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The spatial impact of new urbanization construction on total factor productivity in China

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Abstract

This study examines the spatial impact of new urbanization on total factor productivity (TFP) in China using data from 199 prefecture-level cities from 2011 to 2019. We measured the level of new urbanization using an indicator system and the entropy weight method, and assessed TFP using the stochastic frontier production function model. The spatial Durbin model was employed to analyze the spatial effects empirically. The study found that (1) new urbanization has a positive spatial effect on TFP, and there is a spatial spillover effect. (2) The spatial effect of new urbanization on TFP has obvious city-level heterogeneity and regional heterogeneity. (3) The spatial spillover effect of new urbanization on TFP is most significant in second-tier cities and third-tier and lower cities. There is a "diffusion effect" of the spatial effect of the central and western cities on the neighboring areas, and a "siphon effect" of the spatial effect of the eastern cities, but both of these spatial effects are not significant. The spatial spillover effect of new urbanization on TFP in non-provincial capitals is significant, whereas the spatial effect in non-provincial capitals is not significant. These findings highlight the importance of considering regional context in urbanization policies to enhance TFP.

Keywords: New urbanization, Spatial Durbin model, Spatial spillovers, Total factor productivity.
JEL Classification: R11; O47; C23; R58.

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Contents

Contribution of this paper to the literature
This study uniquely examines the spatial impact of new urbanization on total factor productivity (TFP) across 199 Chinese cities using a spatial Durbin model. It reveals city-level and regional heterogeneity in spatial spillovers, providing novel insights for targeted urbanization policies.

1. Introduction

The new urbanization is a variegated urban structure that is not simply concentrated in a limited area but is unevenly and densely distributed, unlike traditional metropolitanism or the urban/rural dichotomy (Brenner, 2013). The Chinese government plans for new urbanization mainly in three aspects: improving the existing urbanization model, promoting the citizenship of the agricultural transfer population, and achieving sustainable development (Chen, Ye, Lu, Sui, & Guo, 2019; Wang, Hui, Choguill, & Jia, 2015; Yu, 2021). In the process of China's urbanization, there was a single, crude, and blind pursuit of an increase in the urbanization rate at the expense of the quality and core significance of urbanization. Although this has boosted China's rapid economic growth, it has also caused a series of environmental and economic problems, mainly encroachment on arable land, widening of the income gap, and impacts on the upgrading of industrial structure and innovation (Liang & Yang, 2019). As China's economy enters the stage of high-quality development, there is an even more urgent need to break the traditional crude urbanization development model to adjust the development of the economy.

In economics, total factor productivity (TFP), also known as multifactor productivity, refers to the portion of output that cannot be explained by traditional measures of labor and capital inputs (Avila & Evenson, 2010; Lipsey & Carlaw, 2004; Sargent & Rodriguez, 2001). TFP serves as a key indicator of how productivity drives economic growth by accounting for output increases that are not attributable to input growth (Van Ark, 2014). In China, promoting new urbanization and leveraging its economic benefits, particularly through TFP increases, has become a crucial strategy to address current economic development challenges, such as regional disparities and sustainable growth.

As the construction process of new urbanization continues to deepen, it is extremely important to measure the level of new urbanization and study its spatial effect on total factor productivity under the condition of leading high-quality economic development. In the construction of the evaluation index system of new urbanization level, there has been a shift from the early single consideration of urban-rural integration to the development of three levels: environment, economy, and society. After China's 18th National Congress, with the accelerated pace of urbanization, achieving steady and coordinated high-quality development to build new urbanization has become the main theme. According to the new requirements of China's 18th National Congress for high-quality economic development, the evaluation index system of new urbanization was significantly adjusted to include multiple dimensions such as population development, public services, scientific and technological innovation, environmental protection, and integrated urban and rural development into the index system of new urbanization (Fang, 2022).

A large body of literature suggests that urbanization affects productivity levels (Bertinelli & Black, 2004; Burgess & Venables, 2004; Landes, 2003; Williamson, 1988). Urbanization provides economies of scale that allow specialization among firms, which reduces production costs, and economies of scale in cities reduce transaction costs. The high population density of cities allows both workers with different skills and firms with specific needs to reduce their search costs. As a result of this agglomeration effect, urbanization enhances the flow of ideas and knowledge between cities and between firms, which in turn has an impact on productivity (Henderson, 2005). Meanwhile, along with the development of urbanization, it has different impacts on total factor productivity, mainly in the early stages due to the construction process of urbanization, which brings about an increase in factor costs, and excessive competition has a negative impact on TFP. However, with the deepening of urbanization, it has a significant contribution to TFP (Kumar & Kober, 2012), and the consequent emergence of new types of urbanization is more capable of increasing TFP.

Technological imitation effects exist between countries and can increase the basic innovation capacity of the host country (Driffield, 2001). Compared to inter-country factor flows, inter-provincial economic, cultural, and other factors face relatively fewer impediments to free flow, which is more conducive to the spatial agglomeration of factors, making technological imitation more likely to take place and generating spatial spillover effects (Henderson, 2003). China's "people-centered" new urbanization aims to break down the urban-rural dichotomy, encourage the free movement of people, absorb the inflow of highly skilled labor, promote the dissemination and exchange of advanced management experience, technology, and enterprise culture, and strengthen regional industrial interaction. This provides a basis for the realization of technological imitation between the region and its neighbors, eliminating the "mutual exclusion effect" of market segmentation, enhancing the spatial spillover of total factor productivity, and raising the total factor productivity of neighboring cities. The construction of new urbanization is a top-down policy implemented by the central government (Chen, Liu, Lu, Chen, & Ye, 2018). Government competition is essentially an interactive strategy, and local government competition not only affects the level of total factor productivity in the region through technological innovation but also generates spillover effects to other regions. In addition, positive spatial spillovers from population agglomeration and economic development objectively lead to cross-regional factor flows, improving and optimizing regional allocation efficiency.

