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Exploration of Spatio-Temporal Evolution and Threshold Effect of Shrinking Cities

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Abstract: Shrinking cities are a global issue with regional characteristics. This paper focuses on the county-level administrative units in the Three Northeastern Provinces in China to identify and classify shrinking cities using a two-step identification method and explores their spatial-temporal evolution. The paper utilizes the panel threshold regression model for empirical testing. The results indicate the following: (1) The number of shrinking cities in the region is large and deep. Quantitatively, the shrinking cities account for about 50% of the whole; spatially, there are six major shrinking city "groups", showing the distribution trend around the "Ha-Da" urban corridor. (2) The threshold effect test reveals that GDP is a critical threshold variable influencing the formation of shrinking cities. Moreover, cities are classified into three types based on the threshold values: Type I (GDP > 2,270,731 yuan), Type II (434,832 < GDP ≤ 2,270,731), and Type III (GDP < 434,832). (3) The results of the dual-threshold and grouped regression models show significant variations in the dominant factors of shrinking cities of different scales. Variables such as impervious area, fiscal revenue, and grass area demonstrate relatively stable promoting effects.

Keywords: shrinking cities; spatio-temporal evolution; influencing factors; panel regression; threshold effect; three northeastern provinces in China

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1. Introduction

In the second half of the 20th century, the development pattern of rapid urbanization gradually slowed down or even reversed under the intersecting influences of globalization, resource scarcity, suburbanization, and other factors. These led to issues such as population outflow in some cities and the emergence of shrinking cities [1]. Over time, the spatial distribution of shrinking cities has become more intensive, and the severity of shrinkage has deepened [2]. Furthermore, related research has gradually emerged.

Early studies on shrinking cities originated in developed countries but were relatively decentralized. Scholars typically used keywords such as "urban shrinkage", "urban decline", or "urban decay" to categorize such issues as "local" phenomena within specific regions. They did not recognize the logical flaws of urban growth ideology and failed to perceive shrinkage as a "normal" or "transitional" phase within the development process [3]. It was not until 1988 when German scholar Huremann et al. [4] conducted empirical research on population loss in the Ruhr industrial region due to factors such as resource scarcity and industrial restructuring and the concept of shrinking cities was explicitly proposed. The concept of shrinking cities paved the way for further research on this phenomenon.

Research on shrinking cities mainly covers three aspects: (1) Definition of the connotation of shrinking cities and the construction of identification methods. The academic community [5,6] generally agrees on the following conclusions: shrinking cities refer to cities where multiple dimensions, such as population, economy, capital, construction, or technology, experience a reduction or decline, with population decline as the core characteristic [3]. Population size is a fundamental indicator for measuring shrinking cities [7].

Therefore, mainstream identification systems are often based on population changes and typically focus on the extent of population decrease or sustained loss. However, as research deepens and academic debates evolve [8], research approaches based on comprehensive assessments with multiple indicators have also emerged [9], emphasizing the multidimensional contraction in time, space, and structure. The multi-indicator evaluation methods suggest that shrinking cities often involve the dissipation of multiple dimensions, such as population loss, economic stagnation, and land contraction [10]. (2) Patterns and types of shrinking cities. Scholars [11,12] have conducted classification studies based on the spatio-temporal distribution of population, economy, or buildings to identify different patterns or types of shrinking cities. For example, in the Rust Belt region of the United States, which has been affected by suburbanization and privatization of transportation, a "doughnut" pattern of shrinking cities has emerged, characterized by population outmigration from the inner city and population growth in the suburbs [13]. Long et al. have used multi-source data [14,15], combined with research results on the "perforated" type [16], "doughnut" type [12], and "edge" type to classify shrinking cities and analyze their causes. Meanwhile, some scholars focus on macro factors, such as population and economy, using matrix classification and quadrant division methods to categorize types of shrinking cities [17]. (3) Causes and influencing factors of shrinking cities. The causes of shrinking cities have also received attention from many scholars [18,19]. Scholars have analyzed the differentiated characteristics of influencing factors of shrinking cities from various perspectives, such as regional [20], national [21], or central cities [22]. They have utilized diverse analytical methods, including logistic classification models [19], decision models [23], factor analysis [24], or analogical analysis [25], to explore the influencing factors of different shrinking cities. Throughout this process, the academic community has recognized that city size is an important feature influencing urban growth or contraction [26,27]. For example, at the end of the 20th century, socialist countries such as East Germany and Poland were affected by the post-socialist process of "shock therapy" and other factors, which led to the collapse of the once pillar industry of the state-run economy, resulting in the rapid contraction of small and medium-sized cities [28,29]. On the other hand, in France, a crucial continental country, shrinking cities are often concentrated around the "diagonal of emptiness", characterized by small cities isolated from the well-connected and well-equipped central cities [20]. Similar shrinking characteristics can be observed in some areas of Japan and China in East Asia [30–32], where small cities continue to shrink as the population flows to metropolitan areas. Some even argue that in China, smaller cities are more prone to shrinkage [33]. However, the situation in the UK is diametrically opposite, as before the opening of immigration policies, most metropolitan areas, except for London, experienced sustained shrinkage [34]. These examples demonstrate significant variations in the development and influencing factors of shrinking cities in different regions and scales. Therefore, how to measure the impact of city scale on shrinkage and whether there are structural transformations in city scale that result in different effects on the development of shrinking cities are crucial issues that need to be addressed in future research. In summary, although there is a relative abundance of research on shrinking cities, some limitations remain including (1) the relative lack of robust methods for identifying shrinking cities based on the population scale, (2) the difficulties in accurately representing the urban development process with short time series studies, and (3) the lack of means to measure the differentiated impact of structural changes in city size on the development of shrinking cities, as global homogenization analysis approaches may mask the individual characteristics of different cities.

The Three Northeastern Provinces of China have experienced a long period of fluctuation between prosperity and shrinking, with significant differences in city sizes and a severe phenomenon of shrinking cities [35]. This paper focuses on the county-level administrative units in the Three Northeastern Provinces and analyzes the panel data from 2001 to 2020. Firstly, based on the two-step identification method, this paper identifies the shrinking cities and their types, investigating the spatio-temporal patterns and characteristics of shrinking cities in this region. Subsequently, ordinary panel regression models and panel threshold regression models considering structural changes are constructed for empirical research. The study aims to clarify the following issues: (1) the spatio-temporal evolution and spatial agglomeration characteristics of shrinking cities in the Three Northeastern Provinces, and whether there is a spatio-temporal homogenization trend in the development of shrinking cities; (2) whether there is a nonlinear relationship and threshold effect between city size and the formation and development of shrinking cities; (3) whether there are differentiated characteristics in the influencing factors of shrinking cities of different sizes. The goal is to provide a theoretical basis and practical support for constructing a new urbanization path, the development of livable and business-friendly cities, and making structural adjustments.

2. Materials and Methods

2.1. Study Area

As shown in Figure 1, the paper selects the Three Northeastern Provinces as the research area, including Heilongjiang, Jilin, and Liaoning provinces. According to the Seventh National Population Census, the net outflow of the population in this area has reached over 1.8 million in the past decade. It has gradually become a region with a concentrated distribution of shrinking cities in China [36,37].

