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Population Density and Urban Resilience in Chinese Mega-Cities: Evidence of a Medium-Density Trap

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Abstract: Urban resilience has become a central framework for advancing sustainable development in the context of escalating urban risks. To investigate the role of population density in shaping resilience, panel data from 114 large Chinese cities covering the period 2006–2021 (excluding the COVID-19 years to avoid potential distortions) were analyzed. A multidimensional urban resilience evaluation system was constructed, encompassing five key domains: economy, society, institutions, environment, and infrastructure. Resilience levels were assessed through the entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), while a panel threshold regression model was applied to capture potential nonlinearities in the density–resilience relationship. Results demonstrate that urban resilience in China has exhibited a sustained upward trajectory, largely driven by advances in infrastructure provision and economic capacity. However, population density exerts a nonlinear "double-threshold effect". At low levels of density, the effect on resilience is statistically insignificant; within a medium-density range, a pronounced negative impact emerges, constituting a "medium-density trap"; and at high densities, the adverse effects are attenuated, suggesting that urban systems may gradually adapt to intensified population pressures. This trap is most evident in regional center cities and rapidly developing urban areas, where governance capacity, infrastructure investment, and resource allocation have lagged behind demographic expansion. These findings highlight the stage-dependent vulnerabilities embedded in urbanization processes and indicate that resilience is not solely a function of density itself but also of institutional capacity and infrastructural adequacy. Differentiated governance strategies are therefore required, including targeted improvements in public infrastructure, strengthened institutional and administrative capacities, and the optimization of spatial configurations to accommodate density-specific challenges. By identifying the thresholds at which population density alters resilience trajectories, this study contributes to a deeper theoretical understanding of urban vulnerability and offers actionable insights for policymakers seeking to enhance resilience under conditions of rapid urban growth and high-density development.

Keywords: Urban resilience; Population density; Evaluation system; Threshold regression; Medium-density trap

1 Introduction

Amid rising global risks and increasing urban complexity, urban resilience has become a key indicator for assessing a city's capacity to achieve sustainable development [1, 2]. It reflects a city's ability to withstand and recover from disasters and public health crises as well as its adaptability to maintain essential functions under continuous change [3, 4]. As high-density development and compound risks intensify, balancing risk management and functional performance has become a major challenge for urban planning and governance [5].

Population density is a core structural factor shaping urban resilience, influencing land use patterns, resource allocation, infrastructure capacity, and environmental pressures [6]. Moderate density can enhance infrastructure efficiency, promote social cohesion, and improve resource utilization, strengthening a city's capacity to absorb and adapt to external disturbances [7, 8]. In contrast, excessive density often correlates with higher pollution levels, infrastructure overload, and increased psychological stress from noise and environmental discomfort [9–11]. Low-density sprawl, on the other hand, is linked to spatial fragmentation, underutilized land, and inefficiencies in public service delivery, which together undermine urban resilience [12].

Existing studies have indicated that the relationship between population density and urban resilience is not strictly linear; the direction and intensity of this effect may vary significantly across different density intervals [13–15], implying that threshold effects may exist rather than a simple one-way response pattern. Particularly during the transition from low to high density, differences in systemic pressure and regulatory capacity across different phases may lead to fluctuations in resilience performance. While some research has preliminarily revealed such nonlinear associations, the mechanisms underlying these patterns, especially across different types of cities and density stages, remain underexplored and lack systematic empirical validation.

Based on this, the study takes 114 prefecture-level and above cities in China as the research sample. It constructs an urban resilience index system covering the five dimensions mentioned above, evaluates resilience levels using the entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method, and applies panel regression and threshold regression models to explore the nonlinear effects and underlying mechanisms of population density on urban resilience and its subsystems. The goal is to provide theoretical support and policy recommendations for managing urban population density and advancing resilience-oriented urban development.

2 Related Works

The study of urban resilience has evolved into a comprehensive multi-dimensional framework encompassing five key dimensions: economic, social, environmental, institutional, and infrastructural. Within this framework, population density is a central structural factor influencing all subsystems.

In the economic system, moderate population density can help optimize resource allocation and promote the effective concentration of production factors, thereby enhancing a city's capacity to respond to economic fluctuations and external shocks. On one hand, higher density facilitates information exchange and collaboration among firms, stimulating innovation and industrial synergy, which contributes to faster recovery and greater adaptability of the economic system [7, 8, 16]. On the other hand, excessive density may constrain production space, increase operational costs, and intensify pressure on small and medium-sized enterprises, ultimately undermining economic stability and resilience [17].

In the social system, moderate population density can facilitate neighborhood interaction and the accumulation of social capital, thereby enhancing community-based mutual support and the ability to respond to unexpected events [18]. However, when population concentration is high and spatial distribution is uneven, it may lead to strained public resource allocation and weakened community identity, triggering social isolation, competition for resources, and group tensions, which in turn exacerbate disparities in resilience across communities [19, 20].

Population density plays a critical role in shaping a city's capacity to cope with environmental risks by influencing land use patterns, energy consumption structures, and ecological spatial layouts [21, 22]. A moderately high density is more conducive to the deployment of ecological infrastructure such as green transportation systems, centralized energy supply, and rainwater recycling, thereby enhancing urban adaptability to climate change and natural hazards [23]. Despite these benefits, when population density exceeds ecological carrying thresholds, it often intensifies air pollution, urban heat island effects, and green space degradation, weakening urban ecosystems' self-regulation and recovery capacity [14, 15].

Higher population density places greater demands on urban institutional systems such as disaster response, public service delivery, and interdepartmental coordination [24]. In densely populated areas, the urgency and complexity of governance often drive improvements in risk early-warning and emergency response mechanisms, thereby enhancing institutional adaptability and responsiveness [25]. Nevertheless, in the absence of effective coordination mechanisms, such complexity can also lead to fragmented administration and delayed policy implementation, ultimately undermining the stability of institutional structures [26].

Regarding infrastructure resilience, population density is crucial in shaping urban systems' spatial configuration and emergency response capacity. Densely populated cities are more likely to develop networked and large-scale infrastructure layouts, enhancing the operational efficiency and responsiveness of essential services such as water supply, electricity, transportation, communications, and healthcare [27, 28]. Nevertheless, when density becomes excessive, these systems may face overload risks. The failure of a single critical node can lead to cascading disruptions, exposing vulnerabilities in the overall resilience of urban infrastructure [15].

In summary, although their emphases differ, domestic and international studies have examined the complex relationship between population density and urban resilience. International research, primarily based on experiences from Europe, North America, and the Middle East, has emphasized the vulnerabilities of high-density cities in relation to public service provision, traffic congestion, and environmental carrying capacity [11, 18] . It has also stressed the importance of infrastructural resilience and ecological restoration in mitigating these risks [19, 23]. By contrast, studies in the Chinese context have focused more on the challenges of rapid urbanization, particularly the lag in public service expansion and governance capacity during the medium-density stage [12, 14]. These differences suggest that the mechanisms through which density shapes resilience in Chinese cities may diverge from those observed in developed economies, owing to distinct developmental trajectories and institutional contexts. Engaging more directly with international scholarship can help to identify the generalizable aspects of the density–resilience relationship, while at the same time underscoring the distinctive significance of the "medium-density trap" as a phenomenon characterizing large Chinese cities.

