, market size and demand conditions reflect localized economic environments, which modulate the extent to which urban rail transit contributes to value creation [64]. In addition, the air quality index is included as an environmental control variable following the PSE lifecycle perspective to reflect the ecological context of urban rail transit operations, thereby more comprehensively controlling for externalities affecting economic innovation activities. By explicitly aligning each control variable with the corresponding level of the PSE framework, the model ensures theoretical consistency, isolates the direct economic effects of urban rail transit, and integrates the multi-level socioeconomic mechanisms through which transit infrastructure interacts with urban development. This approach operationalizes the multi-level logic of value creation and destruction and provides a rigorous theoretical basis for interpreting the economic impacts of urban rail transit investment and operation.

Technically, the analysis follows a dual-model approach. The FET model is applied primarily to the construction phase, identifying nonlinear threshold effects of URT investment on value creation and destruction [31]. In the operational phase, we employ the IFE model [32]. This model has the advantage of controlling for city-specific unobserved differences through the inclusion of city-specific intercepts, while incorporating time-varying unobserved factors into the error term, thereby enabling a robust estimation of the true effect of passenger flow density on economic growth. This stepwise modeling strategy constitutes a clear technical roadmap: First, control variables are integrated based on the multi-level value creation structure, including macro-level government expenditure, meso-level technological capacity, micro-level human resources, and sub-micro-level consumer demand. Second, drawing on the core service-dominant logic of the PSE framework and a lifecycle perspective, the role of consumers is emphasized, placing the often-overlooked operational-phase effects on equal footing with construction-phase effects [24]. Finally, nonlinear relationships and regional variations are quantified, linking each phase's mechanisms to observable outcomes and addressing theoretical and empirical gaps in previous studies [66]. The technical framework is shown in Figure 2.

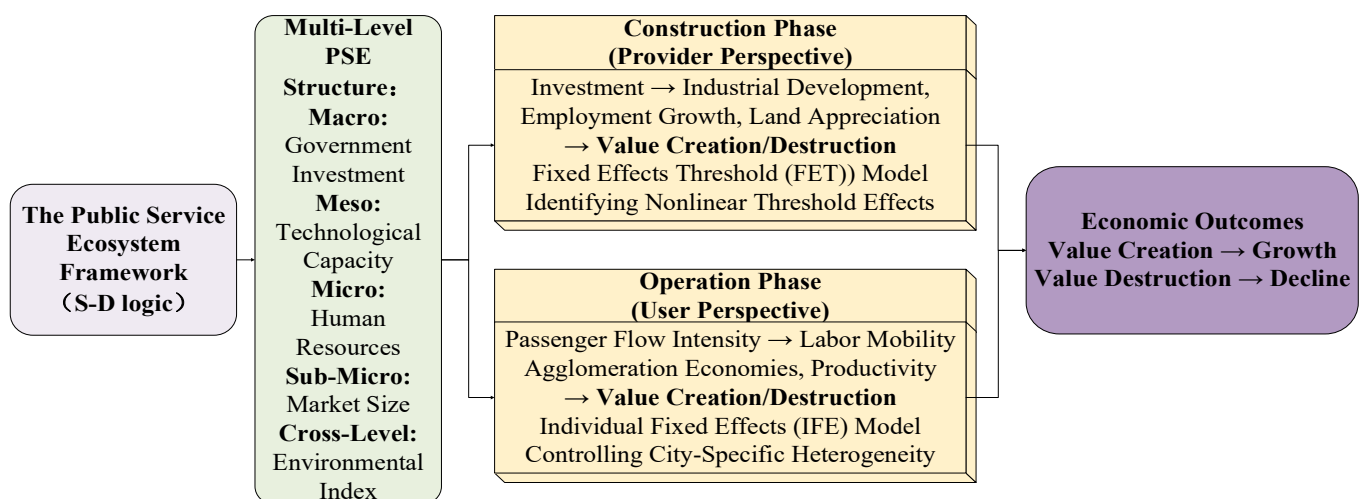


Figure 2. Technical framework.

3.2. Hypothesis Development

Despite being widely acknowledged as a booster of economic development, the impacts of URT exhibit a dynamic duality shaped by lifecycle evolution and governance capacities within PSE. During the initial construction stage, limited network density constrains agglomeration economies, resulting in short-term construction stimulus-induced subdued returns [41]. As systems expand beyond the critical density threshold, the acceleration of economic returns occurs mostly through industrial linkage effects and labor market expansion [67]. The growth trajectory may follow a nonlinear pattern, where excessive network saturation leads to diminishing returns, turning URT from a growth driver into a fiscal burden. This transition is also known as a paradigm shift mediated by PSE governance mechanisms, namely, the shift from value creation to value destruction [68–70].

Regional disparities in PSE maturity fundamentally reconfigure dynamic changes. Eastern cities leverage institutionalized public-private partnerships and TOD synergies to regulate saturation thresholds and transform infrastructure density into sustained operational value through service innovation [71–73]. In contrast, central-western cities experience accelerated threshold transitions at lower network densities. Fragmented governance structures robustly impede modular service adjustments, and weak stakeholder coordination dramatically aggravates resource mismatches [74]. Although emerging systems initially benefit from infrastructure scarcity effects, limits in labor force and economic attractiveness make the diminishing returns even stronger, which in turn weakens their early growth advantages. As a result, this divide may lead to a paradoxical development trap [75].

Hypothesis 1. *URT construction investment exhibits a density-dependent threshold effect on urban economies and transitions from growth stimulation to diminishing returns as the network density increases. And the threshold effect is stronger for regions with more advanced institutions or better local socioeconomic status.*

Although systematic investigations remain scarce, URT operational efficiency has recently come into focus. This is rational for the following reasons: (1) high ridership concentrates labor markets and commercial activities along transit corridors, fostering agglomeration economies that enhance productivity and service-sector diversification [76]; (2) the improvement of accessibility near URT stations elevates property values and thus attracts residential and commercial capital [77]; (3) transit hubs further amplify localized economic activity by channeling consumer flows into retail and hospitality clusters [78]; (4) the modern URT infrastructure strengthens a city's global competitiveness, attracting tourism and foreign investment [79,80].

However, the metrics of total passenger volume cannot fully reflect economic efficacy. A critical gap arises when evaluating how efficiently cities convert infrastructure investments into tangible growth outcomes. For example, two cities with identical annual ridership may exhibit distinct economic returns if one achieves the ridership with a 100 km system, while the other requires 200 km of track. This distinction highlights the need to assess operational performance through a demand-supply equilibrium perspective, a framework that focuses on the efficiency of transportation service utilization (i.e., ridership per unit of infrastructure). Overbuilt systems with low utilization dilute capital productivity through excessive maintenance costs and underused capacity, while undersized networks in high-demand areas constrain economic potential due to congestion and unreliable service [81].

Compared to other regions, the eastern regions have a higher population density, a stronger economic foundation, and more favorable conditions for optimizing resource

allocation. These advantages may amplify the marginal contribution of improved URT operational efficiency to economic growth. The high population density in eastern cities yields a strong demand for efficient transportation services. The enhancement of operational efficiency can significantly reduce commuting costs by increasing the economy of scale, promoting cross-regional labor mobility and stimulating consumer activity. The knowledge-intensive industries as well as the rise of the tertiary sector in the eastern regions heavily rely on the timeliness and reliability of public transportation infrastructure [82]. URT operational innovations accelerate the flow of production factors, directly boosting service-sector productivity and innovation spillovers. For example, the Shanghai Shentong Group's Metro app allows cross-city QR code scanning and combines data and service resources from URT systems in the Shanghai metropolitan area [83]. Additionally, the well-developed market mechanisms and digital infrastructure in the eastern region provide a robust framework for collaborative governance and technological progress, enabling more precise and efficient resource reallocation, such as big data-driven commercial development. In contrast, the central and western regions face fiscal constraints and technological adaptation challenges. In these cases, operational optimizations focus mainly on maintaining basic services, weakening the capacity to drive systemic economic gains.