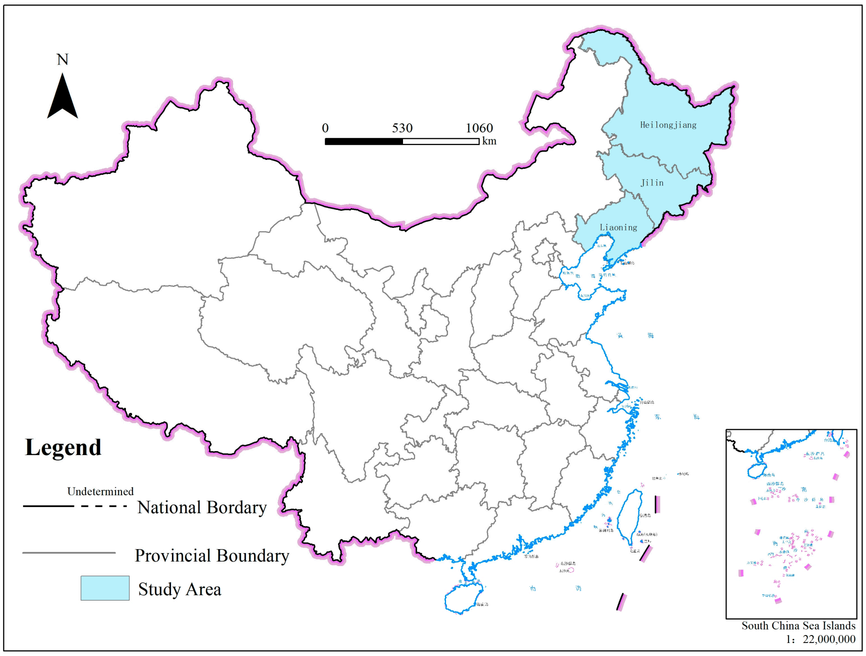

Figure 1. Study area map.

This paper selects 281 county-level administrative units under the jurisdiction of the Three Northeastern Provinces as the research objects. It considers urban and rural areas within each unit for regional analysis. The scope and code of administrative units' criterion come from the Ministry of Civil Affairs of the People's Republic of China in 2020. This study selects 206 from 281 county-level administrative units' data to conduct a multi-model comparative analysis of shrinking cities to ensure the data's availability, continuity, and integrity.

2.2. Methods

2.2.1. Ordinary Panel Regression Model

Due to the abundant information, high degree of freedom, and notable individual heterogeneity that panel data possesses, this study utilizes panel regression models to investigate the influencing factors of the formation and development of shrinking cities. The general model of panel regression is as follows:

$$y_{it} = \sum_{k=1}^{k} \beta_{ki} x_{kit} + u_{it} (i = 1, 2, \cdots, N; t = 1, 2, \cdots, T) \tag{1}$$

where i represents the individual, t represents time, with N representing the number of individuals or cross-sectional units, and T represents the number of periods or the time series dimension. y_{it} denotes the observed value of the i-th individual at period t, x_{kit} represents the observed value of the k-th explanatory variable for the i-th individual at period t, β_{ki} means the corresponding estimated parameters, and u_{it} is the random error term.

The panel regression model has many advantages but requires higher data distribution and form requirements. Generally, this model involves panel data to be static data tested by white noise and data co-integration verification is carried out to prevent the appearance of pseudo-regression. On this basis, it is necessary to check the form of the model and select the most appropriate format. Usually, feasible generalized least square estimation, the least square dummy variable estimation, the analysis of covariance estimation, and other methods are used to test the applicability of random or fixed effect models. The merits and demerits of information criteria, such as Akakike information criteria, can also select the model form.

2.2.2. Panel Threshold Regression Model

In traditional regression analysis, only a constant regression coefficient can be obtained. However, many social and economic issues, such as the formation and development of shrinking cities, exhibit structural mutations, where the influence of a particular factor can vary significantly at different stages. Conventional regression methods often fail to accurately identify threshold effects and capture the points of structural mutation. In contrast, the threshold regression model effectively addresses this challenge and enhances analysis accuracy. The threshold effect refers to the occurrence of a structural transformation when a specific parameter reaches a particular value, causing another parameter to deviate abruptly from its existing development pattern. These specific values are known as the threshold values of threshold variables. When examining urban issues like shrinking cities, multiple thresholds are often observed due to the complexity of socioeconomic problems.

To investigate the presence of significant nonlinear characteristics and threshold effects in the influencing factors of shrinking cities at different sizes or stages of development, this study adopts Hansen's nonlinear threshold regression model [38] to explore the specific mechanisms at play.

The general form of the panel threshold regression model is as follows:

$$y_{it} = \mu_i + \beta_1 x_{it} \cdot I(q_{it} \le \gamma) + \beta_2 x_{it} \cdot I(q_{it} > \gamma) + \varepsilon_{it} \tag{2}$$

where $I()$ represents the indicator function, The formula is as follows:

$$I(q_{it} \le \gamma) = \begin{cases} 1, \ if \ q_{it} \le \gamma \\ 0, \ if \ q_{it} > \gamma \end{cases}; I(q_{it} > \gamma) = \begin{cases} 0, \ if \ q_{it} \le \gamma \\ 1, \ if \ q_{it} > \gamma \end{cases} \tag{3}$$

where q_{it} denotes the threshold variable (which can also serve as an explanatory variable), γ refers to the threshold value to be estimated, and ε_{it} should conform to independent and identically distributed residuals.

Firstly, the threshold effect model conducts a hypothesis test to determine the presence of a threshold effect. The estimation principle of the threshold model is achieved using ordinary least squares estimation, which is traditional within the estimation. When γ is known, the estimates of $\hat{\beta}_1(\gamma)$ and $\hat{\beta}_2(\gamma)$ are consistent estimators, and the residual sum of squares (RSS) is minimized with γ. When γ is unknown since γ cannot exceed the range of q_{it} values, $\gamma\epsilon\{q_{it}: i = 1,2,...,N, t = 1,2,...,T\}$, where are at most NT possible values. Among them, one value can be chosen that minimizes the $RSS(\hat{\gamma})$, resulting in parameter estimates of $\hat{\beta}_1(\gamma)$ and $\hat{\beta}_2(\gamma)$.

Furthermore, a hypothesis test is conducted to examine the threshold effect: H_0:$\vec{\beta_1} = \vec{\beta_2}$. If the null hypothesis is rejected, indicating the presence of a threshold effect, further testing of the threshold value is performed. The likelihood ratio (LR) test statistic for this test is as follows:

$$LR = \frac{(RSS^* - RSS(\hat{\gamma}))}{RSS(\hat{\gamma})/N(T-1)} \tag{4}$$

where RSS* represents the residual sum of squares when there is no threshold effect, and $RSS(\hat{\gamma})$ represents the residual sum of squares when there is a threshold effect.

If the LR test rejects the null hypothesis, it indicates the presence of a threshold effect. Therefore, a test is conducted on the threshold value: H_0: $\gamma = \gamma_0$, where γ_0 is a specific threshold value. The LR test statistic is constructed as follows:

$$LR(\gamma) = \frac{(RSS(\gamma) - RSS(\hat{\gamma}))}{RSS(\hat{\gamma})/N(T-1)} \tag{5}$$

In the equation, $RSS(\hat{\gamma})$ represents the residual sum of squares of the threshold model when the null hypothesis is true, and $RSS(\gamma)$ represents the residual sum of squares when there is a threshold effect. By examining these values, it is possible to test the presence of a threshold effect and determine the corresponding threshold value.