In addition, China's new type of urbanization is guided by the concept of optimizing spatial layout, which rationalizes the regional division of labor within cities, reduces traffic congestion, increases transportation costs for enterprises, and causes long-distance separation of employees due to the chaotic division of functional districts. It also realizes the centralized supply and utilization of infrastructure (Chen et al., 2019). This is an important foundation for enhancing the efficiency of public facilities utilization and improving the spatial spillover effect of new urbanization. Neighboring cities will be more prone to regional cooperation, such as the construction of cross-city highways (Li & Wang, 2023). Therefore, the supply of local public services not only affects local total factor productivity but also influences total factor productivity in neighboring regions through spatial spillover effects.

Although some studies are aware of the role of new urbanization on China's total factor productivity, they do not take into account the spatial spillover effects between cities at the spatial level and focus more on the macro-provincial level. Therefore, this paper uses the data of 199 prefecture-level and above cities from 2010 to 2019 to estimate the spatial impact effect of new urbanization on total factor productivity using spatial measurement methods. Based on this, this paper adopts the entropy weighting method to hierarchically process and assign corresponding weights to 11 comprehensive indicators and 38 impact factors, and measures new urbanization by comprehensively considering many aspects, such as economic growth, population development, social construction, public services, livelihood welfare, ecological environment, digital infrastructure, business innovation, industrial upgrading, urban-rural integration, and financial development, etc. Additionally, it adopts spatial correlation-based methods to construct a spatial measurement matrix of total factor productivity using the neighboring geographic distance weights and the inverse threshold distance matrix. Based on the spatial correlation, the spatial panel data model is constructed by using neighboring geographic distance weights and the inverse threshold distance matrix to analyze the spatial spillover effect of China's new urbanization.

2. Methodology

2.1. Spatial Panel Model

2.1.1. Spatial Modeling

In order to analyze the spatial impact of new urbanization on total factor productivity, this paper first constructs a panel spatial autoregressive model.

$$y_{i,t} = \rho \boldsymbol{w}_i' \boldsymbol{y}_t + \boldsymbol{x}_{i,t}' \boldsymbol{\beta} + \mu_i + \varepsilon_{i,t} \quad (i = 1, \cdots, n; t = 1, \cdots, T) \tag{1}$$

Where $\boldsymbol{w}_i'$ is the i-th row of the spatial weight matrix $\boldsymbol{W}$, and $\boldsymbol{w}_i' \boldsymbol{y}_t = \sum_{j=1}^{n} w_{i,j} y_{j,t}$. u_i is an individual effect. If the spatial lag term $\rho \boldsymbol{w}_i' \boldsymbol{y}_t$ is not considered, Equation 1 is a standard static panel model. It is a fixed effects model if u_i is correlated with $\boldsymbol{x}_{i,t}$ and a random effects model if it is not.

For maximum likelihood estimation (MLE) of spatial panel models, the following spatial panel models can be estimated.

$$\begin{cases} y_{i,t} = \tau y_{i,t-1} + \rho \boldsymbol{w}_i' \boldsymbol{y}_t + \boldsymbol{x}_{i,t}' \boldsymbol{\beta} + \boldsymbol{d}_i' \boldsymbol{X}_t \boldsymbol{\delta} + \mu_i + \gamma_t + \varepsilon_{i,t} \\ \varepsilon_{i,t} = \lambda \boldsymbol{m}_i' \varepsilon_t + v_{i,t} \end{cases} \tag{2}$$

Where $y_{i,t-1}$ is the first-order lag of the explanatory variable $y_{i,t}$; $\boldsymbol{d}_i' \boldsymbol{X}_t \boldsymbol{\delta}$ denotes the spatial lag of the explanatory variable, $\boldsymbol{d}_i'$ is the i-th row of the corresponding spatial weight matrix $\boldsymbol{D}$; γ_t is the time effect, and $\boldsymbol{m}_i'$ is the i-th row of the spatial weight matrix $\boldsymbol{M}$ of the disturbance term. In Equation 2, if $\lambda = 0$, it is a spatial Durbin model (SDM); if $\lambda = 0$ and $\boldsymbol{\delta} = 0$, it is a spatial autoregression model (SAR); if $\tau = 0$ and $\boldsymbol{\delta} = 0$, it is a spatial autocorrelation model (SAC); and if $\tau = \rho = 0$ and $\boldsymbol{\delta} = 0$, it is a spatial error model (SEM).

2.1.2. Setting of the Spatial Weighting Matrix

The w_{ij} in Moran's I index is called the spatial weight matrix, which is used to measure the "distance" between the sample areas, portraying the proximity of cities or the economic distance considering the level of economic development, indirectly reflecting the correlation between cities. In this paper, we use the adjacency matrix and the inverse threshold distance matrix as spatial weighting matrices to analyze the interactions of new urbanization on TFP among cities. These two matrices cover both geographic and economic distances, ensuring the robustness of the results as much as possible.