3 Theoretical Mechanism Analysis

3.1 Conceptual Definition

In existing studies, the notion of "optimal density" is typically understood as the level of population agglomeration that balances the benefits of concentration with the costs of congestion, thereby maximizing social welfare or economic efficiency [29, 30]. This notion reflects a single-point optimum in terms of static equilibrium. Related to this argument is the concept of the "nonlinear effects of density", which suggests that the relationship between population density and urban development performance may exhibit an inverted U-shape or segmented pattern, revealing differences in marginal effects across stages [31].

Against this backdrop, this study introduces the concept of the "medium-density trap" to describe a stage-specific dilemma that may arise as cities evolve from low-density to high-density conditions. Specifically, when population density enters a certain range, cumulative pressures may emerge simultaneously across the economic, social, ecological, infrastructural, and governance dimensions, while the corresponding support and regulatory capacities fail to expand in parallel. As a result, urban resilience may stagnate or even decline. Urban resilience is understood as a multi-dimensional coupled system that encompasses the economic, social, ecological, infrastructural, and institutional domains [2, 32].

Accordingly, the "medium-density trap" is not equivalent to the single-point notion of "optimal density", nor is it merely a descriptive reference to the nonlinear form of the density–performance relationship. Rather, it emphasizes a cross-dimensional zone of systemic vulnerability. The purpose of introducing this concept is to provide a theoretical reference for subsequent empirical analysis and policy discussion. In this sense, the concept differentiates itself from "optimal density" and "nonlinear effects" and offers a new explanatory framework for identifying stage-specific vulnerabilities in urban development.

3.2 Mechanism of Influence

The impact of population density on urban resilience is not unidirectional or linear, and its mechanisms vary across different density stages. Based on existing studies and theoretical reasoning, the potential pathways can be understood through three stages: low density, medium density, and high density.

In the low-density stage, the concentration of population and economic activities is limited, and economies of scale and network externalities are not yet fully realized. Public services and infrastructure utilization remain relatively inefficient, and governance demands are modest. As a result, the relationship between density and resilience is relatively weak.

As density increases, cities enter the medium-density stage. At this stage, agglomeration effects emerge, but congestion, environmental stress, and governance challenges also intensify. Public service demand grows faster than supply expansion, infrastructure systems approach their capacity limits, pollution and heat island effects accumulate, and governance complexity rises. The convergence of these pressures may heighten systemic vulnerability, leading to what can be termed the "medium-density trap". Thus, the medium-density stage may be associated with greater fragility in urban resilience. This theoretical reasoning provides a framework for subsequent empirical analysis.

Some cities may gradually mitigate density-related pressures in the high-density stage through long-term investments and institutional development. Infrastructure redundancy, public service maturity, ecological restoration, and governance capacity improvements can help moderate negative impacts. However, these outcomes are not universal and depend on resource endowments, governance capacity, and developmental trajectories.

3.3 Insights from the Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) posits an inverted U-shaped nonlinear relationship between economic development and environmental quality. In the early stages of development, environmental quality tends to decline as economic growth accelerates. Once development reaches a certain level, environmental quality may gradually improve [33]. This theory reflects the stage-based logic of "agglomeration effects–congestion effects–institutional catch-up" during development.

A similar perspective can be applied to the relationship between population density and urban resilience. In the low-density stage, the effects of density may remain limited. In the medium-density stage, pressures from resource constraints and environmental degradation, combined with institutional lag, may become more pronounced. In the high-density stage, some cities may alleviate negative impacts through governance improvements and technological advancement. This nonlinear and stage-specific framework provides important theoretical insights for interpreting the "medium-density trap". Moreover, the concept of the "middle-income trap" in development economics also highlights the risk of stage-specific stagnation [34], offering a useful analogy for understanding potential dilemmas in spatial agglomeration.

3.4 Research Hypotheses

Based on the above analysis, this study proposes the following hypotheses:

Hypothesis 1: Population density and urban resilience may exhibit a nonlinear relationship, with heterogeneous marginal effects across different density stages.

Hypothesis 2: In the low-density stage, the impact of population density on urban resilience may be relatively weak. In the medium-density stage, population density may exert negative effects on resilience, while in the high-density stage, these effects may be moderated.

Hypothesis 3: Population density influences urban resilience through multiple mechanisms, including economic, social, ecological, infrastructural, and institutional dimensions. The "medium-density trap" may represent the outcome of these pressures converging at a specific stage.

4 Research Design and Empirical Methods

4.1 Urban Resilience Evaluation Index System

Drawing on the theory of sustainable development and previous studies [35, 36], this study conceptualizes urban resilience as comprising five subsystems: economic, social, environmental, institutional, and infrastructural. For each subsystem, a corresponding set of objectives was established. Based on these objectives, 32 specific indicators were selected to construct a comprehensive evaluation system for measuring urban resilience. The detailed indicator framework is presented in Table 1.

Table 1. Urban resilience evaluation index system

Dimension	Target	Indicator	Weight	Attribute
A: Economic resilience (0.2404)	Economic development	A_1 : GDP per capita	0.0427	+
		A_2 : Fiscal expenditure per capita	0.0446	+
		A_3 : General public budget revenue per capita	0.0553	+
		A_4 : FDI as a share of GDP	0.0014	-
	Industrial structure	A_5 : Tertiary industry as a share of GDP	0.0221	+
		A_6 : Science and technology expenditure as a share of GDP	0.0590	+
		A_7 : Education expenditure as a share of GDP	0.0153	+
B: Social resilience (0.1818)	Social development	B_1 : Natural population growth rate	0.0034	-
		B_2 : Urbanization level	0.0136	+
		B_3 : Built-up area per capita	0.0235	+
	Residents' livelihood	B_4 : Consumption expenditure per capita	0.0371	+
		B_5 : Proportion of urban employment	0.0623	+
		B_6 : Urban employees covered by pension insurance	0.0419	+
C: Institutional resilience (0.2343)	Urban civilization	C_1 : Urban-green space per capita	0.0242	+
		C_2 : College students per 10,000 people	0.0441	+
		C_3 : Public library books per 100 people	0.0602	+
	Medical services	C_4 : Hospital density	0.0767	+
		C_5 : Doctors per capita	0.0291	+
D: Environmental resilience (0.0308)	Living environment	D_1 : Green coverage in built-up area	0.0025	+
		D_2 : CO_2 emissions per capita	0.0065	-
		D_3 : Average PM2.5 concentration	0.0082	-
		D_4 : Energy efficiency	0.0003	-
	Sanitation	D_5 :Centralized sewage treatment rate	0.0060	+
		D_6 : Harmless treatment rate of household waste	0.0051	+
		D_7 : Comprehensive utilization rate of general industrial solid waste	0.0022	+
E: Infrastructure resilience (0.3129)	Municipal infrastructure	E_1 : Completed investment in municipal utilities	0.1362	+
		E_2 : Water supply pipeline density	0.0271	+
		E_3 : Road area per capita (m^2)	0.0158	+
		E_4 : Buses per 10,000 people	0.0306	+
	Responsive infrastructure	E_5 : Mobile phone users per capita	0.0320	+
		E_6 : Internet users per capita	0.0488	+
		E_7 : Drainage pipeline density in built-up areas	0.0224	+

4.2 Variable Design and Measurement

The dependent variable is urban resilience (UR). Based on the indicator system described above, we first standardize all indicator data and then apply the entropy-weighted TOPSIS method to calculate the indicator weights. The comprehensive UR score for each city is obtained by aggregating the weighted indicators. The weights and attributes of each indicator are shown in Table 1.