It should be noted that the common form of the double threshold panel model is as follows:

$$y_{it} = \alpha_i + I(q_{it} \le \gamma_1)x'_{it}\beta_1 + I(\gamma_1 < q_{it} \le \gamma_2)x'_{it}\beta_2 + I(\gamma_2 < q_{it})x'_{it}\beta_3 + \varepsilon_{it} \tag{6}$$

where values are defined as $\gamma_1 < \gamma_2$, and the indicator function is similar to Equation (3). The main operations of the relevant model are based on the xthreg command developed by Wang Qunyong [39].

2.3. Variable Selection and Source

Just as Rome was not built in a day, the development and formation of cities underwent a gradual and evolutionary process over an extended period. The study of shrinking cities aims to observe and analyze the long-term developmental patterns of urban areas. Hence, this research focuses on the time range from 2001 to 2020.

Shrinking cities are typically characterized by population decline, leading to delayed economic growth, imbalanced industrial structure, reduced investment output, declining enterprise efficiency, and inefficient land use. Slow economic growth [2,37], weak investment [40,41], and relatively unfavorable natural conditions [42,43] are among the primary causes contributing to the emergence of shrinking cities. With the requirements of the panel threshold regression model in mind, this study selects the following factors for regression analysis:

(1) Explained variables: Population size is a crucial indicator for measuring shrinking cities and a key element in characterizing urban development [44]. Thus, population size is chosen as the dependent variable in this study. To ensure the continuity and stability of population data, the study utilizes modified Worldpop population grid data with a resolution of 100 m from 2001 to 2020. This data is the constraint for identifying shrinking cities, allowing for population size analysis based on county-level administrative units.

(2) Explanatory variables: This study primarily selects explanatory variables from three dimensions—economy, investment, and nature—that may influence the formation or development of shrinking cities.

Economic dimension: The formation and development of a city are closely tied to its economic size, which serves as a critical indicator of urban development. Urban scale expansion and advancement are intricately linked to economic growth and industrial structure optimization [45]. The secondary and tertiary industries play pivotal roles in China's urban development, as they drive economic growth and provide ample employment opportunities, attracting population inflow. However, shrinking cities need more economic power and urbanization capacity for rapid development, resulting in a lack of jobs and advantages to attract population and capital. Hence, this study selects GDP, the scale of the secondary industry, and the scale of the tertiary industry as measures of the economic dimension in shrinking cities [46]. Shrinking cities may exhibit characteristics such as idle land or vacant buildings, leading to "perforated type" and "doughnut type" patterns, which can be reflected in the reduction of urban construction land. Urban construction land, which supports economic and social activities, can also provide insights into urban development capacity and potential. Therefore, this study includes the scale of urban construction land for analysis. Additionally, given the central role of GDP in urban development and its symbolic significance [47], this study selects GDP as the threshold variable to differentiate between city types and examine potential fundamental differences in shrinking cities across different stages of development.

Investment Dimension. As a long-term driving force of China's investment-driven development model, investment in fixed assets is essential to maintain domestic demand in China [48]. Fiscal expenditure and fiscal revenue represent the capacity of local governments to safeguard and improve people's livelihoods, playing a crucial role in promoting infrastructure construction, economic development, and urban prosperity [49]. However, for shrinking cities, the phenomenon of population outflow and aging population, to some extent, leads to a decline in investment, which in turn affects urban development [50]. Therefore, this paper selects investment in fixed assets, fiscal revenue, and fiscal expenditure as the main variables for the investment dimension.

Natural Dimension. Regional ecological conditions can influence residents' choices to migrate or stay, as they tend to "vote with their feet". The Three Northeastern Provinces are located in high-latitude areas with severe cold winters. The relatively low surface temperatures negatively impact the quality of life for residents, leading to a significant outflow of "bird-like" populations migrating southward [51,52]. Forest and grass areas offer diverse ecosystem functions, such as climate regulation, soil and water conservation, air purification, aesthetic landscapes, and recreational activities. Sufficient forest and grass areas can enhance the livability of a region and create high-quality living spaces, attracting population inflows [53,54]. Therefore, this study selects variables such as Mean Annual Land Surface Temperature, forest area, and grass area as the main variables for the natural dimension.

The data sources used in this study are presented in Table 1 below, along with their correlations with the dependent variables. Some data needed to be supplemented using local government work reports or internal and external linear interpolation methods.

2.4. Identification of Shrinking Cities

The continuous decline in urban population is a significant characteristic of shrinking cities [18]. However, there currently needs to be a consensus on the criteria for measuring population loss. Therefore, this study employs a "two-step recognition method" to identify and classify shrinking cities into different types. This approach aims to enhance the accuracy and scientific rigor of shrinking city identification while mitigating the influence of emergencies on the identification process. The first step involves calculating the cumulative number of years and the magnitude of population loss. This is achieved by analyzing the changes in population size over the years and determining the cumulative count of population decreases (denoted as n). Cities experiencing population loss within a specific year are classified as losing populations. The rate of population size change (marked as %, r) during the study period is also calculated, and the cumulative count and range of change are classified accordingly (see Table 2). Subsequently, a quadrant diagram, as depicted in the figure, is constructed to identify different city types. This diagram employs the number of population decreases on the x-axis, the rate of population change on the y-axis, and the origin (0,0) as the reference point. Specifically, cities in the first quadrant are classified as steadily growing cities, those in the second and fourth quadrants as progressively shrinking cities, those in the third quadrant as steadily shrinking cities, and cities on the positive axis as cities tending to grow. The city situated at the origin and the negative axis is considered a city overlooking to shrink. Cities exhibiting gradual shrinkage, stable shrinkage, and tendency shrinkage are all regarded as shrinking cities.

Table 1. Variables.

Dimensions	Variables	Data Sources	Mean	Std.Dev.	Correlation
Predicted Variable	Population(POP)	Worldpop	424,317.9 (person)	265,204.3	-
Economic Dimension	Gross Domestic Product(GDP)	China County Statistical Yearbook	1247.8 (million CNY)	1663.7	0.55 ***
	Output Value of the Secondary Industry(OVSI)	China County Statistical Yearbook	510.5 (million CNY)	907.2	0.49 ***
	Output Value of the Tertiary Industry(OVTI)	China County Statistical Yearbook	536.1 (million CNY)	903.4	0.41 ***
	Impervious Areas(IMP)	China Land Cover Dataset [55]	160,757.1 (hm^2)	136.7	0.50 ***
Investment Dimension	Investment in Fixed Assets(IFA)	China County Statistical Yearbook	684.0 (million CNY)	1175.8	0.38 ***
	Fiscal Revenue(FR)	China County Statistical Yearbook	77.1 (million CNY)	191.6	0.33 ***
	Fiscal Expenditure(FE)	China County Statistical Yearbook	166.2 (million CNY)	186.9	0.43 ***
Natural Dimension	Mean Annual Land Surface Temperature(LST)	MODIS/006/MOD11A1	13.2 (°C)	3.92	0.23 ***
	Forest Areas(FOR)	China Land Cover Dataset [55]	1,803,012 (hm^2)	3,763,292	−0.20 ***
	Grass Areas(GRA)	China Land Cover Dataset [55]	113,688.4 (hm^2)	286,685.5	0.04 **

Note: **, and *** are significant at the confidence level of 5%, and 1%, respectively.