Hypothesis 2. *URT operational efficiency positively correlates with economic growth across Chinese cities, with a stronger effect in eastern regions.*

3.3. Data Collection and Sample Selection

To validate the hypotheses, we constructed a balanced panel dataset covering 26 Chinese cities with operational URT systems from 2007 to 2020. The study sample includes 16 eastern cities (Beijing, Tianjin, Shanghai, Guangzhou, Changchun, Dalian, Shenzhen, Nanjing, Shenyang, Suzhou, Hangzhou, Harbin, Ningbo, Wuxi, Qingdao, and Fuzhou) and 10 central-western cities (Wuhan, Chongqing, Chengdu, Xi'an, Kunming, Zhengzhou, Changsha, Nanchang, Nanning, and Hefei). The sample covers the major Chinese cities with operational URT prior to 2016 [84].

The sample selection followed three criteria: (1) cities with URT systems in stable operation for at least five years were selected to ensure sufficient longitudinal data for assessing long-term economic impacts; (2) 16 cities from the eastern region and 10 from the central-western region were included, reflecting the proportional distribution of URT systems across China, with key central-western cities such as Chongqing and Chengdu included to ensure regional diversity and URT network maturity, thereby strengthening the representativeness of the analysis; (3) the classification standard of the China Association of Metros (CAMET) was followed, focusing on metro and light rail systems as the main forms of URT, which are treated as a combined category in the analysis. Importantly, metro and light rail systems account for 92.86% of operational URT systems in China, providing sufficient and valid coverage for analyzing the URT network [37,84].

The data were sourced from authoritative sources, including the China City Statistical Yearbook, National Bureau of Statistics Databases, and the CAMET. To improve data robustness, rigorous preprocessing was conducted. Missing values were filled using linear interpolation based on adjacent years, which estimates the missing data by assuming a linear change between the known values before and after the missing year and calculating the proportional value accordingly [85,86]. For example, if data for 2015 and 2017 are available but missing for 2016, the 2016 value is estimated by calculating the point halfway between 2015 and 2017 using the formula

$$X_t = X_{t_0} + \frac{X_{t_1} - X_{t_0}}{t_1 - t_0}(t - t_0) \quad (1)$$

where X_t is the estimated value for the missing year t , and X_{t_0} and X_{t_1} are the known values in years t_0 and t_1 , respectively. To reduce the influence of extreme values or outliers that could distort the analysis, values in the lowest and highest 1% of the data were winsorized, meaning they were replaced with the values at the 1st and 99th percentiles, respectively, rather than being removed. This approach retains all observations and improves the reliability of the results [87].

The dependent variable, regional per capita GDP, was selected in line with conventional approaches to measuring macroeconomic performance. Two core independent variables were used: (1) URT Construction Investment, quantified as annual URT investment to capture capital injection effects; and (2) URT Passenger Flow Intensity, calculated as the ratio of annual ridership to network mileage, which facilitates cross-regional comparisons of operational efficiency [88,89].

A threshold variable, URT density (mileage per 10,000 population), was introduced to account for potential nonlinear relationships. The reasons are as follows: First, its capacity to reflect transportation systems' sustainability thresholds [90]; second, its superior characterization of network spatial complexity compared to absolute mileage [91]; and third, its policy relevance in identifying critical investment levels for economic returns [92].

Control variables were systematically selected through the lens of PSE, encompassing four hierarchical dimensions: macro-level government expenditure (local fiscal budgets), meso-level technology inputs (R&D expenditures), micro-level human capital (employment figures), and sub-micro-level consumer demand (retail sales of consumer goods) [24,92]. Beyond these four levels, environmental factors such as air quality and carbon emissions were also included to account for externalities [93]. This comprehensive factor reflects the systemic capacity constraints cities face in generating economic value through URT construction and operation.

The multi-level structure of value creation within the PSE emphasizes how value is progressively generated across different stages and ecosystem levels. In this study, value creation in the theoretical framework corresponds to the increase in per capita GDP in the empirical model. During the construction phase of URT, value is primarily created through public investment (i.e., the construction effect model). In contrast, during the use or operational phase, value is more closely associated with service delivery and user interaction (i.e., the operation effect model). Since service delivery and user interaction are difficult to measure directly, we use URT operational efficiency as a proxy variable, represented by passenger flow intensity [94,95].

Table 1 presents the basic information of the 26 cities examined in this study, including URT mileage for metro and light rail systems (excluding suburban railways/trams) as of 31 December 2020, based on official data reported by CAMET [84].

3.4. Variable Selection and Definition

3.4.1. Dependent Variables

Economic growth is a critical determinant of national competitiveness and a central socioeconomic priority for governments globally [96]. Empirical studies predominantly measure economic growth through two metrics: Gross Domestic Product (GDP) and GDP per capita (PERGDP). GDP measures the total market value of final goods and services produced within a nation during a specified period, reflecting macroeconomic output and production-based growth sustainability [97]. PERGDP, calculated by dividing GDP by the resident population, serves as a proxy for average living standards and equitable resource distribution [98].

Table 1. Information of URT systems in 26 Chinese cities.

No.	City	URT System Name	Region	Year Opened	Length (km)	Number of Lines
1	Beijing	Beijing Subway	Eastern	1969	696.364	24
2	Tianjin	Tianjin Rail Transit	Eastern	1984	231.998	6
3	Shanghai	Shanghai Metro	Eastern	1993	694.890	18
4	Guangzhou	Guangzhou Metro	Eastern	1997	504.610	16
5	Changchun	Changchun Rail Transit	Eastern	2002	100.17	5
6	Dalian	Dalian Metro	Eastern	2003	159.95	4
7	Shenzhen	Shenzhen Metro	Eastern	2004	411.363	12
8	Nanjing	Nanjing Metro	Eastern	2005	177.140	12
9	Shenyang	Shenyang Metro	Eastern	2010	116.566	10
10	Suzhou	Suzhou Metro	Eastern	2012	165.936	6
11	Hangzhou	Hangzhou Metro	Eastern	2012	307.180	7
12	Harbin	Harbin Metro	Eastern	2013	30.600	2
13	Ningbo	Ningbo Rail Transit	Eastern	2014	154.550	5
14	Wuxi	Wuxi Metro	Eastern	2014	89.420	3
15	Qingdao	Qingdao Metro	Eastern	2015	249.350	6
16	Fuzhou	Fuzhou Metro	Eastern	2016	54.918	2
17	Wuhan	Wuhan Metro	Central-Western	2004	337.843	12
18	Chongqing	Chongqing Rail Transit	Central-Western	2005	341.730	9
19	Chengdu	Chengdu Metro	Central-Western	2010	518.441	13
20	Xi'an	Xi'an Metro	Central-Western	2011	214.483	8
21	Kunming	Kunming Rail Transit	Central-Western	2012	138.390	5
22	Zhengzhou	Zhengzhou Metro	Central-Western	2013	204.038	7
23	Changsha	Changsha Metro	Central-Western	2014	142.448	6
24	Nanchang	Nanchang Metro	Central-Western	2015	88.710	3
25	Nanning	Nanning Rail Transit	Central-Western	2016	108.200	5
26	Hefei	Hefei Metro	Central-Western	2016	114.780	4

While sustained increases in both indicators are often interpreted as economic progress, PERGDP offers distinct advantages [99]. By accounting for demographic dynamics, it addresses the limitations of raw GDP, which may obscure disparities caused by population growth or unequal resource allocation [100]. Furthermore, PERGDP aligns more closely with holistic development objectives by offering a population-adjusted view of economic performance [101]. This metric enables a more detailed assessment of whether economic growth contributes to balanced and inclusive development.