The core explanatory variable is population density (PD). It refers to the number of permanent residents per unit of land area. Considering that the resilience indicators are measured at the city level, and to ensure consistency in statistical scope, this study adopts the internationally accepted method: PD is calculated as the ratio of the year-end permanent population within the administrative boundary of a city to the total land area.

Control variables (CVs). Drawing on previous studies [35, 37], this study includes a set of control variables to account for the potential influence of government policy, economic structure, and market conditions on the relationship between population density and urban resilience. Specifically, four control variables are selected: financial investment (FI), measured by the ratio of general government fiscal expenditure to the city's GDP; industrial structure (IS), represented by the proportion of tertiary industry in the city's GDP; degree of marketization (DM), assessed by the share of private and self-employed workers in total urban employment; and government self-sufficiency capacity (GSC), calculated as the ratio of local general public budget revenue to expenditure.

4.3 Research Methods

4.3.1 Panel model

This study employs a panel data regression model to examine the relationship between population density and urban resilience. Specifically, we adopt a fixed effects panel model to control for unobserved heterogeneity across cities. The basic form of the model is expressed as following Eq. (1):

$$UR = B + \alpha_1 PD + CV + \varepsilon_1 \tag{1}$$

where, the variables in the model are defined as follows: UR is the dependent variable, representing urban resilience; B is the intercept term; PD is the core explanatory variable, referring to population density; α_1 denotes the regression coefficients, reflecting the influence of the core and control variables on urban resilience; CV is a set of control variables; ε_1 is the error term.

4.3.2 Panel threshold model

The panel regression model is employed to verify whether population density directly impacts urban resilience. If a significant relationship is identified, a panel threshold regression model is applied to further examine whether this effect varies across different population density intervals. The threshold regression model is specified as following Eq. (2):

$$\begin{aligned} UR = K + \beta_1 PD \cdot I\,(PD \leq \gamma_I) + \beta_2 PD \cdot I\,(\gamma_1 < PD \leq \gamma_2) + \cdots + \beta_n PD \cdot I\,(\gamma_{n-1} < PD \leq \gamma_n) + \\ \beta_{n+1} PD \cdot I\,(\gamma_n < PD \leq \gamma_{n+1}) + \alpha_2 CV + \varepsilon_2 \end{aligned} \tag{2}$$

where, K denotes the constant term; $I(\cdot)$ is the indicator function; β represents the coefficient of the core explanatory variable; γ denotes the threshold value; CV refers to the control variables with α_2 as their coefficients; ε_2 is the error term.

4.4 Study Area and Data Source

According to the Tabulation on 2020 China Population Census by County [38] and the China Urban-Rural Construction Statistical Yearbook 2022 [39], Chinese cities are classified into mega, very large, and large cities based on the number of permanent residents in built-up areas. This study focuses on large cities with a population of more than one million people in built-up areas. After excluding cities with significant data gaps, a final sample of 114 cities was selected for analysis.

The indicator data are primarily sourced from the China Statistical Yearbook (2006–2021) [40], the China Statistical Yearbook on Environment [41], and various provincial and municipal yearbooks. For missing values, supplementary data were estimated using linear interpolation and trend extrapolation based on historical records.

4.5 City Clustering

Based on the average population size levels and land use during the study period, this paper uses SPSS 24.0 for statistical analysis to classify the 114 cities into three major clusters. Cluster 1, consists of 34 national core cities, primarily composed of municipalities, provincial capitals, and economically dominant metropolises such as Beijing, Shanghai, and Shenzhen. These cities typically hold provincial or sub-provincial administrative status, possess administrative advantages, large-scale economies, and well-developed infrastructure systems, and serve as national hubs in innovation, finance, and internationalization. Cluster 2 includes 46 regional center cities and industrially specialized cities, represented by Wenzhou and Luoyang. These cities have moderate economic development levels, with GDP ranging between 300 and 800 billion yuan, and fulfill specialized functional roles within provincial urban systems. Cluster 3 comprises 34 developing cities, including Sanming and Zhaoqing, characterized by smaller economies with GDP typically between 200 and 300 billion yuan, mainly serving localized development needs.

5 Empirical Results and Analysis

5.1 Temporal Evolution of Urban Resilience in Chinese Large Cities

To better understand the changing relationship and distribution between population density and urban resilience over time, this study uses bivariate kernel density estimation to plot joint distribution maps for four representative years: 2006, 2011, 2016, and 2021 (Figure 1). These maps illustrate the dynamic evolution of the sampled cities across China.

The distribution pattern of the full sample cities remained relatively stable from 2006 to 2021. The central aggregation zone consistently appeared in the range of 1.0 to 1.5 (10,000 people/km^2) for population density and 0.1 to 0.2 for resilience scores, indicating that urban resilience across the country generally stayed low to medium. Although a secondary aggregation zone representing high-density and high-resilience cities began to emerge in the upper-right corner of the graphs around 2016 and expanded slightly by 2021, the full sample distribution pattern showed little shift. This overall stability in distribution implies that improvements in urban resilience in China have primarily occurred through localized breakthroughs rather than widespread systemic progress.

From 2006 to 2021, Cluster 1 cities showed a pattern of decreasing population density and increasing resilience. The central density index shifted from 1.0-1.5 to 0.5-1.0, while the resilience index increased from 0.10-0.15 to 0.15-0.25, reflecting progress in system optimization and spatial restructuring. Since 2016, a small sub-aggregation zone has appeared in the lower-right corner of the graph. By 2021, its density rose to 3.0, but resilience remained below 0.1, indicating that some ultra-dense cities lag in resilience building.

The distribution pattern of Cluster 2 cities exhibited relatively slow structural changes. The density index shifted from approximately 1.0 to 1.5, while the resilience index remained stable within the range of 0.10 to 0.20, indicating a generally moderate evolution. The contour of the density surface became gradually more compact, and the shading intensified, suggesting a narrowing gap in resilience levels among cities. However, the central aggregation zone did not shift significantly, nor did any high-resilience sub-aggregation zone emerge. Such a pattern indicates that these cities are still in the early stages of resilience platform development, with relatively weak structural stability.

The distribution of Cluster 3 cities has remained concentrated within a low-density and low-resilience range, approximately 0.5 to 1.5 in population density and 0.10 to 0.20 in resilience index, indicating generally low resilience levels and limited capacity for structural improvement. In 2021, the density-resilience structure exhibited signs of divergence, with two distinct density peaks emerging near 0.5 and 1.5, centered around a resilience index of 0.10 to 0.15. Such divergence suggests that while some cities have made incremental progress alongside population growth, others remain stagnant under low-density conditions due to the lack of effective resilience enhancement mechanisms. The spatial structure of this group remains relatively fragmented, with underdeveloped system foundations and insufficient governance capacity.

Overall, from 2006 to 2021, the evolution of urban resilience in Chinese cities exhibited a general pattern of "stable core with structural differentiation". Cluster 1 cities experienced a "declining density-rising resilience" trajectory; although a few cities achieved high-density breakthroughs, their resilience improvements remained relatively limited. Cluster 2 cities entered an initial stage of population concentration with unstable structural characteristics, while Cluster 3 cities had a weak foundation for resilience building, with emerging differentiation but limited overall progress. In general, the temporal evolution of urban resilience does not clearly align with changes in population density, indicating that resilience improvement is not solely driven by population agglomeration. Instead, it is likely shaped by a combination of governance capacity, resource allocation efficiency, and systemic coordination. Although population density remains a key factor influencing urban resilience, its impact mechanism warrants further investigation across different city types and development stages.