Table 2. Cumulative count and variation range classification.

Assignment	−2	−1	0	1	2
Criteria	$16 \leq n$ $-0.20 \leq r < -0.10$	$13 \leq n < 16$ $-0.10 \leq r < -0.05$	$9 \leq n < 13$ $-0.05 \leq r < 0$	$4 \leq n < 9$ $0 \leq r < 0.15$	$0 \leq n < 4$ $0.15 \leq r$

3. Results

3.1. Analysis of Time Evolution of Shrinking Cities

Firstly, identifying shrinking cities in the Three Northeastern Provinces is conducted based on the methodology described in Section 2.4. The study then analyzes the temporal evolution trend, focusing on understanding these cities' development context and characteristics.

Figure 2 presents the analysis chart of population loss cities and the magnitude of change in the Three Northeastern Provinces, in conjunction with Table 1. The figure reveals a steady increase in population loss cities across the three provinces, rising from less than 100 in 2002 to 180 in 2020. Moreover, the growth rate of cities experiencing population loss displays significant fluctuations, with peak losses exceeding 15% in 2006 and 2016. Notably, two distinct "peaks and valleys" can be observed between February 2007 and February 2010, as well as in February 2017. It can be inferred that these "peaks and valleys" represent the delayed effects of favorable policies introduced to revitalize the old industrial base in Northeast China in 2003, as well as the subsequent new round of revitalization strategies implemented in 2016. These initiatives have positively impacted production capacity, attracting talent and mitigating the continuous population loss. The timely implementation of national policies effectively reduced the peak of population loss. However, more was needed to reverse the overall trend of sustained population decline and urban contraction.

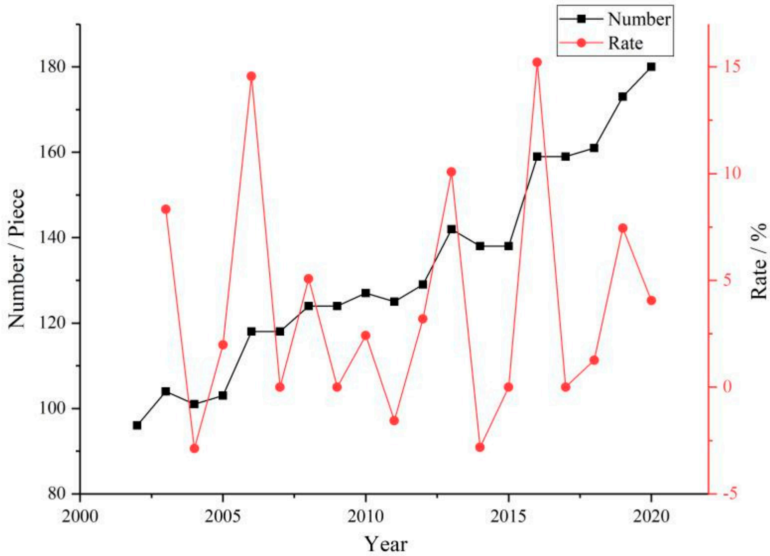

Figure 2. The number and rate of population loss in the three northeastern provinces.

Furthermore, the shrinking city types quadrant diagram (Figure 3) and bidirectional table (Table 3) are drawn, and the shrinking city types and their characteristics are defined.

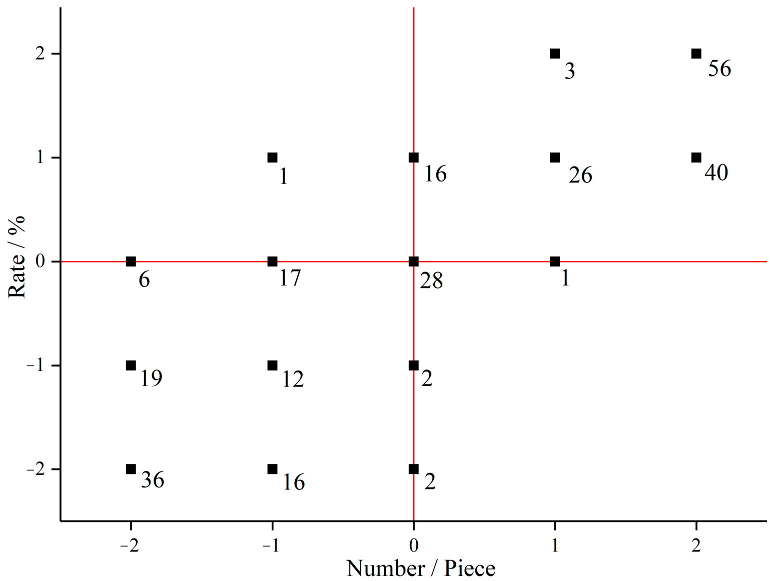

Figure 3. The type division of shrinking cities.

Table 3. Shrinking cities identification bidirectional table.

Rate / Number	−2	−1	0	1	2	Total
2	0	0	0	40	56	96
1	0	0	1	26	3	30
0	2	2	28	16	0	48
−1	16	12	17	1	0	46
−2	36	19	6	0	0	61
Total	54	33	52	83	59	281

The analysis of both the figure and the table reveals a significant number of shrinking cities with substantial degrees of contraction in the three provinces of Northeast China. Despite adopting stringent identification criteria, 138 cities, accounting for nearly 50%, still display a clear trend or stable contraction pattern. Notably, more cities (125) exhibit steady growth compared to those experiencing regular contraction (83), while the remaining cities fall within the intermediate threshold of contraction and expansion, leaning towards shrinkage.

Furthermore, 36 cities demonstrate a dual decline in population size and change magnitude. Among these cities, there are relatively underdeveloped counties such as Xifeng County and Fenglin County, as well as municipal districts like Haizhou District in Fuxin City and Friendship District in Yichun City. This observation leads to the conclusion that the development challenges faced by shrinking cities are complex and diverse. Despite the presence of policy preferences and historical legacies in some municipal districts, they may still exhibit a substantial degree of shrinkage.

3.2. Study on the Spatial Distribution of Shrinking Cities

Draw the spatial distribution map of shrinking cities and focus on distinguishing the spatial distribution characteristics and clustering characteristics of shrinking cities.

Based on the analysis depicted in Figure 4, the overall spatial distribution characteristics of shrinking cities exhibit a gradual decline pattern surrounding the "Harbin-Dalian" urban corridor, which serves as a "plateau". Along this corridor, the city shows a strong growth trend. In contrast, the shrinking cities intersect and surround the corridors between "Harbin and Dalian" cities, forming a distribution characterized by regional contraction and expansion. These two trends intertwine with each other. However, variations exist in the years and magnitude of cumulative population loss. In terms of years of cumulative loss, the shrinking cities (0 or below) are dispersed around the region's core cities, forming a prominent "O-shaped encircling circle" that stretches from northwest to southeast and then northeast. The shrinking cities within the loss range are scattered along the border and within the middle of the "Harbin-Dalian" corridor.