Based on these strengths, PERGDP was selected as the dependent variable to capture subtle spatiotemporal differences in economic development.

3.4.2. Independent Variables

This study employs two core explanatory variables: (1) annual URT construction investment and (2) URT passenger flow intensity. The selection of URT construction investment as the primary predictor is grounded in its dual analytical utility. As a key indicator of infrastructure capital allocation, it enables direct cross-city comparisons of URT funding priorities [102]. Moreover, its established association with urban economic dynamics makes it a widely accepted proxy for evaluating the relationship between transportation infrastructure and economic growth [103,104]. Operationally, this variable consists of three investment components: fixed assets (e.g., track systems, stations), intangible assets (e.g., signaling technologies, design patents), and ancillary expenditures (e.g., construction

contingencies, capital interest). These are defined according to standardized infrastructure accounting frameworks [105,106]. We use URT density, measured by operational mileage per capita, as a threshold variable to evaluate investment impacts. This approach accounts for the nonlinear effects of infrastructure spending on economic growth and reflects how population density influences URT service accessibility [107,108].

The second explanatory variable, URT passenger flow intensity, reflects operational efficiency through the ratio of annual passenger numbers to total URT mileage. This indicator combines two aspects: service demand, measured by annual ridership, and network capacity, measured by the total length of operational lines. By combining passenger use with system size, it reflects how effectively the URT system is used and how widely it serves the population [108].

3.4.3. Control Variables

According to the multi-level structure of value creation within the PSE, we selected technology investment, human resource level, government expenditure level, market size, and environmental index as control variables [109].

Technology investment has a significant spillover effect [110,111]. Numerous empirical studies show a long-term equilibrium relationship between technology investment and economic growth. Although there is a time lag, technology investment still contributes to economic growth. This study employs local government science and technology budgets as a control variable to measure government technology investment [112].

The level of human resources represents the potential labor force level of a city and has a significant impact on economic development [113]. Economic development and social progress are accompanied by a slowdown in population growth and an increase in the extent of the population aging. Population aging will lead to a decrease in the labor force and hinder technological progress, impairing economic growth [114,115]. As it is one of the variables worthy of attention, we used the ratio of the number of employees at the end of the year in urban units to the regional population as an indicator of the level of human resources [116].

Government expenditure in a narrow sense refers to the government's direct financial investment in public goods [117]. In a broad sense, it refers to the total investment made by the government to sustain the production of public goods or provide public services, including financial input, tax exemptions, and other forms of policy support [117]. Government expenditure can promote various aspects of economic growth, including infrastructure development, education and skills training, scientific research and innovation, and industrial development [118]. We used annual government budget expenditure to evaluate government expenditure.

Market size mainly refers to the total value or output of the target product or industry within a specific period of time. It is based on demographic surveys, including population size, consumer demand, age distribution, and regional wealth levels. In this study, market size is represented by the total retail sales of consumer goods, which reflects the quantity of goods supplied to residents and social groups through various distribution channels across industries [119].

The environmental index is a crucial tool for assessing environmental conditions and sustainability in urban or regional areas, utilizing various environmental indicators such as air quality, water quality, soil quality, noise levels, green coverage, carbon emissions, renewable energy proportions, and more [120]. The selection of specific indicators depends on the research objectives and the nature of environmental issues [121,122]. Through assessment using the environmental index, a more holistic understanding of environmental conditions in cities or regions can be achieved, providing important information and data

to support environmental protection and sustainable development [123,124]. To ensure consistency across cities, this paper uses the proportion of days with air quality at or above Grade II, as reported in the China Urban Air Quality Report, to represent the environmental index. It offers a clear and straightforward reflection of urban environmental quality, with practical value for policy and public awareness [124,125].

3.5. Model Design

3.5.1. Construction Effect Model (Model I)

To empirically test Hypothesis 1 regarding the nonlinear relationship between URT construction and economic growth, this paper employed the Fixed Effects Threshold (FET) model to construct Model I [126]. We set URT density (mileage per 10,000 population) as the threshold variable, reflecting the role of network coverage and maturity in moderating economic returns. Annual construction investment (CI) serves as the core explanatory variable, with coefficients allowed to vary across density regimes [127–129].

This study adopts the Fixed Effects Threshold (FET) model with time-varying intercepts, as proposed by Hansen. We further incorporate a modified approach from Tiba's threshold model to include relevant control variables when analyzing the impact of URT construction on regional economies [130–132]. We argue that the effect of URT construction on the regional economy is influenced by the level of URT infrastructure. We now establish the FET model for the URT construction effect, which can be written as follows:

$$PERGDP_{it} = \mu_i + \beta_{11}CI_{it}g(DEN_{it} \leq \gamma) + \beta_{12}CI_{it}g(DEN_{it} > \gamma) + \omega HUM_{it} + \eta TEC_{it} + \phi GOV_{it} + \psi TRS_{it} + \theta ENV_{it} + \varepsilon_{it} \quad (2)$$

When there are two threshold values, the model can be written as

$$PERGDP_{it} = \mu_i + \beta_{21}CI_{it}g(DEN_{it} \leq \gamma_1) + \beta_{22}CI_{it}g(\gamma_1 < DEN_{it} \leq \gamma_2) + \beta_{23}CI_{it}g(\gamma_2 < DEN_{it}) + \omega HUM_{it} + \eta TEC_{it} + \phi GOV_{it} + \psi TRS_{it} + \theta ENV_{it} + \varepsilon_{it} \quad (3)$$

where $PERGDP_{it}$ is the per capita GDP of region i in year t , CI_{it} is the annual URT construction investment of region i in year t , and the transition function $g(DEN_{it})$ depends on the threshold candidate variable DEN_{it} . HUM_{it} is the human capital, TEC_{it} is the technological input, GOV_{it} is the government expenditure, DEN_{it} is the URT density, TRS_{it} is market size, and ENV_{it} is the environmental index, all measured for region i in year t . γ is the threshold value that divides different URT density regimes. The coefficients β are denoted with double subscripts: the first subscript indicates the number of threshold values in the model, and the second subscript represents the coefficient associated with each regime under that threshold specification. For example, β_{11} and β_{12} correspond to the regimes below and above the threshold when there is one threshold, while β_{21} , β_{22} , and β_{23} correspond to the three regimes when there are two thresholds. The coefficients ω , η , ϕ , ψ and θ represent the parameters associated with the control variables HUM_{it} , TEC_{it} , GOV_{it} , TRS_{it} and ENV_{it} , respectively. μ_i represents the individual fixed effect, which captures unobserved characteristics specific to each region that do not change over time. ε_{it} represents the error term for region i in year t , which captures the random disturbances or unobserved factors that vary both across regions and over time. It should be noted that in fixed-effects threshold models, the constant term is typically not included directly. This is because each individual's fixed effect already captures the intercept, effectively accounting for the overall mean across individuals. Including both a constant term and individual fixed effects would lead to a dummy variable trap. Stata/MP 17(64-bit) addresses this automatically via the within transformation, and the reported constant term essentially

reflects the mean of all individual fixed effects. Table 2 presents the symbol descriptions for each variable used in the analysis.

Table 2. Symbol description for each variable.