5.2 Descriptive Statistics and Multicollinearity Test

Pearson correlation coefficients were first used to assess the relationships among the variables to ensure the robustness of the regression results. The results show that the absolute values of the correlation coefficients between variables in all three models are less than 0.5, indicating relatively weak correlations. Subsequently, variance inflation factors (VIF) were calculated to test for multicollinearity among the explanatory variables. All VIF values were below 5, suggesting no significant multicollinearity in the regression models. Detailed results are presented in Table 2.

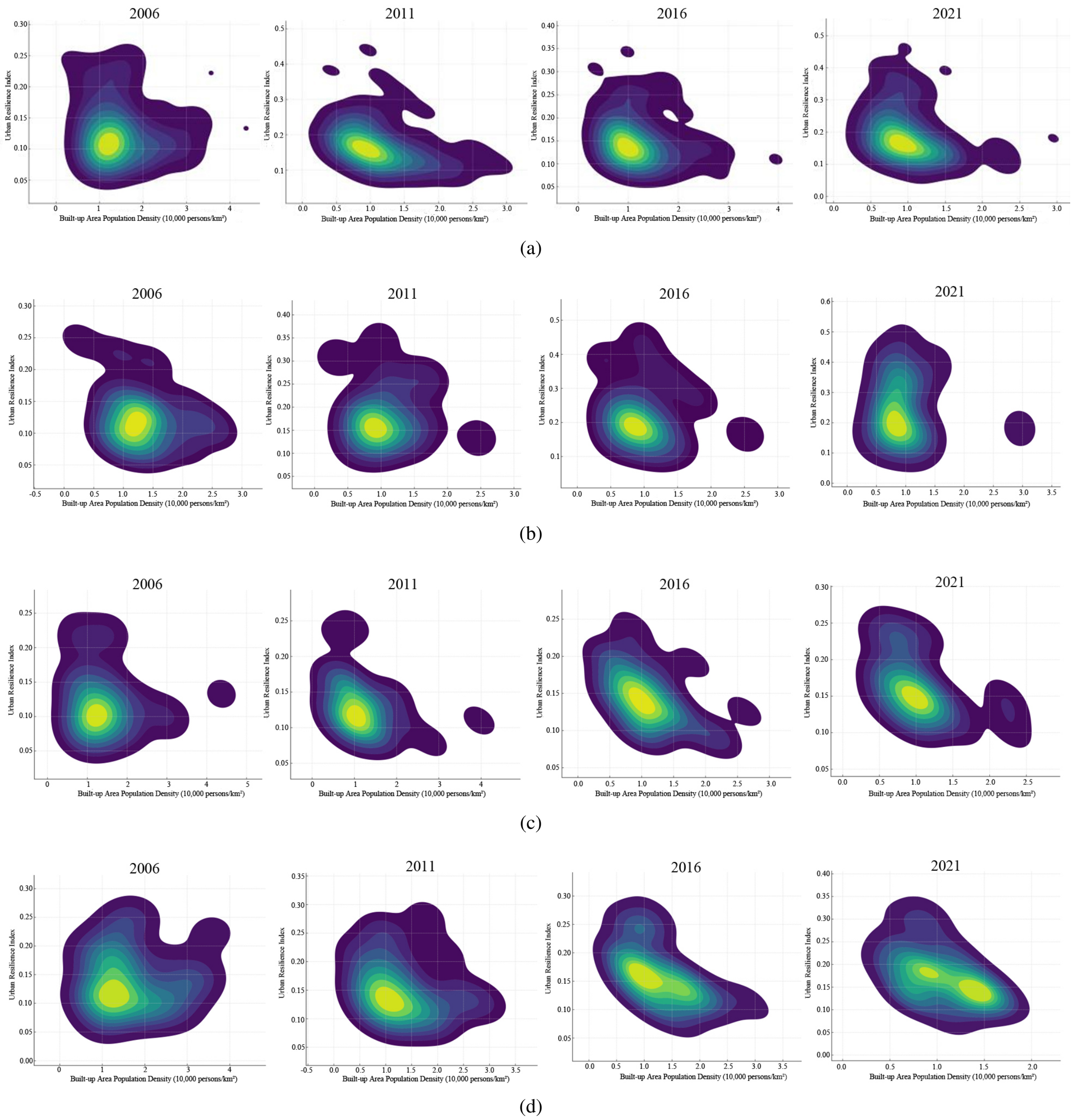


Figure 1. Joint distribution maps of Chinese large cities: (a) Joint distribute of full sample cities; (b) Joint distribute of Cluster 1 cities; (c) Joint distribute of Cluster 2 cities; (d) Joint distribute of Cluster 3 cities

Table 2. Test results of classification

Variable	No.	Min	Max	Mean	SD	Median	VIF	PD	FI	IS	DM	GSC
UR	1824	0.070	0.500	0.158	0.059	0.145						
PD	1824	0.273	4.371	1.176	0.538	1.056	1.105	1				
FI	1824	0.044	1.485	0.139	0.060	0.129	1.064	-0.029	1			
IS	1824	0.038	0.839	0.445	0.105	0.431	1.213	-0.242**	0.204**	1		
DM	1824	0.034	12.314	1.290	0.955	1.050	1.059	-0.027	0.091**	0.156**	1	
GSC	1824	0.069	1.541	0.610	0.215	0.607	1.170	-0.247**	-0.071**	0.264**	-0.124**	1

Note: UR: Urban resilience; PD: Population density; FI: Financial investment; IS: Industrial structure; DM: Degree of marketization; GSC: Government self-sufficiency capacity; SD: Standard deviation; VIF: Variance inflation factors; ** denote significance at the 5% levels.

5.3 Panel Regression Results

As shown in Table 3, population density significantly negatively affects urban resilience, with notable heterogeneity across both time and city type. In the full sample, the regression coefficient of population density is -0.023, indicating that population density generally inhibits improvements in resilience. The period-specific results show that this suppressive effect was strongest between 2006 and 2013, with a coefficient of -0.026; it declined to -0.014 in the 2014-2021 period, suggesting that environmental governance and system regulation improvements have somewhat alleviated density-induced pressures. By city cluster, the regression coefficient for Cluster 1 cities is -0.034, indicating the strongest negative effect among the three groups. This result is closely tied to their long-term exposure to ultra-high-density development. Although these cities generally possess advanced infrastructure, efficient resource allocation, and robust governance capacity, prolonged high-density pressure may have led to structural fatigue within their urban systems, significantly undermining resilience. In contrast, Cluster 2 cities have a coefficient of -0.030, reflecting the strain caused by weaker resource carrying capacity and emergency response systems, which render them highly susceptible to the adverse effects of increasing density. Cluster 3 cities show the weakest negative impact, with a coefficient of -0.012, likely due to their relatively low-density levels, and their urban systems have yet to face the pressures of dense development. However, this also suggests that their resilience capacity remains nascent, with limited system responsiveness.