Further classification and analysis of the cities can be observed in Figure 5. The stable growth cities are predominantly concentrated along the "Harbin-Changchun-Shenyang-Dalian" urban corridor and its surrounding areas, demonstrating a continuous distribution across all provinces. The shrinking cities exhibit a spatial pattern characterized by pronounced contraction in the north and south, with growth tendencies in the middle. The stable shrinking cities are also distributed in clusters, forming six distinct "groups" centered around county-level administrative units such as Yimei District, Mishan City, Tiefeng District, Fengman District, Qinghe District, and Shuangta District. The "northern group" area, encompassing Yimei District and Mishan City, exhibits a higher number of cities with a certain distance between each other. On the other hand, the "southern group" area, including Fengman District, Qinghe District, and Shuangta District, features a smaller number of cities but showcases mutual penetration and a continuous development trend. In terms of area and quantity, the stable growth cities in Heilongjiang Province cover a substantial area with a large number of cities. They are characterized by a radiating center in Harbin, extending outward to Jiamusi City and Yanbian Korean Autonomous Prefecture on the border and inward to Changchun City. This highlights the vibrant economic development and continuous improvement of these regions' internal and external economies.

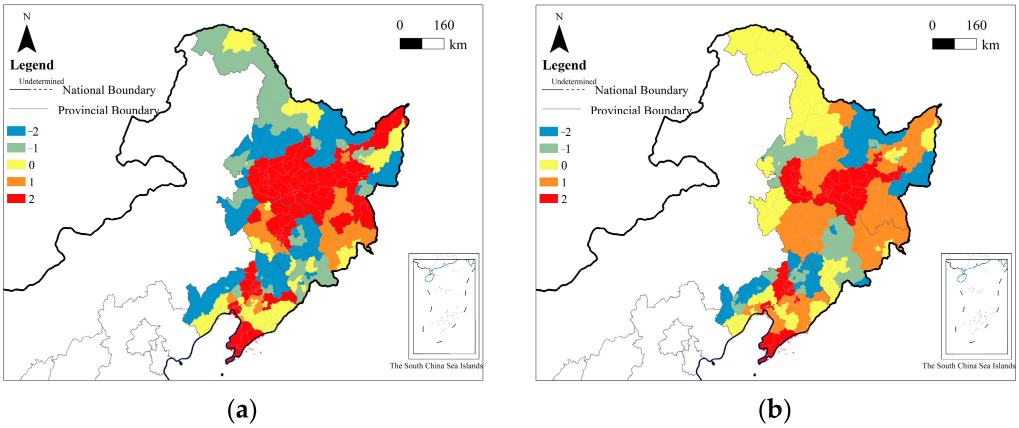

Figure 4. (**a**) Cumulative count (number) classification spatial distribution; (**b**) Spatial distribution of population loss range (rate) classification.

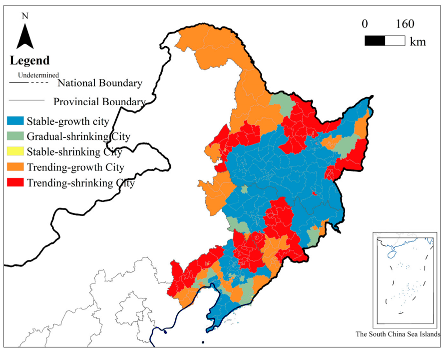

Figure 5. Spatial distribution of shrinking city types.

3.3. Panel Regression Model Analysis of Influencing Factors on Shrinking Cities

Population size change is the most critical and commonly used indicator to identify and measure shrinking cities [56]. Based on the current status and historical development of shrinking cities in the Three Northeastern Provinces, this study focuses on the population size as the dependent variable. It selects various economic, investment and natural dimensions factors as explanatory variables. Panel regression models are employed to analyze the spatial-temporal heterogeneity and the role of influencing factors in shrinking cities.

To ensure data robustness and meet the requirements of panel regression models, a sample of 206 county-level administrative units with comprehensive and representative data is selected for analysis. Additionally, tests are conducted for white noise, unit root for short panels, Hausman, and collinearity tests. The results confirm the stationarity of the data and low levels of collinearity, thereby validating the suitability for panel regression analysis. The estimation results are presented in Table 4.

Table 4. Test results of the ordinary panel data model.

Variables		Ordinary Linear Regression Model	Random Effects Model	Fixed Effects Model
Economic Dimension	GDP	0.91 *** (8.59)	−0.01 (−0.25)	0.003 (0.26)
	OVSI	−0.23 *** (−3.66)	0.03 (0.76)	0.02 ** (2.31)
	OVTI	−0.24 *** (−4.06)	0.04 (1.53)	0.04 *** (6.05)
	IMP	0.34 *** (19.28)	0.09 ** (2.14)	0.10 *** (11.04)
Investment Dimension	IFA	−0.06 *** (−3.24)	−0.01 (−0.90)	−0.004 ** (−2.41)
	FR	−0.16 *** (−6.67)	0.01 (1.44)	0.002 (1.22)
	FE	0.07 *** (3.23)	0.003 (0.35)	0.01 *** (4.4)
Natural Dimension	LST	0.07 *** (4.65)	−0.002 (−1.14)	−0.01 *** (−3.68)
	FOR	−0.07 *** (−5.55)	−0.07 (−0.74)	−0.04 (−0.73)
	GRA	−0.13 *** (−8.62)	0.06 *** (2.96)	0.06 *** (10.38)
Constants		−0.02 (−1.36)	0.00007 (0)	0.02 *** (3.82)
R^2		0.45	0.38	-
Adj.R^2		0.45	0.45	0.34
Pseudo R^2		-	−0.237	-
AIC		8808.38	−9264.15	−11,312.33
BIC		8877.38	−9182.61	−11,130.44

Note: Samples in 2001 were excluded to maintain sample consistency; t or z test values are in parentheses, ** and *** indicate significant performance at 5%, and 1% confidence levels, respectively.

The information criteria in Table 4 indicate that the fixed effects model outperforms other models in terms of fit. The fixed effects model controls for individual and time-specific effects, capturing heterogeneity, and is based on the assumption that the independent studies are drawn from the same population, aligning closely with the data selection. Therefore, the fixed effects model demonstrates the most muscular explanatory power and is selected for further analysis.

The fixed effects model reveals significant relationships between OVIS, OVTI, IFA, FE, LST, GRA, and IMP variables and population size. Among them, OVTI, OVTI, FE, GRA, and IMP show significant positive effects on population size. Based on the standardized regression coefficients, IMP, GRA, and OVTI have the most potent promoting effects. The expansion of urban construction land area is driven by the agglomeration effects of factors such as capital and population within the urban scope, and a larger urban construction land area signifies abundant living space and contributes to positive feedback on population size. Additionally, larger grass areas can attract population inflow from an ecological perspective. The output value of the tertiary industry, as a significant factor measuring urban development level and structure, provides high-quality jobs, and attracts residents to enjoy improved life services. On the other hand, IFA and LST variables exhibit inhibitory effects. In the study area, heavy industries such as petroleum and coal still dominate fixed asset investment, which promotes economic growth but often causes particular environmental pollution. In addition, the relatively cold climate in high-latitude areas prompts population outflows through the phenomenon of “voting with their feet”.