The expression for the adjacency matrix is $w_{ij} = \begin{cases} 1, \ \textit{Region } \boldsymbol{i} \textit{ is adjacent to } \boldsymbol{j} \\ 0, \ \textit{Regions } \boldsymbol{i} \textit{ and } \boldsymbol{j} \textit{ are not adjacent} \end{cases}$. This means that the corresponding element of the spatial adjacency matrix is assigned a value of 1 if there are geographically adjacent boundaries in different regions, and 0 otherwise. The economic factors are further considered on the basis of the geographic distance matrix, with a view to incorporating both economic and geographic factors into the model and portraying the complexity of the spatial effects. The economic-geographic weighting matrix is set to $wij = w_d \cdot diag\left(\frac{\overline{x_i}}{\overline{\overline{x}}}\right)$, where $w_d = \begin{cases} \frac{1}{d_{ij}}, \ i \neq j \\ 0, i = j \end{cases}$. The set matrix $diag\left(\frac{\overline{x_i}}{\overline{\overline{x}}}\right)$ is a diagonal matrix whose diagonal element is the ratio of the mean value of the cross-section economic variable to the overall economic variable, and the economic variable selected in this chapter is the per capita provincial GDP.

2.2. Total Factor Productivity Measurement Methodology

The explanatory variable in this paper is total factor productivity (TFP). We measure urban total factor productivity based on the stochastic frontier production function (SFPF) model proposed in the literature by Battese and Coelli (1992) and Battese and Coelli (1995). The advantage of this model is that the efficiency obtained from the measurement of SFPF eliminates the interference of the stochastic error term, and the specific model is set as follows.

$$y_{it} = f(x_{it}, t, \beta) exp(v_{it} - u_{it}), i = 1, 2, ...I; t = 1, 2, ...T \tag{3}$$

$$u_{it} = u_i exp[-\eta(t - T)] \tag{4}$$

The model consists of two parts: Equation 3 is the stochastic frontier production function, and Equation 4 is the time-varying technical inefficiency function. where y_{it} is the amount of output of the i-th decision unit in period t; $f(\cdot)$ is an expression for the stochastic production frontier function; x_{it} denotes the vector of inputs of the i-th decision unit in period t; β denotes the unknown to-be-estimated parameter; v_{it} is the stochastic error term; u_i is a non-negative random variable; and η is the to-be-estimated parameter, with $\eta > 0$, $\eta = 0$, and $\eta < 0$ denoting diminishing, unchanging, and increasing technological inefficiency over time, respectively. The deterministic production frontier function is.

$$y_{it} = f(x_{it}, t, \beta) \cdot exp(-u) \quad (5)$$

That is, $ln y_{it} = lnf(x_{it}, t, \beta) - u$. Based on the index of change in total factor productivity.

$$TFP = \dot{y} - X = \dot{y} - \sum_{n=1}^{N} S_n \dot{X}_n \quad (6)$$

Where "." on the variable denotes the rate of change, $S_n = \frac{W_n X_n}{E}$ is the share of expenditures on input factors, E denotes total expenditures, and W_n is the price of input factors.

2.3. Entropy Weight Method

The core explanatory variable of this paper is new urbanization construction (NewUrban), and the entropy weight method is used to assign corresponding weights to each indicator for hierarchical processing, and finally calculate the score of the new urbanization level of each city. The calculation steps of the entropy weight method are as follows.

(1) Transformation of data. In order to avoid the influence of different scales on the calculation results as much as possible, the evaluation indexes should be dimensionless before applying the entropy weight method.

$$E_{ij} = \begin{cases} \frac{X_{ij} - min(X_{ij})}{max(X_{ij}) - min(X_{ij})}, \text{ If } X_{ij} \text{ is an egative indicator} \\ \frac{max(X_{ij}) - X_{ij}}{max(X_{ij}) - min(X_{ij})}, \text{ If } X_{ij} \text{ is an positive indicator} \end{cases} \quad (7)$$

In Equation 7, X_{ij} represents the indicator value, $max(X_{ij})$ represents the maximum value of the indicator, $min(X_{ij})$ represents the minimum value, and E_{ij} is the processed indicator data and $E_{ij} \in [0, 1]$.

(2) Calculate the weight of the jth indicator for the ith region.

$$p_{ij} = \frac{E_{ij}}{\sum_{i=1}^{n} E_{ij}} \quad (8)$$

(3) The entropy value and the coefficient of variation of the indicator were calculated.

$$b_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad g_j = 1 - b_j \quad (9)$$

For the jth indicator, the greater the degree of dispersion of X_{ij}, the smaller its entropy value b_j; when the difference between the values of the indicators of the samples is greater, the smaller the value of b_j, the greater the comparative role of the indicator for the samples, and the greater the weight given to it in the composite indicator. g_j is the coefficient of variation.

(4) Calculate the weight of the jth indicator in the metric.

$$W_j = \frac{g_j}{\sum_{i=1}^{m} g_j} = \frac{1 - b_j}{\sum_{i=1}^{m} (1 - b_j)} \quad (10)$$

(5) The composite indicator calculated is $Z_i = \sum_{j=1}^{m} W_j E_{ij}$. In general, the larger Z_i is, the higher the level of development of the system.

3. Data

3.1. Explained Variable

The explained variable in this paper is the total factor productivity level (tfp). Building on Section 2.2, we further refer to the Solow model extended by Karras (2010), where Y is gross output expressed in terms of city GDP (Gross Domestic Product), deflated using the Gross Domestic Product (GDP) deflator price index with 1998 as the base period. The labor force L is expressed in terms of the number of persons employed in municipal units at the end of the period and the number of persons employed in private and self-employment in urban areas. The capital stock K is represented by the amount of fixed-asset investment in the calendar year, and the land resource R is expressed by the built-up area of each region, while the level of economic development, government fiscal expenditure, industrial upgrading index (three industries compared to the second), human capital (years of education per capita), foreign trade dependence (the total amount of imports and exports as a share of GDP), fixed-asset investment, and the green area per capita are selected as the environmental variables that affect the efficiency of production. Finally, the total factor productivity of the city was measured using the SFPF model.