Variable Name	Meaning	Description
PERGDP	GDP per capita	With 2007 as the base period; data source: Statistical database of China Economic Network
CI	Total annual investment in URT construction	It does not include some projects approved by local governments; data source: Annual Statistics and analysis report of URT in China
DEN	URT density	URT kilometer per 10,000 people; data source: Annual Statistics and analysis report of URT in China; China City Statistical Yearbook
TEC	Investment in science and technology	Expenditures on science and technology in municipal local general public budget revenue and expenditure status; data source: China City Statistical Yearbook
HUM	Human capital	The ratio of the working population to the annual average population of the city; data source: China City Statistical Yearbook
GOV	Government purchase	Municipal local general public budget expenditures; data source: China City Statistical Yearbook
IPR	Passenger flow intensity	The ratio of annual ridership to mileage of URT; data source: Annual Statistics and analysis report of URT in China; China City Statistical Yearbook; Official Website of the National Bureau of Statistics
TRS	Total retail sales of consumer goods	Expressed in terms of total retail sales of consumer goods; data source: China City Statistical Yearbook
ENV	Environmental index	The proportion of days with air quality reaching or exceeding Level II (API index less than or equal to 100); data source: China City Statistical Yearbook

3.5.2. Operational Effect Model (Model II)

To investigate the relationship between URT operation and regional economic growth, we built a threshold model focusing on passenger flow density, while holding the control and threshold variables constant.

$$PERGDP_{it} = \mu_i + \beta_{11}IPR_{it}(DEN_{it} \leq \gamma) + \beta_{12}IPR_{it}(DEN_{it} > \gamma) + \omega HUM_{it} + \eta TEC_{it} + \phi GOV_{it} + \psi TRS_{it} + \theta ENV_{it} + \varepsilon_{it} \quad (4)$$

Given that the operational effect represented by passenger flow density may not exhibit a threshold effect, we employ the Individual Fixed Effects (IFE) model. This model controls for unobserved heterogeneity across cities by introducing city-specific intercepts, while time-varying unobserved factors are captured by the error term, ensuring robust estimation of the operational effect.

$$PREGDP_{it} = \mu_i + \alpha IPR_{it} + \omega HUM_{it} + \eta TEC_{it} + \phi GOV_{it} + \psi TRS_{it} + \theta ENV_{it} + \varepsilon_{it} \quad (5)$$

3.5.3. Linearity Testing and Robustness Analysis

To verify the model's nonlinear features, we test its linearity using the Likelihood Ratio (LR) test, which is based on maximum likelihood estimates and effectively detects threshold effects. The test examines whether $t \gamma = \gamma_0$. When there exists a threshold ($\beta_1 \neq \beta_2$), Hansen has shown that the identity is equal to γ_0 (the true value of γ), and the asymptotic distribution is highly nonstandard [126]. To test hypothesis $H_0: \gamma = \gamma_0$, the likelihood ratio test is to reject LR1 (γ_0).

$$LR_1(\gamma_0) = (S_1(\gamma) - S_1(\tilde{\gamma})) / \sigma^2 \quad (6)$$

According to Hansen's Theorem 1 [126], the effective asymptotic information interval of the model is

$$c(\alpha) = -2 \log(1 - \sqrt{1 - \alpha}) \quad (7)$$

According to Hansen's theory, it is then easy to calculate the critical value. For example, the critical value is 6.53 at 10%, 7.35 at 5%, and 10.59 at 1%. If $LR1(\gamma_0)$ exceeds $c(\alpha)$, then $H_0: \gamma = \gamma_0$ is rejected. The model has nonlinear characteristics. Our model chooses the 5% critical value of 7.35.

For robustness checks, this study accounted for potential lagged effects of construction and operation by introducing 1–3 period lags for the independent, threshold, and control variables. Additionally, the urban innovation index was used as an alternative dependent variable in place of per capita GDP, and the results remained consistent, confirming the stability of the findings. To further strengthen causal inference and address potential endogeneity, the Generalized Method of Moments (GMM) was employed, providing additional verification of the model's reliability.

In addition, in the robustness checks, we incorporated urban carbon emissions (unit: million tons) as an environmental factor, combining air quality and carbon emissions into a single composite environmental index using the principal component analysis (PCA) method, which integrates multiple related indicators into one factor that reflects overall environmental conditions. PCA was chosen because it simplifies the model, reduces the number of variables, and makes the regression analysis more robust and easier to interpret, thereby ensuring the model's robustness.

3.5.4. City Tier Heterogeneity Analysis

To further investigate inter-regional heterogeneity, cities are stratified into first-tier and second-tier groups based on urban scale and economic development status, as classified by the China City Business Attractiveness Ranking (CCBAR) published by the China Urban Competitiveness Research Center. Specifically, the first-tier group includes 12 cities: Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin, Chongqing, Chengdu, Wuhan, Hangzhou, Nanjing, Xi'an, and Suzhou. The second-tier group comprises 14 cities: Changchun, Dalian, Shenyang, Harbin, Ningbo, Wuxi, Qingdao, Fuzhou, Kunming, Zhengzhou, Changsha, Nanchang, Nanning, and Hefei. This stratification facilitates the assessment of whether the effects of URT construction and operation differ across cities of varying hierarchical levels, which also complements the regional comparison between eastern and central-western cities. The model specifications outlined in Sections 4.2.4 and 4.3.4 are applied separately to these subgroups to examine tier-specific effects.

4. Results

4.1. Descriptive Statistics

Table 3 presents descriptive statistics for the key variables measuring the impact of URT on economic growth, including mean, median, standard deviation, skewness, kurtosis, and Jarque-Bera test results. PERGDP has a mean of 7.758, a standard deviation of 3.436, and a positive skewness of 0.507, showing that most cities cluster around moderate growth, while some perform substantially higher. CI and TEC exhibit strong right-skewness, indicating large disparities in infrastructure investment and technological capacity. GOV and TRS show high volatility, reflecting heterogeneous fiscal and transport policies. Jarque-Bera tests reject normality for all variables ($p < 0.001$), supporting the use of nonlinear or threshold regression. Overall, these statistics highlight notable heterogeneity across Chinese cities, which may lead to different responses to URT construction and operation.

Table 3. The descriptive statistics.

Variable	PERGDP	CI	IPR	DEN	TEC	HUM	GOV	TRS	ENV
Mean	7.758	101.094	1.885	9.199	61.600	0.186	1395.475	0.384	0.802
Median	7.300	67.695	1.441	7.080	25.688	0.173	892.651	0.292	0.845
Std. Dev	3.436	100.818	1.895	9.240	91.309	0.064	1474.779	0.298	0.164
Min	1.320	0.980	0.000	0.000	1.706	0.082	116.860	0.044	0.140
Max	16.590	653.300	7.292	41.530	554.982	0.546	8351.536	1.590	1.000
Skewness	0.507	2.200	0.830	1.055	2.774	1.374	2.507	1.705	−1.356
Kurtosis	2.592	9.844	2.701	3.582	11.332	5.722	9.798	6.068	5.084
Jarque-Bera	18.150	1004.000	43.140	72.710	1520.000	226.800	1082.000	319.100	177.400
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	364.000	364.000	364.000	364.000	364.000	364.000	364.000	364.000	364.000

4.2. Threshold Effects of Construction Effect Model (Model I)

4.2.1. Results of Model I

We used Stata/MP 17(64-bit) to estimate threshold regression models with one, two, and three thresholds (see Tables 4 and 5). The statistical tests confirmed two statistically significant thresholds.

Table 4. The overall threshold statistics.