However, the fact that GDP is not significant in the fixed effects model to some extent indicates the limitations of this model. This suggests that the global analysis approach needs to pay more attention to the differences among different types of cities within a region, thereby failing to highlight the complexity, diversity, and heterogeneity of shrinking cities. As a result, it affects the accuracy of the analysis results.

3.4. Threshold Effects and Regression Analysis of Influencing Factors on Shrinking Cities

3.4.1. Results of Threshold Effect Testing on Shrinking Cities

To investigate whether GDP exhibits a threshold effect on shrinking cities and to clarify the characteristics of the impact of different threshold intervals of GDP on population size, this study conducted a multiple threshold regression analysis. The results are presented in Tables 5 and 6.

Table 5. Threshold effect test.

Model	Bootstrap Replications	RSS	MSE	F-Value	p-Value	Critical Value		
						10%	5%	1%
Single Threshold	300	11.43	0	518.21	0	23.90	34.58	49.48
Double thresholds	300	10.64	0	289.09	0	25.59	30.23	37.48
Triple Thresholds	300	10.13	0	194.70	0.69	313.15	335.14	388.76

Table 6. Threshold estimation results.

Model	Estimated Value	Lower Limit	Upper Limit	Non Normalized Estimated Value (yuan)
Single Threshold Value	0.61	0.58	0.64	2270 731
Double Threshold Value	−0.49	−0.49	−0.49	434 832
	0.61	0.58	0.64	2270 731

Based on the results from Tables 5 and 6, it can be concluded that both the single threshold and double threshold models based on GDP representation have passed the significance level test. Moreover, the information criteria of the dual threshold regression model are significantly better than those of the single threshold and panel regression models. Therefore, the double threshold model is chosen for further analysis. Additionally, due to the presence of double thresholds, the county-level administrative units are divided into three categories based on their scale: small-scale cities (GDP < 434,832; Type III cities), medium-scale cities (434,832 < GDP $\leq$ 2,270,731; Type II cities), and large-scale cities (GDP > 2,270,731; Type I cities).

3.4.2. Regression Analysis of Influencing Factors on Shrinking Cities

To facilitate the analysis, panel regressions are conducted separately for each group of samples based on the threshold regression, and the results are shown for Type III cities, Type II cities, and Type I cities, as presented in Table 7.

Table 7. Estimation results of double threshold model and grouped models.

Variables		Double Threshold Model (Full Sample)		Type III Cities	Type II Cities	Type I Cities
Economic Dimension	GDP			0.16 ***	−0.08 ***	0.04 **
				(4.53)	(−4.87)	(2.15)
		GDP < 434,832	−3.43 *** (−15.31)			
		434,832 < GDP ≤ 2,270,731	0.24 (0.4)			
		2,270,731 < GDP	3.77 *** (18.59)			
	OVSI	0.01 ***		−0.13 ***	−0.003	−0.01
		(3.34)		(−5.36)	(−0.27)	(−0.67)
	OVTI	0.03 ***		−0.15 ***	0.13 ***	−0.01
		(16.43)		(−7.13)	(14.28)	(−0.77)
	IMP	0.07 ***		0.01	0.15 ***	0.24 ***
		(9.21)		(1.52)	(9.58)	(8.12)
Investment Dimension	IFA	−0.01 ***		−0.01	0.02 ***	−0.01 ***
		(−5.89)		(−1.22)	6.09	(−4.90)
	FR	0.01 ***		0.0002	0.01 **	0.01 ***
		(4.86)		(0.09)	(1.98)	(3.23)
	FE	0.01 **		0.02 ***	−0.01 ***	−0.02 ***
		(2.32)		(3.86)	(−3.08)	(−3.11)
Natural Dimension	LST	0		0.002	−0.01 ***	−0.01
		(0.37)		(1.52)	(−2.65)	(−1.31)
	FOR	0.04		0.04	−0.07	1.04 **
		(0.82)		(1.34)	(−0.83)	(2.56)
	GRA	0.05 ***		0.03 ***	0.06 ***	0.06 *
		(9.13)		(5.79)	(8.03)	(1.76)
Constants		−0.01 ***		−0.59 ***	−0.03 ***	1.40 ***
		(−6.57)		(−44.86)	(−3.24)	(9.84)
N		3914		1194	2159	561
R^2		0.47		0.20	0.33	0.73
Adj. R^2		0.44		0.05	0.25	0.67
AIC		−11,988.76		−6705.3	−7770.41	−1822.45
BIC		−11,907.22		−6557.83	−7605.76	−1705.55

Note: t or z test values are in parentheses, *, ** and *** indicate significant performance at 10%, 5% and 1% confidence levels, respectively.

The dual-threshold model shows that GDP, as the primary variable measuring urban development level, plays a vital role in the formation of shrinking cities and changes in population size, exhibiting a significant nonlinear relationship under the influence of heterogeneous population dynamics. The threshold effects of GDP are as follows. When GDP is below the first threshold, it strongly inhibits population size. This suggests that in cities with smaller economic scales, there needs to be more internal attractiveness and it is difficult to resist the pull from external cities, leading to a tendency of population outflow. However, when GDP surpasses the first threshold and falls within the interval of (434,832, 2,270,731], the effect of GDP becomes insignificant. This may be due to the limitation of GDP as a single factor in comprehensively assessing cities' developmental stage and level. Additionally, the wide range of the interval obscures internal or subgroup differences, blurring the significance of parameters. When GDP crosses the threshold of 2,270,731, GDP exhibits a strong promoting effect. This indicates that relatively developed county-level administrative units possess strong "blood circulation" and "siphoning" capabilities. Moreover, it shows that once a city's economic scale exceeds a certain threshold, the path dependence of sustained expansion and the cumulative effects of agglomeration often lead to continuous positive development. The differences in threshold intervals and regression results obtained from the dual-threshold regression model when selecting GDP as the threshold variable both validate the significant impact of urban scale on shrinking cities. It also demonstrates the applicability of the threshold regression model in addressing such issues. Other explanatory variables such as OVSI, OVTI, IFA, FR, FE, GRA, and IMP show significant relationships with population size, with only IFA exhibiting an inhibitory effect. The significance results slightly differ from the previous models. In general, a healthy and vibrant local economy, along with a livable and ecologically friendly natural environment, contribute to the retention of the population and attraction of external migrants. The interaction between push and pull factors promotes sustained population growth in cities, thereby avoiding the formation of shrinking cities. The diverse regression results in the grouped models reflect the complexity and heterogeneity of the study, showcasing inter-group and intra-group differences within the sample.

The results of other variables in the economic dimension show significant differences between the dual-threshold model and the grouped regression model. OVSI demonstrates a significant promoting effect in the threshold regression model. However, it exhibits a suppressive effect in Type III cities and has no significant impact on Type II and Type I cities. As the pillar industry in the Three Northeastern Provinces, the second industry has undergone a development process from state-owned to private ownership. Due to institutional reforms and limited resources, its ability to attract the population gradually weakens as the city size expands. With increased environmental awareness and the need for economic transformation, OVSI gradually reveals its drawbacks, such as high pollution, high energy consumption, and high investment. Its development model is challenging to sustain in the Type II and Type I cities, leading to a shift towards the smaller and weaker Type III cities. The threshold regression model shows that OVTI plays a promoting role. However, in Type III cities, OVTI exhibits a suppressive effect, which may be attributed to the relative weakness of the local OVTI industry itself. In other words, the inability to meet the population demands results in population outflow, further leading to the decline of the OVTI industry, forming a negative cycle. Type II cities have a specific industrial foundation and consumer market, and the thriving OVTI industry attracts the population from surrounding cities to come for consumption and even settlement. IMP demonstrates a promoting effect in the threshold regression, Type II, and Type I cities, and this effect gradually strengthens with the expansion of city size. The expansion of IMP signifies the expansion of urban strength and the manifestation of vitality. In the development model of China's land finance, larger-scale cities have more room for development, and the population and land complement each other, mutually promoting efficient urban development.