3.2. Explanatory Variable

The primary explanatory variable of this paper is the level of new urbanization in China (NewUrban). Based on the definition of new urbanization in China, this paper constructs an indicator system for new urbanization from multiple dimensions, such as population development, public services, scientific and technological innovation, and environmental protection. The level of new urbanization is measured using the entropy weight method, as detailed in Section 2.3. The indicator construction and weights are shown in Table 1.

Table 1. New urbanization indicator system.

Evaluation dimension	Specific indicators	Unit/Calculation	Weight	Indicator attributes
Economic growth	GDP per capita	Ten thousand Chinese yuan	0.233	Positive indicator
	Economic density	Billions of Chinese yuan per square kilometer	0.079	Positive indicator
	Capital productivity	GDP/capital stock	0.030	Positive indicator
	Labor productivity	Billions of Chinese yuan per 10,000 persons	0.124	Positive indicator
	Total import and export trade	million Chinese yuan	0.535	Positive indicator
Population development	Human capital	Number of higher education institutions/Total population at the end of the year	0.730	Positive indicator
	Education expenditure per capita	Chinese yuan	0.268	Positive indicator
	Registered unemployment rate of urban population	%	0.002	Negative indicator
Social construction	Highway density	Total road mileage/Total area of the region	0.463	Positive indicator
	High-speed rail mileage	kilometer	0.405	Positive indicator
	Percentage of fiscal general budget expenditure	Fiscal expenditure as a share of GDP	0.132	Positive indicator
Public service	Hospital beds per 1,000 population	—	0.149	Positive indicator
	Health technicians per 1,000 people	—	0.146	Positive indicator
	Ratio of public administration and social organizations	Percentage of employees in the total population	0.132	Positive indicator
	Number of books in public libraries per capita	—	0.573	Positive indicator
People's welfare	Sales price of commercial properties	Chinese yuan	0.145	Positive indicator
	Total retail sales of consumer goods per capita	Chinese yuan	0.158	Positive indicator
	Year-end balance of urban and rural residents' savings	Chinese yuan	0.273	Positive indicator
	Average wage of employees	Chinese yuan	0.059	Positive indicator
	Number of unemployment insurance participants	—	0.365	Positive indicator
Ecological environment	Number of environmental penalties	—	0.003	Positive indicator
	Green space per capita	Square meter	0.997	Positive indicator
Digital infrastructure	Number of international Internet subscribers	A household	0.147	Positive indicator
	Cell phone subscribers at the end of the year	Ten thousand households	0.130	Positive indicator
	Revenue from telecommunication services	Ten thousand Chinese yuan	0.165	Positive indicator
	Number of employees in the information/Computer services and software industry	Number of people	0.411	Positive indicator
	Number of internet broadband access users	Ten thousand households	0.147	Positive indicator
Business innovation	Green invention patent applications	—	0.357	Positive indicator
	Number of green utility model patent applications	—	0.294	Positive indicator
	Number of invention patents granted in the year	—	0.349	Positive indicator
Industrial upgrade	Advanced industrial structure	Value added of tertiary industry/Value added of secondary industry	0.369	Positive indicator
	Rationalization of industrial structure	Theil index (Zhou & Li, 2023)	0.631	Positive indicator
All-in-one city and countryside	Number of urban basic medical insurance participants	Number of people	0.905	Positive indicator
	Engel's coefficient	—	0.095	Positive indicator
Financial development	Number of employees in the financial industry	Number of people	0.196	Positive indicator
	Loan balance of financial institutions at the end of the year	Ten thousand Chinese yuan	0.407	Positive indicator
	Balance of deposits of financial institutions at the end of the year	Ten thousand Chinese yuan	0.344	Positive indicator
	Digital inclusive finance index	—	0.053	Positive indicator

3.3. Control Variables

Based on the existing literature, the control variables affecting regional total factor productivity mainly include (1) the level of financial development (lnfin). The level of financial development is an important source of capital inputs in TFP, which is measured in this paper using the local year-end loan balances of financial institutions as a share of GDP and taking the logarithm of it. (2) Level of economic development (lnpergdp). Local GDP per capita was used for measurement, and logarithmic values were taken. (3) The level of trade development (lntrade). Liang and Wang (2022) found that trade openness presents a promoting effect on total factor productivity, which is measured by taking the logarithm of the total import and export trade in this paper. (4) Education level (lnedu). The level of education affects total factor productivity by influencing the level of human capital, and generally, human capital enhancement is positively correlated with the development of total factor productivity (Liang and Wang (2022), which is measured in this paper by the number of years of education per capita in the region. (5) Public green space (lngreen). Liu, Ouyang, and Cai (2021) showed that the environment is one of the most important factors affecting total factor productivity, which is measured by taking the logarithm of green space per capita. (6) Financial level (lndeposit): measured using the natural logarithm of resident savings in each city. (7) Digital economy development level (lndigeco). The digital economy, as a new engine driving China's economic development, has an important impact on accelerating the transformation of old and new kinetic energy and enhancing total factor productivity, which is measured in this paper using the digital economy derived from principal component analysis (Yu, Zhang, & Gong, 2022).

Table 2. Statistical description of variables.

Variable	Obs.	Mean	SD	Med	Min	Max
NewUrban	1791	0.111	0.314	0.000	0.000	1.000
tfp	1791	1.534	0.750	1.547	0.105	2.940
lnpergdp	1791	10.704	0.580	10.650	8.773	12.579
lntrade	1791	13.761	2.092	13.787	3.219	19.254
lnedu	1791	7.211	0.459	7.159	5.796	9.002
lngreen	1791	-2.446	1.017	-2.405	-6.051	2.394
lndeposit	1791	16.759	0.985	16.642	14.415	20.156
lndigeco	1791	8.522	0.890	8.441	5.801	11.566

This paper uses panel data from 199 Chinese cities from 2011 to 2019 to analyze the impact of China's new urbanization on TFP. The data used are from the China Urban Statistical Yearbook of all years and the CNRDS database (http://www.cnrds.com), and some of the missing data are filled in by consulting the statistical yearbooks of each province or by interpolation, and the descriptive statistics of the variables are shown in Table 2.