Regarding control variables, financial investment and industrial structure are key drivers of enhanced urban resilience. Financial investment generally shows a positive effect, particularly in earlier years and in larger cities, but its impact weakens in the later period and in some city clusters, where it even turns insignificant or negative. This suggests diminishing marginal returns and uneven effectiveness across contexts. This may be due to inefficient allocation of fiscal resources, low investment returns, or insufficient governmental focus on resilience-building, reflecting the varying effectiveness of fiscal expenditure across different development stages and governance contexts. The coefficient of industrial structure ranges from 0.099 to 0.300 across all models. It is most pronounced in Cluster 1 cities, highlighting the role of industrial upgrading in alleviating resource and environmental constraints and strengthening system resilience. In comparison, the effects of the degree of marketization and government self-sufficiency capacity are relatively limited, with small coefficient fluctuations. Moreover, the constant terms in most models are positive, suggesting a baseline level of resilience embedded in city structures; however, for Cluster 1 cities, the constant is negative, implying that rapid population concentration may have led to the accumulation of structural risks.

Table 3. Panel regression results

Variable	Dependent Variable(UR)					
	Full Sample	Full Sample		Cluster 1	Cluster 2	Cluster 3
		2006–2013	2014–2021			
PD	-0.023***	-0.026***	-0.014***	-0.034**	-0.030**	-0.012*
FI	0.085***	0.073***	-0.064	0.572***	-0.001	0.104
IS	0.201***	0.133***	0.095***	0.300***	0.122***	0.099
DM	0.001	0.006**	0.002**	0.005	0.002	0.003
GSC	-0.003	0.026**	-0.013	0.003	-0.016	0.012
Con.	0.083***	0.089***	0.157***	-0.019	0.126***	0.105***
No.	1824	912	912	544	736	544

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.4 Panel Threshold Regression Results

Based on the previous panel regression results, population density generally negatively impacts urban resilience across cities of different scales. However, further investigation is required to determine whether this effect shows heterogeneity in marginal effects. To explore the nonlinear mechanism and evolution pattern of how changes in population density influence urban resilience, this study employs population density as the threshold variable to construct a panel threshold regression model. We use Stata 18.0 to conduct bootstrap threshold effect tests on the full sample and the three city clusters. The results are presented in Table 4.

The full sample, along with Cluster 2 and Cluster 3 cities, revealed a significance double-threshold effect, indicating that the relationship between population density and urban resilience generally exhibits nonlinear characteristics. In contrast, Cluster 1 cities did not show a statistically significant stage-based shift in resilience as density changes. This may be attributed to the fact that resilience improvements in these national core cities depend more on long-term mechanisms such as technological advancement and institutional optimization, making it difficult for short-term density fluctuations to trigger noticeable transitions. Meanwhile, the threshold structures observed in Cluster 2 and Cluster 3 imply that their systems are more sensitive to population density changes and more prone to responsive fluctuations during the process of density adjustment. This reflects both the vulnerability and plasticity of medium and small cities, in stark contrast to the relative stability observed in national core cities.

Table 4. Panel threshold regression results

Sample	Variable	F Statistic	P Value	BS Repetitions	1% Critical Value	5% Critical Value	10% Critical Value
Full sample	PD	100.87	0.000	500	56.4855	37.8627	32.6225
		52.01	0.034	500	117.0025	46.1675	39.0601
		48.40	0.120	500	97.2100	59.6373	50.8404
Cluster 1	PD	8.17	0.822	500	60.8424	39.9922	31.6853
		7.074	0.742	500	32.3314	26.1071	20.5411
		6.37	0.754	500	33.2308	22.6336	18.8853
Cluster 2	PD	78.11	0.000	500	50.8453	36.8697	30.8257
		33.08	0.040	500	39.8734	31.2160	27.9235
		10.17	0.740	500	51.9389	35.2423	27.9541
Cluster 3	PD	81.12	0.000	500	45.9509	33.9200	26.0796
		38.86	0.012	500	39.1961	28.5654	23.5367
		26.25	0.384	500	63.0573	46.5236	39.5706

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

5.4.1 Threshold regression results for full-sample cities

Based on the results of the threshold effect test, a double-threshold panel regression model was constructed using population density as the threshold variable. The estimated parameters are presented in Table 5.

Table 5. Panel threshold regression results

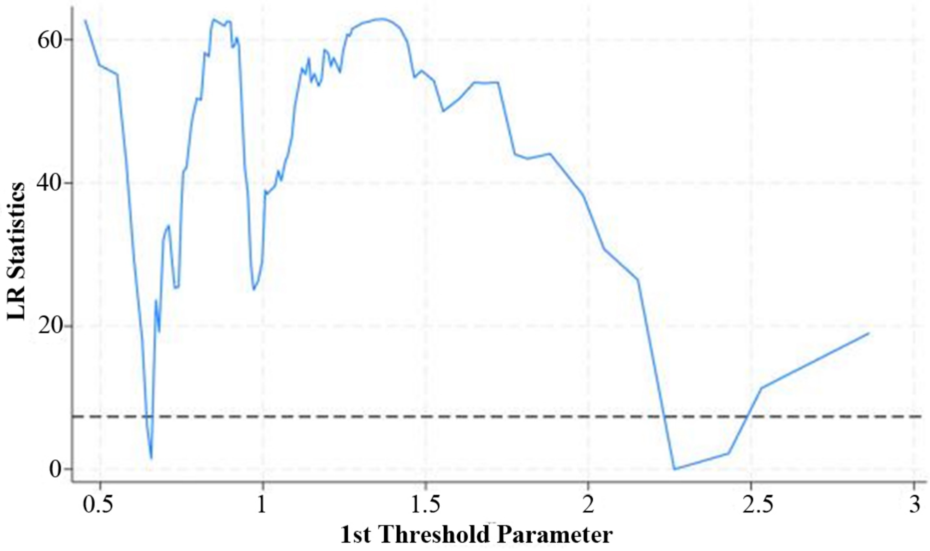
Variable	Regression Coefficient	T Value	95% Confidence Interval
PD $\leq$ 0.869	-0.008	-0.72	-0.029, 0.014
0.869 $<$ PD $\leq$ 2.264	-0.032***	-4.41	-0.047, -0.018
PD $>$ 2.264	-0.014**	-2.64	-0.025, -0.004
FI	0.086	1.35	-0.040, 0.213
IS	0.187***	4.94	0.112, 0.262
DM	0.002	1.12	-0.001, 0.005
GSC	-0.002	-0.11	-0.038, 0.034

Note: Population density is measured as 10,000 people per km^2; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