The variables in the investment dimension exhibit significant differences in the direction and intensity of their effects between the threshold regression model and the grouped regression model. IFA shows a significant inhibitory effect in the threshold regression and Type I cities, while it demonstrates a significant promoting impact in Type II cities. IFA tends to strengthen the existing economic structure and increase investment in pillar industries, often concentrating in developed regions within the area. Considering the characteristics of heavy industrialization in these regions, it can be inferred that in Type I cities with a complete industrial structure and well-developed infrastructure, the continuous concentration of IFA exacerbates regional or social inequality, weakening or even transforming its driving force into inhibition. However, Type II cities still have significant room for industrial growth and infrastructure development. IFA can create employment opportunities and optimize social equity, attracting population inflows. Non-scalable IFA may struggle to reverse Type III cities' relatively weak development status, resulting in insignificant effects. FR exhibits a significant promoting effect in both the threshold regression model and Type II and Type I cities. A strong FR can effectively allocate resources, promote economic development, improve people's living standards, and further enhance social equity. However, in Type III cities with fewer FR resources, it is not easy to achieve economies of scale and have a significant impact on the population. FE shows a significant promoting effect in the threshold model and Type III cities, while in Type II and Type I cities, it exhibits an inhibitory effect. The Three Northeastern Provinces experienced a large-scale wave of layoffs in the 1990s, and the retirement pension expenditures of laid-off workers constitute a significant portion of FE, especially in Type II and Type I cities where the number of layoffs is more severe. The substantial expenditure pressure has forced the government to reduce spending on infrastructure, education, environmental protection, and other areas, limiting its ability to improve people's livelihoods and promote development.

The elements in the natural dimension have varying directions of influence. LST only exhibits a significant inhibitory effect in Type II cities. This could be due to the population's higher income and migration ability in these cities. Thus, when faced with negative externalities such as a relatively cold climate, residents "vote with their feet", and the choice to relocate to areas with more favorable natural conditions, expressing their preferences. On the other hand, Type I cities often provide economic or social compensations that exceed the damages caused by externalities. In contrast, the population in Type III cities struggles to cope with the high migration costs, resulting in a less sensitive response to LST. Regarding FOR, it shows a significant promoting effect in Type I cities. The abundant forest resources serve as a guarantee for an excellent ecological environment, which is considered a bonus for these cities. As for GRA, it exhibits significant effects in both threshold regression and grouping models, with the strength of its influence increasing as city size expands. This indicates that the purification effect of abundant grassland resources and the provision of urban recreational functions meet people's partial pursuit of a green, ecological, and livable environment. In conclusion, the elements in the natural dimension have different directions and magnitudes of influence. By understanding and utilizing the characteristics of natural elements, urban planning, and development can better meet the demands for environmental quality and sustainable ecology.

4. Discussions

4.1. The Importance of Identification of Shrinking Cities

A shrinking city is a comprehensive concept that integrates the "process-phenomenon-issue" aspects, and it has posed significant challenges to the previous "growth-oriented" urban development ideology. Numerous studies have attempted to precisely identify shrinking cities and define the degree of their shrinkage. However, each shrinking city exhibits unique characteristics in terms of dimensions, extent, duration, modes, and causes, making it a regional issue with distinct geographical features. The precise and scientific identification and classification of shrinking cities form the relevant research's foundation and critical focus.

Population size serves as a fundamental factor in evaluating shrinking cities, and studies often define them based on population changes or variations in scale. This approach is characterized by its simplicity, practicality, and accessibility. However, population changes inherently involve a certain degree of lag and complexity. Relying solely on a single identification method or focusing exclusively on changes in a single factor can easily conceal the overall imbalances in development. Therefore, this paper proposes a two-step diagnostic approach to identify shrinking cities. This method ensures accuracy by considering both scale and growth rate while employing a quadrant classification approach to differentiate between different types of cities effectively. The aim is to achieve precise identification of shrinking cities, avoiding the limitations of a single-factor perspective and the subjectivity that arises from constructing a multi-factor indicator system.

However, we should also recognize that shrinking cities can be both the outcome of urban development and a dynamic process in urban growth [57]. Therefore, when identifying shrinking cities, it is important to consider regional contexts and temporal characteristics and adopt a progressive and dynamic approach to their identification and classification rather than using a "one-size-fits-all" method. We should strive for a gradual and dynamic classification to avoid generalizations or biases in our analysis.

4.2. Possible Influencing Factors of Shrinking Cities

The formation of shrinking cities is influenced by multiple factors, including regional contexts and city characteristics. While cities may have limited control over regional development, they can address the challenges of shrinking cities by optimizing their characteristics. Therefore, this paper combines relevant literature and analyzes the results of regression models to explore the influencing factors of shrinking cities.

This paper's results differ slightly from Guan et al. [47] regarding the role of impervious areas about the population size, but they align on the role of GDP. Economic development can provide more employment opportunities and attract both local and external populations, thereby mitigating shrinkage. However, it is important to note that different-sized cities may be affected by GDP in different directions or varying degrees. The expansion of impervious areas typically signifies investment, technological concentration, and subsequent enrichment of production and daily activities, which is why it is significantly promoted in most studies and the regression model results of this study. However, as shown in this study, indiscriminate expansion of impervious areas can have adverse effects on urban development. It is crucial to focus more on improving land quality rather than increasing quantity.

In this paper, the results of the threshold models show that the output value of the secondary or tertiary industry has a promoting effect. However, in small-sized cities (Type III cities), they exhibit a suppressing effect. As Wang et al. [58] pointed out, a diversified industrial structure can maintain urban population size and enhance urban economy and vitality. Small-sized cities that overly rely on a single pillar industry have poor risk resistance and struggle to attract a sufficient population, leading to further urban shrinkage. Therefore, small-sized cities should focus on developing diverse industrial formats, avoiding relying on a single pillar industry, and enhancing their resilience against shrinkage. As stated in the "Opinions of the State Council on Promoting the Sustainable Development of Resource-based Cities", many resource-exhausted cities in the Three Northeastern Provinces heavily rely on industries such as coal and steel. In response to this situation, the region should primarily adopt a diversified industrial development strategy, break free from the cycle of industrial decline under the constraints of resource exhaustion, optimize the industrial structure, enhance the city's ability to withstand risks, and explore new paths for the development of resource-exhausted cities.

The study confirms [59] that the lack of public service facilities contributes to the formation of shrinking cities, especially in small-sized cities. As demonstrated in this study's results, the increase in fiscal expenditure has the most significant promoting effect on small-sized cities. However, as the city size expands, the marginal benefits of investment diminish and may even turn negative.