Threshold Effect Value				Robustness Test		
Threshold	F Test	<i>p</i> -Value	Threshold Value	F Test	<i>p</i> -Value	Threshold Value
1	69.330	0.000	12.539	66.570	0.000	9.328
2	50.740	0.000	9.294	23.310	0.070	9.328
			21.347			21.347
3	27.360	0.827	-	35.920	0.593	-

The empirical analysis reveals a significant threshold effect in Model I. From Table 4, we find that for the single-threshold situation, the estimated threshold value is 12.539. In this specification, the core explanatory variable demonstrates differential impacts: coefficient β_{11} is 0.011 in the low regime and β_{12} is 0.002 in the high regime. This suggests that URT construction generally promotes regional economic growth, but its marginal returns diminish significantly when per capita infrastructure exceeds the estimated threshold value.

The dual threshold specification further refines this relationship, identifying critical values at 9.294 and 21.347. The coefficients display a progressive attenuation pattern: β_{21} is 0.023 in the first regime (less than 9.294), β_{22} is 0.013 in the intermediate regime (9.294 to 21.347), and β_{23} is 0.003 in the high regime (more than 21.347). And the Jarque-Bera statistics in Table 3 confirm non-normal distributions across variables, justifying the threshold regression approach over conventional linear models. Finally, we tested the triple-threshold model, but the results were not significant.

The analysis indicates that the two-threshold model performs better in explaining economic growth rates, as evidenced by its higher R^2 and lower standard error of the residuals. From Table 5, we find that the removal of ENV leads to a decrease in the intercept, a slight increase in the error term, and a marginal reduction in R^2 . Combined with its significantly negative coefficient in the model that includes environmental factors, this suggests that environmental regulation may temporarily hinder growth. For example, air pollution [133].

Table 5. (1) Model I estimation. (2) Model I estimation without environment impact.

Dependent Variable: Economic Growth (PERGDPit)					
Variable		One Threshold	p-Value	Two Threshold	p-Value
(1)					
CI	1st regime (β_1)	0.011	(0.000)	0.023	(0.000)
	2nd regime (β_2)	0.002	(0.036)	0.013	(0.000)
	3rd regime (β_3)	—	—	0.003	(0.000)
	GOV	0.001	(0.000)	0.001	(0.000)
	TEC	0.004	(0.015)	0.005	(0.001)
	HUM	1.577	(0.312)	2.161	(0.128)
	DEN	0.213	(0.000)	0.265	(0.000)
	TRS	1.546	(0.033)	1.477	(0.024)
	ENV	−0.985	(0.016)	−0.418	(0.264)
	CONSTANT	4.004	(0.000)	3.419	(0.000)
	City Fixed-Effects (σ_u)	2.443	—	2.456	—
	Error Term (σ_ϵ)	0.906	—	0.848	—
	R ²	0.874	—	0.890	—
	Number of Observations	364	—	364	—
(2)					
CI	1st regime (β_1)	0.011	(0.000)	0.024	(0.000)
	2nd regime (β_2)	0.002	(0.046)	0.013	(0.000)
	3rd regime (β_3)	—	—	0.003	(0.000)
	GOV	0.001	(0.000)	0.001	(0.000)
	TEC	0.004	(0.025)	0.005	(0.000)
	HUM	2.798	(0.061)	2.681	(0.046)
	DEN	0.214	(0.000)	0.267	(0.000)
	TRS	1.527	(0.037)	1.467	(0.001)
	CONSTANT	2.937	(0.000)	2.731	(0.000)
	City Fixed-Effects (σ_u)	2.453	—	2.466	—
	Error Term (σ_ϵ)	0.913	—	0.850	—
	R ²	0.872	—	0.889	—
	Number of Observations	364	—	364	—

The LR statistics results with 1–3 thresholds are shown in Figure 3. From the figure, we can see that for the first threshold, the LR statistic shows a significant fluctuation near the critical value (red dashed line), indicating that the model fit improves significantly, supporting the existence of the first threshold. For the second threshold, the LR statistic exhibits two significant changes near the critical value, suggesting a significant improvement in model fit. However, for the third threshold, the model fit does not show a significant improvement. This supports the conclusion that the two-threshold model is better, as the first and second thresholds have a significant impact, while the third threshold does not. The results align with our hypothesis.

According to the “Urban Comprehensive Transportation System Planning Standard” (GB/T 51328-2018), issued by China’s Ministry of Housing and Urban-Rural Development in 2018, URT express lines should be built mainly along corridors with medium to high passenger flow. The standard recommends a minimum passenger flow density of 100,000 passenger-kilometers per kilometer per day. Additionally, urban planning studies generally recommend that Type I cities maintain a URT network density within the range of 8–12 km per 10,000 population. These documents and recommendations are consistent with the first threshold value found in our study [134].

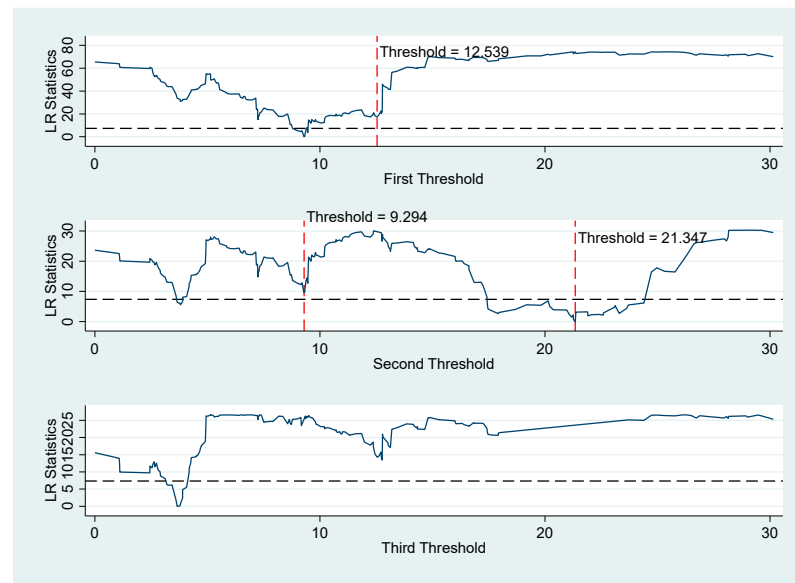


Figure 3. LR statistics.

4.2.2. Regional Difference Test for Construction Effect

From Table 6, the threshold regression reveals systematic spatial variation: under the single-threshold specification, the threshold value in the central and western cities is much lower than that in the eastern cities, indicating that the regional economy in the west area is more sensitive to increases in construction investment.

Table 6. The regional threshold statistics.

Eastern China					Central and Western China			
Threshold	F Test	<i>p</i> -Value	Threshold Value	CI Coefficients	F Test	<i>p</i> -Value	Threshold Value	CI Coefficients
1	71.210	0.000	16.620	0.015 0.004	38.010	0.010	6.576	0.013 0.001
2	40.700	0.000	9.294 17.934	0.017 0.027 0.009	27.870	0.023	6.576 20.369	0.024 0.010 −0.001
3	12.430	0.673			28.500	0.763		

Under the two-threshold specification, we find statistically significant nonlinear relationships in both geographical regions. For eastern cities, we identify a dual-threshold structure at 9.294 and 17.934 of network density, with construction coefficients transitioning from 0.017 in the emerging phase to 0.027 in the growth phase before declining to 0.009 in the mature phase. Central-western regions exhibit different transition patterns, characterized by a lower initial threshold at 6.576 and a wider phase span from 6.576 to 20.369, with coefficients shifting from 0.024 to 0.010 and ultimately turning negative value at −0.001.

Figure 4 shows the LR statistics for eastern cities. The LR statistic curve indicates two regions around 9.294 and 17.934 where the dual thresholds are estimated, confirming significant nonlinear effects in the eastern region. These threshold values are chosen based on model fit rather than corresponding exactly to the curve's peaks or valleys, while the single-threshold value of 16.62 provides a preliminary overview of the marginal construction effects.