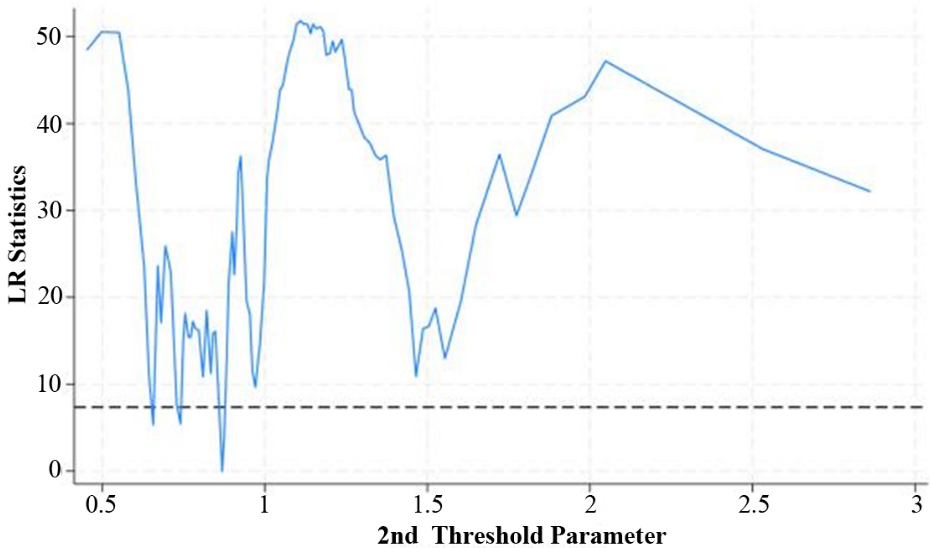
The two identified threshold values for population density are 0.869 and 2.264 (10,000 people/km^2), indicating a nonlinear relationship between population density and urban resilience. When population density is below 0.869, the estimated coefficient is -0.008 and statistically insignificant, suggesting that in low-density areas, changes in population density have a limited impact on urban resilience. This could be due to the lack of agglomeration effects, underdeveloped infrastructure and service networks, and relatively fragmented urban systems with low resistance to external shocks. When population density falls between 0.869 and 2.264, the coefficient becomes -0.032 and is statistically significant at the 1% level. This indicates that in medium-density areas, increases in population density significantly suppress urban resilience. During this phase, rapid population agglomeration imposes considerable stress on city operations, overburdening infrastructure and public services. In addition, planning delays and resource misallocations are more pronounced, reducing the system's capacity to respond effectively to risks. When population density exceeds 2.264, the coefficient is -0.014 and remains statistically significant at the 5% level. However, the absolute value is smaller than in the medium-density stage, suggesting that in high-density areas, the negative impact of further density increases is somewhat mitigated. This may reflect improved governance and risk management mechanisms in high-density cities, where intensive development and refined management help reduce negative externalities, although some resilience suppression persists.

In summary, the impact of population density on urban resilience exhibits a distinct nonlinear pattern: insignificant in low-density, negative in medium-density, and mitigated in high-density contexts. These findings highlight the need for policymakers to focus on preventing unregulated expansion in medium-density zones, optimizing spatial population distribution, and enhancing urban carrying capacity and system redundancy to strengthen resilience under complex conditions.

To further verify the reliability of the identified thresholds, Figure 2 presents the likelihood ratio functions for the two threshold estimates. Both values fall below the critical value of 7.35 at the 95% confidence level, confirming the statistical validity and robustness of the threshold estimates.



(a)



(b)

Figure 2. Double threshold estimates for full sample: (a) First threshold; (b) Second threshold

5.4.2 Threshold regression results for Cluster 2 cities

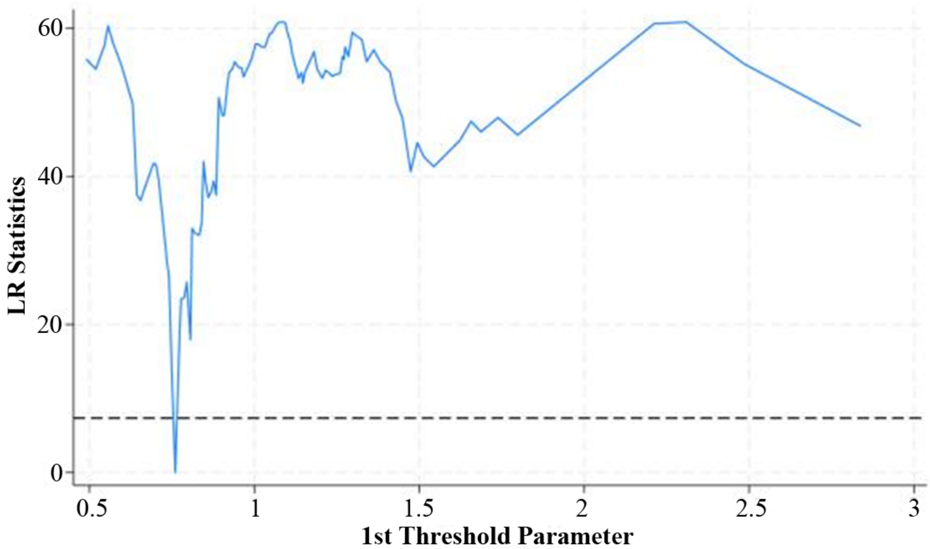
The threshold regression results for Cluster 2 cities are presented in Table 6 and Figure 3. Compared with the full sample, Cluster 2 cities exhibit a more pronounced and well-defined nonlinear threshold effect. The impact of population density on urban resilience shows strong consistency and structural variation across different density intervals. The two identified thresholds are 0.848 and 2.129, close to the thresholds found in the full sample (0.869 and 2.264). However, the significance levels and magnitudes of the regression coefficients in this cluster reveal a more distinct pattern of negative nonlinear transition.

In the low-density stage, where population density is less than or equal to 0.760, the effect of population density on urban resilience is not statistically significant, with a regression coefficient of 0.001. This is consistent with the results for the full sample, suggesting that in the early stages of urban development, when population agglomeration has not yet formed, cities lack sufficient economies of scale and collaborative networks, and population growth has a limited impact on resilience enhancement. As population density enters the medium-density range, greater than 0.760 and less than or equal to 2.310, the regression coefficient sharply decreases to -0.033 and is significantly negative at the 1% level. This indicates that urban systems face the greatest pressure in this phase. Compared to the full sample, the negative effect is more pronounced in Cluster 2 cities, reflecting more prominent weaknesses in resource allocation, public service provision, and institutional resilience. When population density exceeds 2.310, the negative effect is somewhat alleviated, with a regression coefficient of -0.019, which remains significant at the 5% level. Although this trend aligns with the full-sample findings, the degree of mitigation is less evident, suggesting that Cluster 2 cities have not yet fully developed effective governance and service mechanisms to cope with high-density challenges.

Table 6. Cluster 2 panel threshold regression results

Variable	Regression Coefficient	T Value	95% Confidence Interval
PD $\leq$ 0.760	0.001	0.04	-0.028, 0.029
0.760 < PD $\leq$ 2.310	-0.033***	-3.24	-0.054, -0.013
PD > 2.310	-0.019**	-2.35	-0.035, -0.003
FI	-0.002	-0.09	-0.038, 0.034
IS	0.121***	3.05	0.041, 0.201
DM	0.002	1.58	-0.001, 0.006
GSC	-0.005	-0.26	-0.045, 0.035

Note: Population density is measured as 10,000 people per kmkm^2; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.



(a)

(b)

Figure 3. Double threshold estimates for Cluster 2: (a) First threshold; (b) Second threshold

Cluster 2 cities experience the most pronounced negative impact during the medium-density stage and exhibit relatively limited system rebound capacity, reflecting a certain degree of stage-specific vulnerability.