4. Results and Discussion

4.1. Baseline Regression Results

In this paper, the likelihood ratio test and Hausman test are used to determine that the model is a fixed-effects spatial Durbin model (SDM). To compare the estimation results across various models, Table 3 presents the results for the ordinary least squares (OLS), spatial error model (SEM), and spatial autoregressive model (SAR), in addition to the SDM.

Table 3 includes control variables and individual and time dummy variables to account for individual and time effects. The results show that the core explanatory variable (NewUrban) is significant at the 1% level across all models. The spatial regression term in column (4) indicates that local new urbanization has a significant positive effect on the total factor productivity (TFP) of neighboring regions, with a coefficient of 10.6 (significant at the 1% level).

The control variables reveal that the levels of economic development, trade, finance, and environment have significant negative effects on the TFP of neighboring regions. Their coefficients are -2.409, -0.313, -1.661, and -1.409, respectively, all significant at least at the 5% level.

Table 3. Baseline regression results.

Variable	(1)	(2)	(3)	(4)
	OLS	SEM	SAR	SDM
Main				
NewUrban	2.629***	0.667***	0.745***	0.807***
	(6.69)	(2.63)	(2.96)	(3.19)
lnpergdp	-0.351***	0.203***	-0.009	0.258***
	(-5.81)	(3.92)	(-0.20)	(4.92)
lntrade	0.058***	-0.011	-0.030**	-0.013
	(4.17)	(-0.82)	(-2.35)	(-0.99)
lnedu	-0.300***	-0.084	-0.163***	-0.072
	(-4.97)	(-1.63)	(-3.27)	(-1.40)
lngreen	-0.661***	-0.167***	-0.204***	-0.180***
	(-25.44)	(-7.47)	(-8.75)	(-7.91)
lndeposit	-0.490***	0.059	-0.030	0.140*
	(-9.93)	(0.74)	(-0.38)	(1.73)
lndigeco	0.280***	0.032*	0.025	0.030
	(5.99)	(1.69)	(1.27)	(1.58)
_cons	21.7346***			

Variable	(1)	(2)	(3)	(4)
	OLS	SEM	SAR	SDM
	(34.31)			
Wx				
NewUrban				10.606*** (4.39)
lnpergdp				-2.409*** (-6.98)
lntrade				-0.313** (-2.08)
lnedu				0.433 (1.03)
lngreen				-1.409*** (-4.55)
lndeposit				-1.661** (-1.98)
lndigeco				-0.267 (-1.03)
Spatial				
lambda		2.517*** (83.14)		
rho			0.880*** (22.91)	0.714*** (8.80)
Variance				
sigma2_e		0.045*** (29.92)	0.048*** (29.83)	0.044*** (29.80)
N	1791	1791	1791	1791
R^2	0.3723	0.3821	0.0305	0.6703
		196.575	163.616	240.332

Note: Standard errors are in parentheses; *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively.

Why is this regression result? The reason may be due to the siphoning effect of the above control variables, such as economically developed regions attracting talent and capital inputs from neighboring regions, leading to their negative impact on the total factor productivity of neighboring regions.

It also confirms that, based on the lessons learned from urbanization in Western countries, China's new urbanization insists on a people-oriented realization of the integrated use of spatial resources. By maintaining the fairness of spatial resource allocation and the justice of spatial rights in different urban and rural areas and industries, it not only manifests the value principle of spatial justice but also improves the economic development level of the region and neighboring regions, and promotes the enhancement of regional TFP.

4.2. Decomposition of Spatial Effects

Interregional interaction exists in many ways. On the one hand, the region's own new urbanization construction may also have a diffusion effect, spreading technological innovation and knowledge to neighboring regions, which has a positive effect on the total factor productivity (TFP) enhancement of neighboring regions; on the other hand, it can draw the inflow of labor and capital factors from the surrounding areas through the polarization effect, which further promotes the TFP enhancement of the region but, at the same time, inhibits the economic development of neighboring regions.

For this reason, the spatial measurement method uses partial differentiation to decompose the total spatial impact effect into direct and indirect effects, where the direct effect measures the impact of new urbanization on total factor productivity (TFP) in the region, and the indirect effect measures the impact of local new urbanization on TFP in the surrounding areas (LeSage & Pace, 2009). See Table 4 for the results of the decomposition of the effects of the spatial Durbin model.

Two spatial matrices, the adjacency matrix and the inverse threshold distance matrix, were used for the spatial effects estimated by the SDM model in Table 4. As can be seen from the estimation results, the direct effect regression results of the adjacency matrix and the inverse threshold distance matrix indicate that the coefficients of the impact of new urbanization on the total factor productivity of this region are 0.656 and 0.732, respectively, both of which are significant at the 1% significance level. That is, new urbanization has a significant promotional effect on the total factor productivity of this region.

The indirect effect regression results of the adjacency matrix and the inverse threshold distance matrix show that the coefficients of the impact of new urbanization on the total factor productivity of the surrounding areas are 1.595 and 1.237, respectively, which are both significant at the 1% significance level. That is, new urbanization also has a significant contribution to the total factor productivity of the surrounding areas.