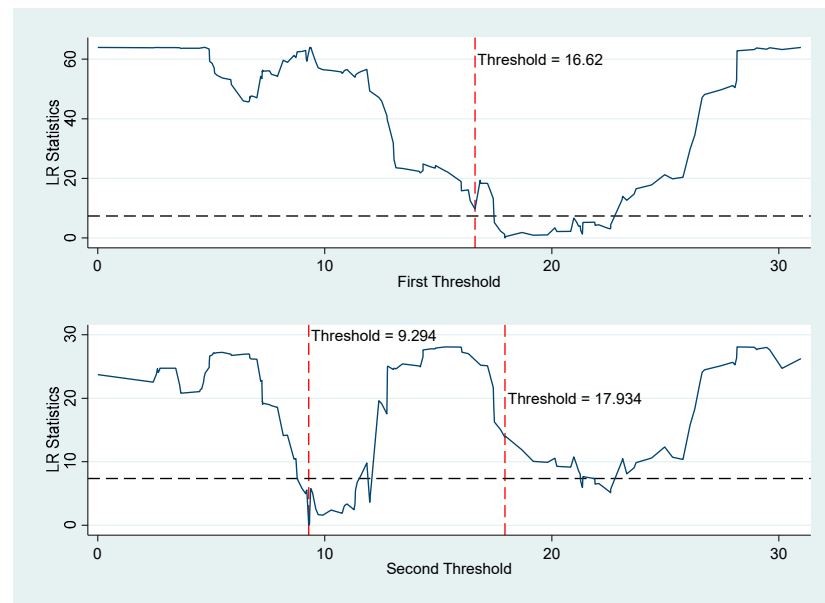


Figure 4. LR statistics for Eastern China.

Figure 5 displays the LR statistics for central and western cities. The LR curve indicates a lower initial threshold at 6.576, with substantial fluctuation across the wider span up to 20.369. This pattern reflects a stronger initial impact of URT construction in these regions, but also a more rapid decline of marginal effects beyond the high threshold.

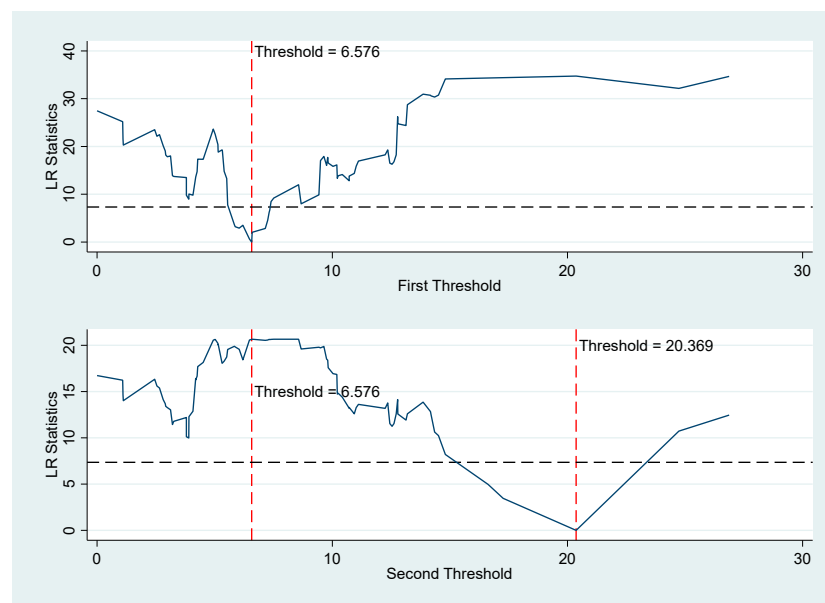


Figure 5. LR statistics for Central and Western China.

The central-western regions initially demonstrate stronger construction-driven growth, consistent with infrastructure multiplier effects in under-saturated markets. This advantage dissipates rapidly as network density approaches the high threshold, where construction investments become economically detrimental. This divergence can be explained by the value creation theory of PSE: Eastern cities' mature service ecosystems better absorb capital shocks through resource orchestration. In contrast, central and western regions face intensified fiscal crowding-out effects due to weaker public participation and underdeveloped collaborative governance mechanisms. Excessive URT investment in these areas may lead to more severe value destruction. The coefficient decay rates further under-

score regional institutional capacities. Central-western cities experience 83% coefficient reduction from the first to third phase versus eastern regions' 47% decline, suggesting that bureaucratic delivery models become counterproductive more quickly in institutionally immature contexts.

4.2.3. Robustness Test for Model I

The robustness test results are shown in Table 7. We lagged the independent variable, threshold variable, and control variable. When the lag period was 1–3, the model results still showed a threshold effect. Moreover, the threshold was stable. We also used the urban innovation index instead of per capita GDP as the dependent variable for robustness tests and found that the results were still valid.

Table 7. The robustness test.

Threshold	Robustness Test (Lag 2)			Robustness Test (Lag 3)			Robustness Test (Dependent Variable: Innovation Index)		
	F Test	p-Value	Threshold Value	F Test	p-Value	Threshold Value	F Test	p-Value	Threshold Value
1	54.050	0.007	11.329	45.730	0.010	3.899	84.670	0.000	10.193
2	41.990	0.007	3.799	30.640	0.020	3.799	34.650	0.023	10.193
			11.329			11.350			25.777
3	20.290	0.730	-	15.640	0.020	-	26.120	0.967	-

Table 8 reports results from a two-step system GMM estimation. The lagged dependent variable and CI are statistically significant, indicating persistence and a positive effect of CI on the dependent variable. Diagnostic tests confirm the absence of second-order autocorrelation and validate the instrument set, thus supporting the model's reliability.

Table 8. System GMM estimation results for Model I.

Variable	Coefficient	Robust SE	p-Value
L.PERGDP	0.872 ***	0.042	0
CI	0.003 **	0.001	0.02
Test	Statistic	p-Value	
AR (1)	Z = −2.15	0.032	
AR (2)	Z = 1.24	0.215	
Hansen	$\chi^2 = 18.22$	0.287	
Number of Instruments	28		
First-Stage F-Statistic	23.5		

Note: *** $p < 0.01$, ** $p < 0.05$. Robust standard errors are reported in parentheses. AR (1) and AR (2) are tests for first and second order autocorrelation in the Arellano-bond GMM framework. Hansen denotes the Hansen J test of overidentifying restrictions.

The robustness check using the composite environmental index incorporating carbon emissions (Env-PCA) confirms the robustness of our main conclusions regarding the impact of URT construction investment on regional economic growth, as detailed in Appendix A.

4.2.4. City Tier Heterogeneity Analysis for Construction Effect

The results in Table 9 reveal pronounced differences in the marginal effects of urban rail transit construction between first-tier and second-tier cities. At the first threshold, first-tier cities show a value of 21.905 with a CI coefficient of 0.015, whereas second-tier cities exhibit a lower threshold of 9.294 with a CI coefficient of 0.009, indicating faster attenuation of marginal returns in second-tier cities. At the second threshold, first-tier cities demonstrate sustained positive effects, with CI coefficients increasing from 0.018 to 0.028 as network density rises, reflecting continued value creation in the growth phase. In contrast, second-tier cities show a sharper decline, with CI coefficients dropping from 0.011 to −0.098 at

higher network densities, suggesting that excessive construction may generate negative marginal returns and potential value destruction.

Table 9. The threshold statistics for first-tier and second-tier cities.