Table 7. Cluster 3 panel threshold regression results

Variable	Regression Coefficient	T Value	95% Confidence Interval
$PD \leq 0.679$	0.022	1.27	-0.013, 0.056
$0.679 < PD \leq 2.120$	-0.033***	-3.89	-0.050, -0.016
$PD > 2.120$	-0.013**	-2.55	-0.023, -0.003
FI	0.125	1.11	-0.105, 0.355
IS	0.086*	1.81	-0.010, 0.183
DM	0.003	1.37	-0.002, 0.008
GSC	0.000	-0.00	-0.039, 0.039

Note: Population density is measured as 10,000 people per km^2;*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

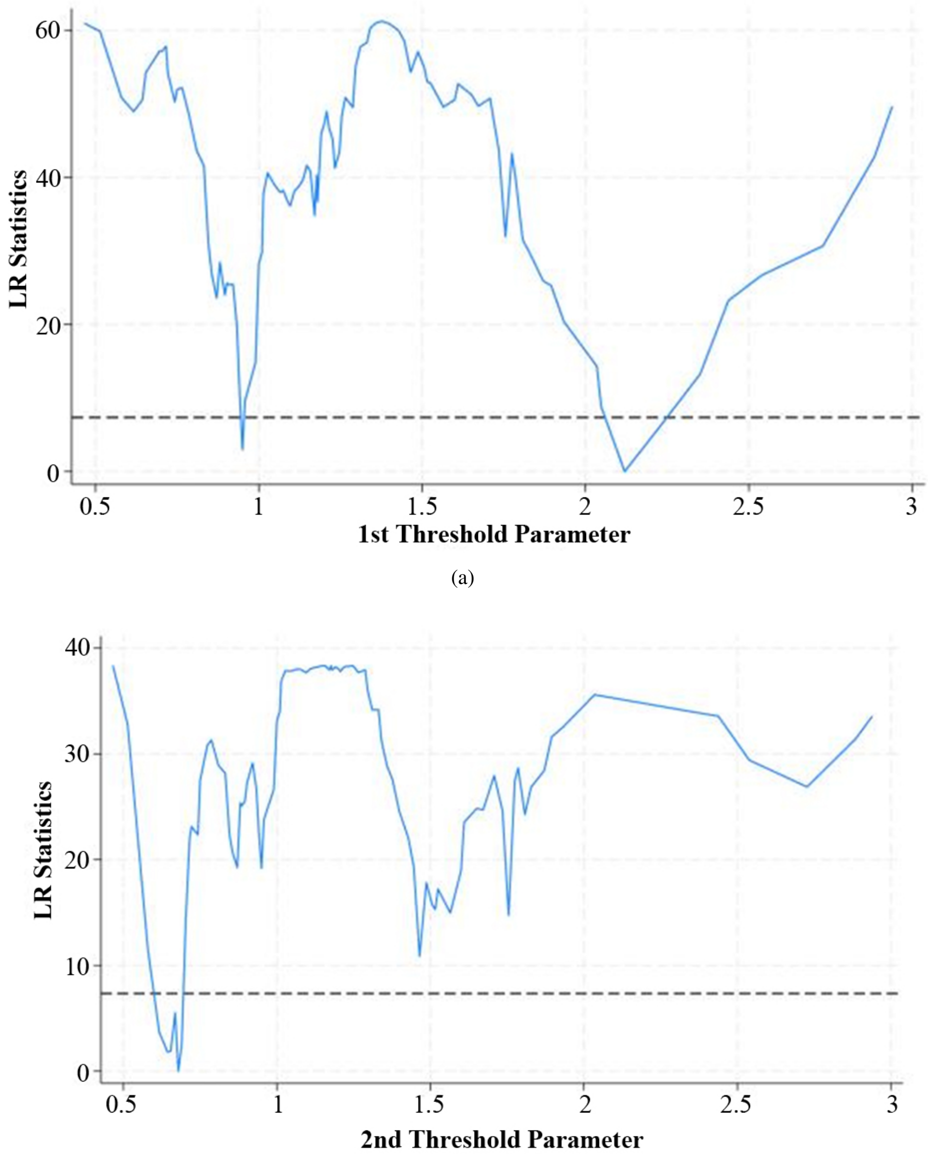


Figure 4. Double threshold estimates for Cluster 3: (a) First threshold; (b) Second threshold

5.4.3 Threshold regression results for Cluster 3 cities

The threshold regression results for Cluster 3 cities, as shown in Table 7 and Figure 4, also exhibit clear nonlinearity. However, compared with the full sample and Cluster 2 cities, the threshold effects in Cluster 3 follow a more segmented pattern, characterized by the stages of "potential–pressure–adjustment". The two estimated thresholds are 0.679 and 2.120, slightly lower than those of the full sample and Cluster 2. This suggests that Cluster 3 cities enter the sensitive range of population density at an earlier stage, which may be attributed to their limited resource-carrying capacity and less mature urban systems.

In the low-density stage, where population density does not exceed 0.679, the regression coefficient is 0.022. Although not statistically significant, it shows a positive trend, indicating that some Cluster 3 cities may benefit from a "population dividend". Their relatively abundant land resources and unsaturated infrastructure networks create favorable conditions for expanding urban system functions and enhancing initial resilience. When population density falls between 0.679 and 2.120, the coefficient declines to -0.033 and becomes significantly negative at the 1% level, suggesting that cities in this range face substantial systemic pressure. The combined effects of fiscal constraints, industrial concentration, and lagging governance lead to a marked decline in resilience. Once population density exceeds 2.120, the coefficient drops to -0.013, remaining significantly negative at the 5% level. This implies a modest alleviation of the negative effect, as some cities have begun to establish preliminary coping mechanisms for high-density shocks through governance interventions. However, the overall resilience recovery capacity in Cluster 3 cities remains limited, indicating substantial room for improvement in resilience enhancement.

5.4.4 Comparative analysis of threshold effects

Figure 5 compares the threshold regression results for the full sample and for the second and third clusters of cities, providing a systematic synthesis of the empirical evidence. The findings show that population density has a significant nonlinear impact on urban resilience, with differences across city types in threshold intervals, regression coefficients, and underlying mechanisms. These differences reflect heterogeneity in developmental stages, resource endowments, and governance capacities.