The direct effect results indicate that new urbanization has a significant contribution to total factor productivity in the region. The indirect effect can be interpreted as a "spatial spillover effect" of new urbanization, indicating that local new urbanization impacts the total factor productivity of surrounding areas. The main reason for this is that new urbanization has led to an increase in total factor productivity in the surrounding areas through factor flows, industrial development, and technological innovation spillovers, creating a strong diffusion effect, which in turn promotes the development of total factor productivity in the surrounding areas.

Table 4. Decomposition of the effects of the spatial Durbin model.

Variable	(1)	(2)
	Neighborhood matrix	Inverse threshold distance matrix
Direct effect		
NewUrban	0.656** (2.51)	0.732*** (2.84)
lnpergdp	0.121** (2.42)	0.132*** (2.62)
lntrade	-0.027** (-2.19)	-0.009 (-0.73)
lnedu	-0.129*** (-2.60)	-0.084* (-1.66)
lngreen	-0.208*** (-9.06)	-0.187*** (-8.26)
lndeposit	-0.038 (-0.46)	0.107 (1.30)
lndigeco	0.040* (1.88)	0.032 (1.56)
Indirect effect		
NewUrban	1.595*** (3.75)	1.237* (1.66)
lnpergdp	-0.489*** (-6.20)	-0.338*** (-3.32)
lntrade	-0.0804** (-3.54)	-0.129*** (-4.03)
lnedu	-0.037 (-0.48)	-0.311** (-2.48)
lngreen	-0.169*** (-3.43)	-0.300*** (-3.79)
lndeposit	0.283*** (2.78)	-0.286 (-1.62)
lndigeco	-0.043 (-1.04)	-0.010 (-0.14)
Total effect		
NewUrban	2.251*** (4.49)	1.969** (2.52)
lnpergdp	-0.367*** (-4.58)	-0.206** (-2.04)
lntrade	-0.108*** (-4.05)	-0.138*** (-3.96)
lnedu	-0.167* (-1.82)	-0.395*** (-3.00)
lngreen	-0.377*** (-6.50)	-0.487*** (-5.65)
lndeposit	0.246* (1.73)	-0.179 (-0.91)
lndigeco	-0.003 (-0.06)	0.022 (0.28)
N	1791	1791
R^2	0.12	0.4120
Log-likelihood	198.661	217.193

Note: Standard errors are in parentheses; *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively.

4.3. Spatial Correlation Test based on Moran's I Index

Moran's I index is subdivided into global and local Moran's I indexes, which are used to measure the spatial agglomeration effect in the vicinity of all samples and a single sample, respectively. We measured the global autocorrelation of new urbanization using a variety of spatial weight matrices, verified the existence of the spatial effect of new urbanization among regions, and provided support for the establishment of spatial measurement models. The Moran's index is calculated using the formula.

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j}^{n} w_{ij}} \tag{11}$$

Where, $S^2 = \frac{\sum_{j=1}^{n}(x_i - \bar{x})^2}{n}$, $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$, w_{ij} in Equation 11 is the spatial weight matrix, which can be set to different forms depending on the problem, x_i is the sample observation in the *ith* region, and *n* is the total number of samples. In this paper, *n* represents the prefecture-level cities under study; x_i represents the new urbanization level of *i* prefecture-level cities (*NewUrban* value); and $\bar{x}$ represents the mean value of the new urbanization level of each prefecture-level city. The Moran's I statistic calculated from Equation 11 takes the range of [-1, 1], where positive values represent positive spatial autocorrelation, negative values represent negative spatial autocorrelation, and 0 represents spatially uncorrelated. Table 5 gives the trends of Moran's I values for the adjacency matrix and the inverse threshold distance matrix for China's new urbanization from 2011-2019, respectively.

Table 5. New urbanization, Moran's I index.

Year	Adjacency matrix			Inverse threshold distance matrix		
	I	z	p-value*	I	z	p-value*
2011	0.149	2.525	0.006	0.155	3.984	0.000
2012	0.150	2.534	0.006	0.159	4.075	0.000
2013	0.228	3.816	0.000	0.213	5.421	0.000
2014	0.240	4.025	0.000	0.240	6.093	0.000
2015	0.248	4.160	0.000	0.232	5.896	0.000
2016	0.263	4.397	0.000	0.245	6.229	0.000
2017	0.274	4.586	0.000	0.266	6.758	0.000
2018	0.311	5.188	0.000	0.313	7.931	0.000
2019	0.282	4.706	0.000	0.305	7.711	0.000

From Table 5, it can be seen that: first, the Moran's I value of the adjacency matrix is in the range of 0.149 to 0.311, indicating that there is a positive spatial correlation between the new urbanization of each city. That is, the new urbanization of a city will have a positive impact on the new urbanization of cities in neighboring provinces, and it shows a yearly strengthening trend from 2011 to 2018, with only a slight decrease in 2019, but still at a high level. Secondly, the Moran's I value of the inverse threshold distance matrix is between 0.155 and 0.313, and has shown a yearly strengthening trend since 2011.

In addition, the Moran's I value of the inverse threshold distance matrix is higher than that of the neighboring matrix as a whole, indicating that there is not only a spatial correlation in geographic location but also a positive spatial correlation in the economy for the new urbanization of each city. It indicates that a certain city with a high level of economic development will have a positive influence on the new urbanization of the surrounding neighboring cities.

5. Heterogeneity Analysis

The promotion effect of new urbanization may also be heterogeneous in its spatial distribution. Since there are large differences in factor endowments between Chinese cities, and cities with larger administrative levels and scales have rich factor possessions and economic development advantages, there will also be regional heterogeneity in spatial spillover effects. On the one hand, enterprises tend to re-industrial agglomeration, technological spillover, and scale economies due to the triple factor incentives, and they prefer to cluster in the larger or higher administrative level of the city radiation belt. On the other hand, in terms of the spatial spillover effect of new urbanization, the economic strength of the city is stronger, and the population size is often more likely to play the role of economies of scale, becoming a spatial agglomeration of the 'centripetal force'.