Threshold	First-Tier Cities				Second-Tier Cities			
	F Test	p-Value	Threshold Value	CI Coefficients	F Test	p-Value	Threshold Value	CI Coefficients
1	31.34	0.000	21.905	0.015 −0.031	20.39	0.012	9.294	0.018 0.009
2	7.96	0.013	9.464 21.905	0.018 0.026 −0.033	14.08	0.018	3.611 9.294	0.028 0.011 −0.098
3	-	-	-	-	-	-	-	-

The analysis of city tiers enhances the understanding of intra-regional heterogeneity. These findings indicate that first-tier cities achieve higher initial and sustained returns due to more developed infrastructure, mature urban systems, and effective governance mechanisms. Second-tier cities, with relatively less developed infrastructure and institutional capacity, experience earlier saturation and even negative returns in high-density phases. Importantly, these city-tier differences are consistent with the regional heterogeneity observed in the east versus central-west comparison.

4.3. Operational Effect Model Effects (Model II)

4.3.1. Results of Model II

Based on Equation (3), we first test whether the operational effect of URT exhibits a threshold effect. The results indicate that passenger flow intensity (IPR) does not display a significant threshold relationship with regional economic performance. Therefore, Equation (4) is applied to examine a linear relationship. The results show that IPR is significantly and positively correlated with per capita GDP, with an estimated coefficient of 0.308, implying that a 1% increase in passenger flow intensity is associated with an approximate 0.308% increase in per capita GDP. The results are reported in Table 10.

Table 10. The Individual Fixed Effects model estimation.

Variable	Coefficient	p-Value	[95% Conf. Interval]	
IPR	0.308	(0.000)	0.221	0.396
GOV	0.001	(0.000)	0.000	0.001
TEC	0.003	(0.085)	0.000	0.007
HUM	2.584	(0.024)	−0.623	5.792
DEN	0.194	(0.000)	0.169	0.219
TRS	1.945	(0.014)	0.462	3.429
ENV	−0.821	(0.064)	−1.689	0.048
Constant	3.813	(0.000)	2.753	4.873
City Fixed-Effects (σ_u)	2.662	-	-	-
Error Term (σ_ε)	0.959	-	-	-
R ²	0.858	-	-	-
Number of Observations	364	-	-	-

4.3.2. Regional Difference Test for Operational Effect

We further investigate whether the operational effect differs across regions. Table 11 presents the IFE model statistics for Eastern China and Central and Western China.

Table 11. The IFE model statistics for Eastern China and Central and Western China.

Variable	Eastern China		Central and Western China	
	Coefficient	<i>p</i> -Value	Coefficient	<i>p</i> -Value
IPR	0.323	(0.001)	0.304	(0.000)
GOV	0.001	(0.031)	0.001	(0.004)
TEC	0.001	(0.774)	0.020	(0.000)
HUM	6.417	(0.008)	−1.146	(0.550)
DEN	0.184	(0.000)	0.148	(0.000)
TRS	3.657	(0.004)	−0.046	(0.961)
ENV	−0.033	(0.957)	−1.667	(0.005)
Constant	2.434	(0.004)	4.908	(0.000)
City Fixed-Effects (σ_u)	3.138	-	1.850	-
Error Term (σ_ϵ)	0.992	-	0.837	-
R ²	0.863	-	0.878	-
Number of Observations	364	-	364	-

The results confirm that URT operational efficiency has a positive effect in both regions, with a stronger effect in the east due to higher URT density, while central-western regions show lower impacts, reflecting less mature infrastructure and weaker market linkages.

4.3.3. Robustness Test for Model II

We lagged the independent variables and control variables and found that the model still exhibited effects with a lag period of 1–3, and the results remained stable, as was the incorporation of the composite environmental index with carbon emissions. Additionally, we used a two-step system GMM estimation (see Table 12). Tests showed first-order autocorrelation but no second-order autocorrelation, supporting the model’s validity.

Table 12. System GMM estimation results for Model II.

Variable	Coefficient	Robust SE	<i>p</i> -Value
L.PERGDP	1.063 ***	0.026	0
IPR	0.423 **	0.230	0.048
Test	Statistic	<i>p</i> -Value	
AR (1)	Z = −2.69	0.007	
AR (2)	Z = −1.00	0.299	
Hansen	$\chi^2 = 4.9$	0.086	
Number of Instruments	25		

Note: *** $p < 0.01$, ** $p < 0.05$. Robust standard errors are reported in parentheses. AR (1) and AR (2) are tests for first and second order autocorrelation in the Arellano-bond GMM framework. Hansen denotes the Hansen J test of overidentifying restrictions.

4.3.4. City Tier Heterogeneity Analysis for Operational Effect

Cities were stratified into first- and second-tier groups. Table 13 presents the IFE results. First-tier cities show stronger positive effects of IPR (0.332, $p = 0.001$) compared to second-tier cities (0.301, $p = 0.005$), indicating that higher infrastructure maturity and institutional capacity amplify operational benefits.

Table 13. IFE model statistics for first-tier and second-tier cities.

Variable	First-Tier Cities		Second-Tier Cities	
	Coefficient	<i>p</i> -Value	Coefficient	<i>p</i> -Value
IPR	0.332	(0.001)	0.301	(0.005)
GOV	0.001	(0.024)	0.003	(0.000)
TEC	0.010	(0.000)	0.011	(0.032)
HUM	6.442	(0.008)	16.477	(0.000)
DEN	0.201	(0.000)	0.110	(0.000)
TRS	3.510	(0.020)	2.981	(0.000)
ENV	−0.036	(0.469)	1.149	(0.026)
Constant	3.032	(0.000)	2.014	(0.013)
City Fixed-Effects (σ_u)	2.896	-	1.839	-
Error Term (σ_ε)	0.708	-	0.682	-
R ²	0.941	-	0.917	-
Number of Observations	140	-	168	-

These results reinforce the main conclusion that URT operational efficiency positively influences economic growth, particularly in cities with more developed infrastructure. Consequently, these results reinforce the policy implication that strategies for URT network optimization should consider both regional location and urban hierarchy, prioritizing service innovation in mature, high-tier cities while expanding coverage in developing, lower-tier cities.

5. Discussion

Several previous studies have drawn contradictory conclusions on the economic impact of URT. This study, grounded in PSE theory, systematically examines the mechanisms through which URT affects regional economies from the perspectives of value creation and value destruction, offering a novel approach to addressing this question. On this basis, this paper further incorporates heterogeneity analysis at both the regional and urban hierarchy levels. The findings reveal that URT construction generates stronger marginal economic returns in central and western cities, as well as in second-tier cities, reflecting their relatively underdeveloped infrastructure and higher sensitivity to investment. In contrast, first-tier cities and eastern regions benefit more from improvements in operational efficiency, which aligns with their more mature urban systems, higher network utilization rates, and stronger governance capacity. These results indicate that the economic effects of URT are not homogeneous, but are shaped by the dual influences of urban hierarchy and regional heterogeneity.

It is noteworthy that, compared with domestic cases, despite differences in institutional and financing models, some international studies also reveal similar patterns. In North America, studies of light rail projects in Houston, Minneapolis, and Los Angeles also indicate that the construction of new lines in suburban or underdeveloped urban areas stimulated local economic activity, while operational efficiency improvements in dense, high-demand corridors produced greater benefits for employment, property values, and business concentration [135,136]. Using firm-level data from 1990 to 2014, Credit et al. found that the opening of the Phoenix light rail system significantly stimulated the formation of new firms in the knowledge, service, and retail sectors along its corridors, although this effect diminished over time and exhibited pronounced spatial decay [137]. Crampton et al. found that in the UK and France, light rail construction can significantly increase the number of customers in city centers, while office property prices or rents along light rail corridors generally rise faster than in other areas. Moreover, the economic development impact of light rail investment is most pronounced in non-residential or less

mature urban areas [138]. This consistency suggests that the conclusions may reflect a more general, potentially globally applicable mechanism, offering valuable insights for international policymakers. However, it should be noted that although some international studies exhibit patterns similar to those observed in our research, these cases are generally isolated and fragmented, and significant differences exist across countries in terms of institutional arrangements and financing models; therefore, the generalizability of these patterns still requires further in-depth investigation.