4.3. Urban Plannings to Tackle Shrinking Cities

Focusing on the current development status of shrinking cities, the traditional urban-rural planning paradigm based on "growth-oriented" approaches has become inadequate in achieving its core objectives. Therefore, shrinking cities should actively respond to the concept of "smart shrinkage" as a stock development strategy, acknowledging the existence of shrinking cities, understanding potential mechanisms leading to shrinking cities, and proposing planning measures to address it.

Firstly, in China, where urban development is government-led, governments at all levels should genuinely recognize the existence of shrinking cities and avoid mindlessly pursuing "growth-oriented" approaches. The central or provincial governments should ensure comprehensive coordination. In contrast, local governments should focus on specific planning measures based on two aspects: (1) recognizing the presence of shrinkage in the local area and (2) analyzing the extent and types of shrinking cities.

It is important to avoid generalized conclusions based on a "one-size-fits-all" approach but rather develop targeted optimization strategies according to different types of shrinking cities, with targeted plans and urban planning to stabilize the decline [60,61]. For most shrinking cities, development plans with a low-growth orientation can still be formulated, emphasizing environmental considerations, infrastructure development, transportation layout, and addressing population aging. In the case of continuously shrinking cities, efforts can be made in areas such as diversified industries, community revitalization, governance optimization, improving living environments, and enhancing facilities for the elderly. Sustainable economic and population stability strategies can be considered in the above-mentioned shrinking cities, with goals of low growth or slow decline [17].

Secondly, shrinking cities should avoid wasting limited resources and pursue development paths with higher marginal effects [62]. According to the results of this study, for Type III cities, a strong emphasis can be placed on developing the economic scale (with a regression coefficient of 0.16) to achieve positive marginal effects. For Type I cities, expansion of impervious land (with a regression coefficient of 0.24) should be pursued to provide sufficient living space while maintaining continuous growth in forest areas (with a regression coefficient of 1.04) and reducing the pursuit of economic growth (with a regression coefficient of 0.04), aiming to achieve stable local population and attract external individuals.

Thirdly, in terms of planning formulation and implementation, top-down planning transmission should be avoided in shrinking cities. Planners should conduct extensive surveys of residents' preferences and actively involve them in the decision-making process to avoid blind spots or errors in the planning process, making full use of the advantages of public participation. In planning implementation, the government can meet the urgent needs of residents by improving community infrastructure, providing convenient transportation networks, and promoting industrial development plans.

Finally, there should be coordination among government levels to increase understanding and awareness of shrinking cities. Cities in the Three Northeastern Province should, guided by provincial and even national governments, avoid internal homogenized competition, leverage their historical, cultural, and natural assets, create local brands, and promote urban development.

4.4. The Limitations and Future Research Directions

This paper still needs to improve the study of shrinking cities.

Firstly, the research scale. This paper analyzed shrinking cities using the grassroots level of county-level administrative units under the Chinese urban administrative system. However, analyzing the county-level administrative units cannot distinguish the differences between urban and rural built-up areas. Therefore, future research could consider using urban and rural built-up areas as a benchmark to explore population flows in depth.

Secondly, type identification. This paper identified city types based on a macro scale of the Three Northeastern Provinces, which has a specific scientific basis and aligns with the Chinese administrative system. However, at the level of individual cities, it is challenging to grasp the spatio-temporal types of their shrinkage accurately, lacking the ability to distinguish whether a shrinking city is experiencing an overall contraction, perforated contraction, or central-peripheral contraction. As a result, the planning strategies proposed in this study are more inclined towards macro-level policies for cities and lack precise planning implementation methods for individual cities. Future research can adopt a more refined research scale to identify the types of shrinking cities accurately.

Thirdly, the selection of city scale indicators and influencing factors. This study selected GDP as the indicator for measuring city scale, which has the issue of poor stability as a single variable. Additionally, in terms of selecting influencing factors, the indicators used in this study lack consideration of regional development backgrounds and fail to fully consider urban characteristics such as population age structure. Therefore, future research should incorporate more influencing factors and focus on analyzing the factors influencing shrinking cities.

5. Conclusions

With urbanization's progression in China's later stages, variations in development trends and situations have emerged in different regions, particularly in the Three Northeastern Provinces. This has led to the emergence of shrinking cities at different stages and degrees. This study focused on the county-level administrative units in the Three Northeastern Provinces, utilizing long-term panel data from 2001 to 2020 on economic, investment, and natural factors. The types of shrinking cities were identified by analyzing the cumulative count of population loss years and the magnitude of population-scale changes, and their spatio-temporal characteristics were comprehensively analyzed. Additionally, panel regression models were constructed to explore the influencing mechanisms. A panel threshold regression model was employed to investigate the impact of GDP at different threshold intervals on shrinking cities in response to population changes.

The research conclusions are as follows:

(1) There are numerous and relatively severe shrinking cities in the Three Northeastern Provinces of China. Using a two-step identification method, the study identifies 83 stable shrinking cities and 125 stable growing cities, with the remaining cities leaning toward shrinkage. Regarding spatial distribution, most cities in the "Harbin-Dalian" urban corridor exhibit a strong growth trend and are classified as stable growing cities. On the other hand, the shrinking cities are mainly located at the northern and southern ends, centered around areas such as Yimei District and Mishan City, forming six spatial clusters.

(2) The fixed effects model exhibits a better fit compared to other panel regression models. The results indicate significant relationships with population size between OVSI, OVTI, FE, GRA, IMP, IFA, and LST. The first five factors positively impact population size, while IMP, GAR, and OVTI exhibit the most potent promoting effects.

(3) The dual-threshold model outperforms other threshold models in terms of fit. The results reveal a significant causal relationship between GDP, which serves as a critical indicator of urban development, and the formation of shrinking cities and changes in population size. Under the influence of population dynamics, this relationship exhibits a significant non-linear pattern. When GDP is below the first threshold value (CNY 434,832), it demonstrates an inhibitory effect, suggesting that cities with smaller economic scale face limited external attractiveness and struggle to generate substantial attraction. When GDP falls within the range between the first and second threshold (CNY 434,832 to CNY 2,270,731 yuan), the significant effects become unclear due to the complexity inherent in this interval. However, once GDP surpasses the second threshold (CNY 2,270,731), there is a powerful promoting effect on population changes, indicating the presence of strong "self-renewal" and "suction" capacities in such cities.

(4) The results of the dual-threshold regression model and grouped models show significant differences in the direction and strength of the explanatory variables in different models. The variables in the economic and investment dimensions show good significance. OVSI and OVTI promote in the threshold regression model, while they inhibit in Type III cities. IFA and FR mainly exhibit significant promotion in Type II and Type I cities, with only IFA showing inhibition in Type I cities. IMP and FR show significant promotion in the threshold regression model, and in Type II and Type I cities, further indicating the promoting role of urbanization and government investment in the development of medium and large cities. The significance of the indicators in the natural dimension is relatively weak. Only LST shows significant inhibition in Type I cities, while FOR shows significant promotion in Type I cities. Overall, the differences are most pronounced in Type III cities, which are smaller in scale. The study demonstrates that shrinking cities are indeed influenced by urban scale. Due to their unique urban scale, urban characteristics, and development backgrounds, smaller cities are more prone to become shrinking cities.

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