Therefore, the magnitude of the impact of new urbanization on the promotion of total factor productivity is influenced by the urban area. For example, in regions where the pilot cities of the new urbanization policy are concentrated, new urbanization may have a promotional effect on total factor productivity mainly through diffusion, while in regions where new urbanization itself is more developed, it may have a "siphoning effect" on the total factor productivity of the surrounding regions, which is not conducive to the development of total factor productivity in the neighboring regions. Therefore, it is necessary to analyze the spatial effect of total factor productivity of new urbanization in terms of urban heterogeneity.

5.1. City-Level Heterogeneity

We have categorized the city levels into Tier 1 cities, Tier 2 cities, and cities below Tier 3 (including Tier 3) based on the latest Chinese city grading list. See Wang, Li, and Jiang (2022) for specific divisions of the city. The regression estimation of city-level heterogeneity was carried out according to the set SDM model, and the estimation results are shown in Table 6.

According to the heterogeneity regression results of city level in Table 6, the spatial spillover effect of new urbanization on total factor productivity is most significant in second-tier cities and third-tier and lower cities, with the impact coefficients of 15.316 and 18.720, respectively, and all of them are significant at the 1% level. This suggests that second-tier and third-tier and lower cities are the main choices for new urbanization policy pilots and are the primary direction of new urbanization policy pilots. Therefore, the spatial diffusion effect of technological innovation and so on brought about by them can be maximized. That is to say, the development of new urbanization in this region will lead to the growth of total factor productivity in the surrounding areas and have a positive impact on them. The coefficient of the spatial spillover effect of the new urbanization of first-tier cities on total factor productivity is -3.201 and is insignificant.

This result can reflect that the spatial effect of the first-tier cities on the surrounding areas is more of a "siphon effect"; i.e., the first-tier cities, due to the business environment and career development opportunities, will attract the inflow of population and capital from the surrounding cities, which is not conducive to the economic development of the neighboring areas and the improvement of total factor productivity.

5.2. Regional Heterogeneity Analysis

Due to the imbalance of development between regions in China, we divide cities into eastern, central, and western cities based on their location (Zhou & Li, 2023). The results of the regional heterogeneity estimates are shown in Table 7. As can be seen from the results of the regional heterogeneity regression in Table 7, the spatial impact coefficients of new urbanization on total factor productivity in eastern, central, and western cities are -0.344, 5.220, and 1.845, respectively, and none of them are significant. However, the impact coefficients in central and western cities are positive. This result suggests that the spatial effect of central and western cities on the surrounding areas is more of a 'diffusion effect,' while the spatial effect of eastern cities may have a 'siphon effect'; however, this spatial effect is not significant.

Table 6. Regression results for city-level heterogeneity.

Variable	(1)	(2)	(3)
	Tier 1 cities	Tier 2 cities	Cities below Tier 3 (Including Tier 3)
Main			
NewUrban	-0.107 (-0.15)	3.715*** (4.17)	-1.260*** (-2.97)
lnpergdp	0.227 (0.77)	-0.100 (-0.97)	0.281*** (4.65)
lntrade	-0.175** (-2.05)	-0.0978** (-2.16)	-0.026* (-1.94)
lnedu	-0.586** (-1.99)	0.052 (0.33)	-0.114** (-2.06)
lngreen	-0.423* (-1.76)	-0.350*** (-3.31)	-0.181*** (-7.65)
lndeposit	-0.512 (-1.12)	-0.503*** (-3.29)	0.273*** (2.93)
lndigeco	-0.005 (-0.03)	-0.065 (-0.91)	0.016 (0.81)
Wx			
NewUrban	-3.201 (-0.64)	15.316*** (4.18)	18.720*** (4.00)
lnpergdp	4.340** (2.33)	-0.197 (-0.70)	-2.558*** (-7.27)
lntrade	-0.898** (-2.10)	-0.587** (-2.52)	-0.276* (-1.95)
lnedu	-3.294* (-1.88)	0.603 (0.78)	0.481 (1.22)
lngreen	-1.941 (-1.52)	0.336 (0.81)	-1.602*** (-5.19)
lndeposit	3.784 (1.47)	0.286 (0.29)	-0.757 (-0.93)
lndigeco	-3.367*** (-4.63)	-0.461 (-1.09)	-0.206 (-0.79)
Spatial			
rho	-0.317 (-1.06)	-0.948*** (-5.16)	0.633*** (6.47)
Variance			
sigma2_e	0.018*** (6.96)	0.024*** (9.60)	0.046*** (27.17)

Note: Standard errors are in parentheses; *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively.

Table 7. Regional heterogeneity results.