Interestingly, the coefficient of the environmental control variable is negative and statistically significant, indicating that environmental conditions are indeed related to economic growth in our sample. Therefore, controlling for environmental factors is necessary to obtain unbiased estimates of URT effects. However, we do not interpret this negative coefficient as evidence that URT construction or operation generates environmental pressures. Rather, it reflects the statistical relationship between the selected environmental indicators, such as days meeting air quality standards or carbon emissions, and economic growth, which may be influenced by factors such as industrial restructuring, the closure of polluting firms, or investment restrictions.

Our study demonstrates the impact pathways of URT construction and operation on economic growth through the PSE framework. Nevertheless, several limitations remain to be solved, and the representative ones provoking future research include the following. (1) The temporal scope of the empirical analysis excludes the structural ruptures induced by the COVID-19 pandemic, which fundamentally altered mobility patterns and revealed URT systems' vulnerability to exogenous shocks. Therefore, we will explore the relationship between the development of URT and the economy in the pandemic and post-pandemic periods to test the resilience of the infrastructure-growth relationship under systemic disturbances. (2) Although we have controlled for environmental variables, these factors remain composite measures. Beyond air quality and carbon emissions, indicators, such as water quality and other greenhouse gas emissions, may also influence the economic impact of infrastructure. Future studies should treat environmental factors as dependent variables or integrate them into a composite sustainability index to further explore the effects of URT construction and operation on environmental outcomes. (3) Given significant differences across countries in institutional arrangements and financing models, future research will incorporate additional international cases to investigate the generalizability of transportation infrastructure's economic effects.

6. Conclusions

This study sheds more light on the academic debate on URT's economic role by introducing a PSE framework that analyzes the impact of URT on regional economic growth from both the construction effect and the operational effect. Through the FET model and IFE estimation on panel data from 26 Chinese cities (2007–2020), we uncovered three findings.

First, URT construction investment has a nonlinear threshold effect on economic growth, consistent with the law of diminishing marginal returns. URT operational efficiency is positively correlated with economic development. Therefore, URT investment strategies should be dynamically adjusted according to different development stages. Policies should focus on construction investment in the early stage and on improving operational efficiency in the mature stage, including enhancing transport performance, service quality, and urban connectivity to sustain economic growth.

Second, regional heterogeneity is reflected through different governance pathways. It is recommended that the national government adopt differentiated development measures based on the characteristics of different regions. Cities with relatively weak economic and

social foundations should prioritize spillover effects during the construction phase, such as labor market integration, while cities with better economic and social foundations and more established institutions should leverage operational synergies through stakeholder co-production, such as innovation clusters driven by TOD.

Third, the government should prioritize the sustainability of URT development. There is a lack of in-depth and long-term research on the environmental effects of URT construction and operation. The government should conduct comprehensive environmental impact assessments to minimize adverse environmental effects. Supporting green technology innovation and research is crucial for promoting the sustainability of URT systems.

At the theoretical level, we apply the value creation theory in PSE to elucidate economic growth issues, thereby bridging the latest theories in public management with economic growth. It interprets economic growth through the lens of value creation. The research outcomes offer a fresh perspective and theoretical foundation for exploring the relationship between infrastructure and economic growth. Furthermore, this article enriches the value creation theory in PSE and demonstrates its application in practical situations. It contributes to understanding the impact of individual transportation infrastructure on urban development. Decoding the URT-economic growth nexus through the perspective of PSE, this study provides a new perspective on URT's economic impact and proposes a framework that may be applied in similar contexts.

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Appendix A

By comparing the results with and without carbon emissions, as shown in Tables 4 and 5(1) versus Tables A1 and A2, we find that including carbon emissions has only a minor impact on the estimated coefficients and threshold values. For example, incorporating carbon emissions causes only minor changes in the coefficients of URT construction and the environmental index, while their statistical significance remains largely unchanged.

Table A1. The threshold statistics for Env-PCA.

Threshold	Threshold Effect Value			Robustness Test		
	F Test	p-Value	Threshold Value	F Test	p-Value	Threshold Value
1	67.950	0.000	9.328	50.270	0.000	9.294
2	49.450	0.000	9.294	36.790	0.047	9.294
			20.934			20.971
3	20.960	0.677	-	21.020	0.717	-

Table A2. The model I estimation for Env-PCA.

Dependent variable: Economic Growth (PERGDPit)					
Variable		One Threshold	p-Value	Two Threshold	p-Value
CI	1st-regime (β_1)	0.013	(0.000)	0.014	(0.000)
	2nd-regime(β_2)	0.003	(0.002)	0.004	(0.000)
	3rd-regime (β_3)	-	-	-0.002	(0.000)
GOV		0.003	(0.022)	0.036	(0.016)
TEC		0.006	(0.000)	0.009	(0.000)
HUM		1.043	(0.301)	0.286	(0.246)
DEN		0.207	(0.000)	0.231	(0.008)
TRS		1.194	(0.003)	0.085	(0.024)
Env-PCA		-0.827	(0.008)	-0.618	(0.108)
CONSTANT		2.105	(0.001)	1.975	(0.001)
City Fixed-Effects (σ_u)		2.950	-	2.839	-
Error Term (σ_ϵ)		0.878	-	0.823	-
R ²		0.882	-	0.897	-
Number Of Observations		364	-	364	-

These results indicate that whether carbon emissions are included as a separate control variable or as part of the composite environmental index, the main conclusions regarding the effects of URT construction and operation on regional economic growth remain robust. The minor variations observed likely reflect the relatively low variance of carbon emissions across the sample cities during 2007–2020, as well as the dominant effect of urban rail transit construction and operation through mechanisms such as resource flow and agglomeration. Overall, this comparison confirms the reliability of our original model and supports the robustness of our empirical findings.

From Table A3, by comparing the model results using Env-PCA and the ENV index as environmental control variables, we find that the conclusions of the two models do not differ significantly. Although the coefficient of the environmental variable is 0.276 and highly significant when using Env-PCA, and -0.821 when using the air quality index alone in Table 10, which is marginally significant at the 10% level, the change is consistent with the inverse relationship between carbon emissions and environmental quality. Additionally, the coefficients of other variables exhibit only minor variations across the two models. HUM, although positively signed, remains statistically insignificant, which may suggest lagged or indirect effects. The high R² of 0.888 further confirms the robustness of the model.

Table A3. The Individual Fixed Effects model estimation with Env-PCA.

Variable	Coefficient	p-Value	[95% Conf. Interval]	
IPR	0.287	(0.000)	0.184	0.389
GOV	0.001	(0.001)	0.000	0.002
TEC	0.003	(0.032)	0.001	0.007
HUM	1.989	(0.223)	-1.219	5.197
DEN	0.194	(0.000)	0.169	0.217
TRS	1.885	(0.012)	0.414	3.669
Env-PCA	0.276	(0.005)	0.085	0.467
Constant	3.346	(0.000)	2.766	3.926
City Fixed-Effects (σ_u)	2.676	-	-	-
Error Term (σ_ϵ)	0.952	-	-	-
R ²	0.888	-	-	-
Number of Observations	364	-	-	-

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