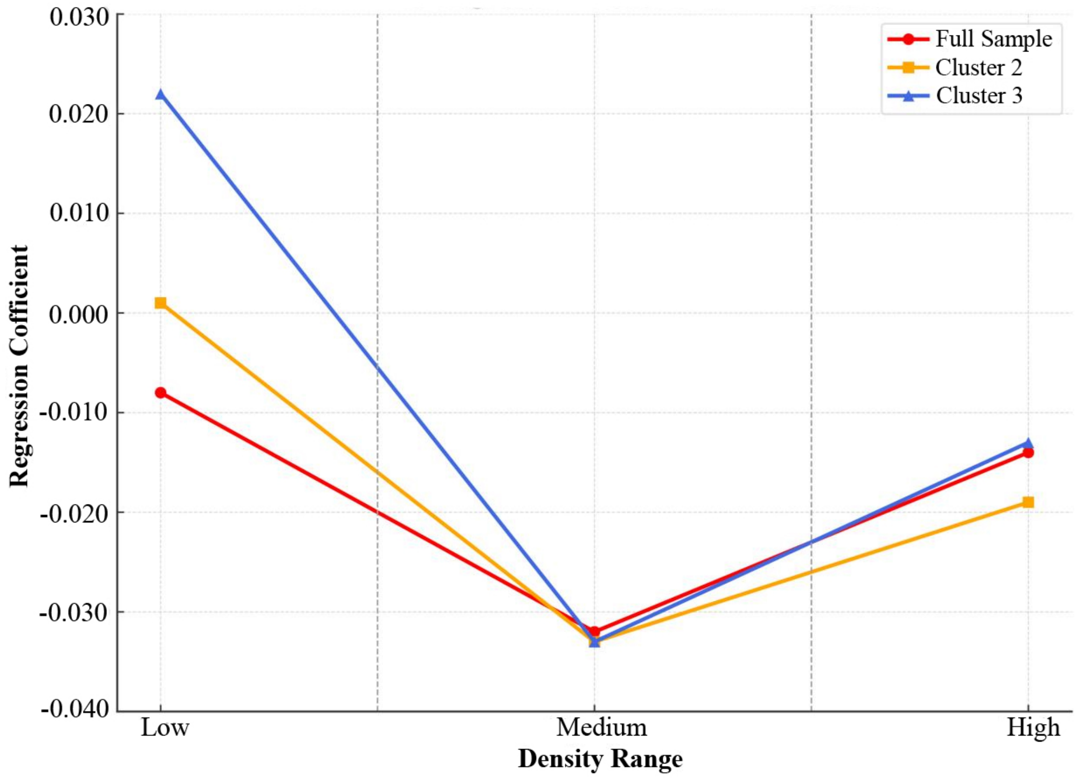


Figure 5. Threshold regression results by city cluster

6 Discussion

This study identifies the "medium-density trap" as a critical stage-specific barrier to enhancing urban resilience in Chinese cities and demonstrates the nonlinear influence of population density on urban resilience. Within the medium-density range, cities often become systemically vulnerable due to delayed resource allocation, inadequate infrastructure, and limited governance capacity, resulting in a marked decline in resilience. This pattern is most pronounced in the second and third clusters of cities, reflecting weaker institutional flexibility and insufficient support systems. By contrast, the first cluster does not exhibit clear threshold transitions, although the panel regression results still indicate negative density effects. The resilience of these cities appears to be shaped primarily by institutional accumulation and governance inertia, with density fluctuations alone insufficient to induce systemic change in the short term.

Overcoming the "medium-density trap" requires more than isolated efforts by individual cities. It should be embedded within the broader framework of regional spatial restructuring and national institutional arrangements. Urban resilience should be regarded as a systemic outcome of integrated resource management, coordinated governance, and institutional collaboration rather than an independent attribute of single cities. Under resource constraints, resilience enhancement depends on spatial restructuring and institutional reform. These processes in turn strengthen governance capacity and improve the resilience of the urban system as a whole.

6.1 Differentiated Pathways for Density Governance

In response to the challenges of the "medium-density trap", a differentiated, stratified, and coordinated mechanism for density governance and resilience enhancement needs to be established.

Regional central cities should continue to strengthen their primacy and regional influence by building systemic resilience and collaborative capacity under high-density conditions. Improving resource allocation efficiency, enhancing public service provision, and expanding green space networks can help reshape the density–resilience relationship in a positive direction, achieving a stable configuration characterized by both high density and high resilience.

Regional sub-central cities represent the critical nodes of density transition and require targeted interventions. With fiscal support, industrial relocation, and institutional incentives, these cities should establish independent and comprehensive service systems and spatial structures, thereby forming new secondary growth poles and generating spillover effects once the trap is overcome.

Ordinary medium-sized cities should avoid the path dependence that equates scale expansion with resilience improvement. Instead, they should adopt compact spatial structures and forward-looking governance approaches. Establishing density monitoring and risk identification mechanisms together with early investment in infrastructure and public services can simultaneously achieve both density control and efficiency gains.

Resource-based cities need to pay particular attention to vulnerabilities associated with industrial monocultures. During the medium-density stage, they should focus on promoting industrial diversification, introducing infrastructural redundancy, and strengthening ecological restoration and environmental governance. These measures can reduce systemic risks and prevent resilience decline under the "medium-density trap".

6.2 Practice-Oriented Approaches and Policy Instruments

At the practical level, the above strategies need to be aligned with existing planning and policy instruments. On the one hand, a dynamic monitoring and early-warning system for population density should be established, incorporating key threshold indicators into urban risk management and fiscal budgeting frameworks. On the other hand, policy instruments such as territorial spatial planning, urban regeneration, and intergovernmental fiscal transfers should be embedded in the density–resilience logic, linking infrastructure standards and public service capacity to population density levels to strengthen the coordination between planning indicators and governance capacity.

In addition, infrastructure design in medium-density areas should adopt moderate redundancy strategies. For example, water and electricity systems could be configured at 120 percent of the threshold demand, while around 30 percent of road network capacity should be reserved for emergency access. Such engineering-based resilience measures can substantially enhance the capacity of urban systems to self-regulate and recover under high stress levels.

6.3 Avoiding Development Pitfalls

Two common pitfalls must also be avoided. The first is the blind pursuit of urban sprawl, which neglects the coordination of density governance with spatial structure, leading to inefficient land use and resource waste. The second is increasing density without adequate supporting systems, which reduces spatial efficiency and exacerbates systemic risks. These problems indicate that overcoming the "medium-density trap" requires both improvements in urban governance capacity and the strengthening of regional spatial coordination mechanisms together with nationally differentiated policy support systems.

7 Conclusions

Based on panel data from 114 large Chinese cities covering the period 2006–2021, this study develops an urban resilience evaluation system encompassing five dimensions: economy, society, institutions, environment, and infrastructure. This study applies the entropy-weighted TOPSIS method and a threshold regression model to examine the nonlinear impact of population density on urban resilience. The main conclusions are as follows:

(1) During the study period, the overall resilience of large cities increased steadily. Infrastructure and the economy made the most significant contributions among the five dimensions, providing the foundation for systemic improvement.

(2) The relationship between population density and resilience follows a three-stage pattern. The effects are insignificant at low density, most negative at medium density, and alleviated at high density. The medium-density stage represents the most vulnerable period for urban resilience. (3) The sensitivity of resilience to changes in density varies across city types. The second and third clusters show more pronounced vulnerability, whereas the first cluster is influenced more strongly by institutional accumulation and governance inertia.

(4) The optimal density for resilience is not a fixed value. It is determined by the dynamic balance between density-induced pressures and the capacity of cities to mitigate them. High resilience is not inherently associated with either low or high density and instead depends on whether cities can effectively overcome the challenges of the medium-density stage.

The dataset used in this study is limited to the period 2006–2021, as data for 2022 and later years have been substantially disrupted by the COVID-19 pandemic, with gaps and abnormal fluctuations that may compromise analytical reliability. In addition, the analysis is restricted to 114 Chinese cities with urban resident populations exceeding one million, so the findings mainly reflect the dynamics of large urban centers. Consequently, the conclusions may not be fully generalizable to medium- or small-sized cities, or to resource-dependent cities with distinct developmental trajectories. Future research should extend both the temporal coverage and the range of city types to evaluate whether the “medium-density trap” exhibits heterogeneous manifestations across different urban contexts.

Author Contributions

Conceptualization, B.D.; methodology, B.D.; software, B.D.; validation, B.D. and L.D.; formal analysis, B.D.; investigation, B.D.; resources, B.D.; data curation, B.D.; writing—original draft preparation, B.D.; writing—review and editing, L.D.; visualization, B.D.; supervision, B.D.; project administration, B.D.; funding acquisition, B.D. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The panel dataset used in this study was compiled from publicly available official statistical sources, including the Tabulation on 2020 China Population Census by County [38], the China Urban-Rural Construction Statistical Yearbook 2022 [39], the China Statistical Yearbook (2006–2021) [40], and the China Statistical Yearbook on Environment [41]. Processed datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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