Variable	(1)	(2)	(3)
	Eastern cities	Central cities	Western cities
Main			
NewUrban	1.388*** (3.56)	0.862* (1.84)	0.153 (0.30)
lnpergdp	0.150 (1.58)	0.407*** (5.41)	0.104 (1.00)
lntrade	-0.127*** (-3.02)	0.006 (0.36)	-0.005 (-0.27)
lnedu	-0.053 (-0.51)	-0.129* (-1.75)	-0.087 (-0.90)
lngreen	-0.254*** (-4.38)	-0.104*** (-3.90)	-0.202*** (-3.79)
lndeposit	0.274** (2.17)	-0.053 (-0.39)	0.088 (0.56)
lndigeco	0.018 (0.46)	-0.055* (-1.92)	0.107*** (3.19)
Wx			
NewUrban	-0.344 (-0.15)	5.220 (1.30)	1.845 (0.38)
lnpergdp	-2.033*** (-5.09)	-0.823*** (-2.62)	-0.726 (-1.22)
lntrade	-1.395*** (-4.42)	-0.125 (-1.16)	-0.272 (-1.62)
lnedu	1.706*** (3.62)	-0.990* (-1.94)	0.855 (1.25)
lngreen	1.344*** (2.58)	-0.626** (-2.46)	0.117 (0.21)
lndeposit	-0.596 (-0.59)	-1.198 (-1.38)	1.527 (1.14)
lndigeco	-0.185 (-0.69)	0.163 (0.57)	-0.653** (-2.00)
Spatial			
rho	0.595*** (6.15)	0.453*** (3.73)	-0.129 (-0.59)
Variance			
sigma2_e	0.0462*** (17.38)	0.0328*** (18.49)	0.0472*** (15.58)

Note: Standard errors are in parentheses; *, **, and *** indicate significant at the 10%, 5%, and 1% levels, respectively.

5.3. Heterogeneity Analysis of Whether a City is a Provincial Capital

China's capital cities are economically developed and have a siphoning effect on talent and resources from neighboring cities. For this reason, we divided the sample into capital cities and non-capital cities for regression, and the regression results are shown in Table 8. As shown in Table 8, the spatial spillover effect of new urbanization in non-capital cities on total factor productivity is more significant, with an impact coefficient of 16.067, which is significant at the 1% level. This indicates that non-capital cities are the main choice of cities for new urbanization policy pilots, which can maximize the spatial diffusion effect of knowledge spillover. That is to say, the development of new urbanization in non-capital city areas will lead to the growth of total factor productivity in the surrounding areas and have a positive impact on them.

The coefficient of the spatial spillover effect of new urbanization on total factor productivity in provincial capital cities is -4.7703 and is not significant. Although it is not significant, the coefficient is negative, which can reflect that provincial capital cities have the same characteristics as first-tier cities and eastern cities; that is, their spatial effect on neighboring areas is more of a "siphon effect."

That is, as economic and political centers, provincial capital cities often have more developed infrastructure and investment convenience, which may attract the flow of population and capital to their surrounding cities, which is not conducive to the economic development and total factor productivity of the surrounding areas.

Table 8. Results from regressions of heterogeneity in whether a city is a provincial capital.

Variable	(1)	(2)
	Provincial capital cities	Non-provincial capital cities
Main		
NewUrban	1.384*** (2.76)	-0.019 (-0.05)
lnpergdp	-0.034 (-0.17)	0.267*** (4.85)
lntrade	-0.041 (-1.26)	-0.019 (-1.42)
lnedu	0.208 (1.54)	-0.108** (-1.98)
lngreen	-0.173 (-1.24)	-0.176*** (-7.48)
lndeposit	-0.164 (-1.17)	0.174** (1.97)
lndigeco	0.021 (0.29)	0.025 (1.24)
Wx		
NewUrban	-4.770 (-1.42)	16.067*** (5.17)
lnpergdp	-4.798*** (-3.61)	-2.260*** (-6.57)
lntrade	0.076 (0.49)	-0.302** (-2.05)
lnedu	0.934 (1.30)	0.520 (1.24)
lngreen	-0.786 (-0.82)	-1.583*** (-5.07)
lndeposit	2.005** (1.97)	-1.976** (-2.27)
lndigeco	0.199 (0.54)	-0.207 (-0.77)
Spatial		
rho	-0.558** (-2.02)	0.687*** (7.90)
Variance		
sigma2_e	0.0138*** (8.33)	0.0463*** (28.50)

Note: Standard errors are in parentheses; **, and *** indicate significant at the 5%, and 1% levels, respectively.

6. Conclusion

This paper empirically examines the spatial impact effect of new urbanization construction on total factor productivity (TFP) by using a spatial Durbin model on panel data from 199 prefecture-level cities in China. The results show that (1) the Moran's I value of China's new urbanization, based on the adjacency matrix and the inverse threshold distance matrix, indicates that new urbanization has a spatial positive impact on TFP and there is a spatial spillover effect. (2) The results of the heterogeneity analysis show that the spatial effect influence of new urbanization on total factor productivity exhibits obvious city-level heterogeneity and regional heterogeneity. (3) The spatial spillover effect of new urbanization on total factor productivity is most significant in second-tier cities, third-tier cities, and the following cities; the spatial effect of central and western cities on the surrounding areas has a 'diffusion effect', while the spatial effect of eastern cities has a 'siphon effect'. There is a 'diffusion effect' in the spatial effect of central and western cities on the surrounding areas, while there is a 'siphoning effect' in the spatial effect of eastern cities, neither of which is significant; the spatial spillover effect of new urbanization on total factor productivity is more significant in non-provincial capital cities.

Therefore, it is important to seize the opportunity of new urbanization to develop the economy in accordance with local conditions and to strengthen interregional exchanges and learning. To this end, it is necessary to combine the characteristics of the industrial and economic development of the region and the neighboring regions. On the one hand, develop the regional economy in accordance with local conditions, taking into account the region's own geographic advantages and resource endowment base. Formulate economic development policies in a targeted manner and explore the development paths of the new type of urbanization with their own characteristics in order to enhance total factor productivity. On the other hand, strengthen communication and exchanges between the regions to avoid homogeneous industrial competition. The experience of the pilot reforms of new urbanization should be better absorbed by exploring staggered competition and differentiated development, so as to maximize the use of regional advantages to develop their own economies and enhance total factor productivity.

References

Avila, A. F. D., & Evenson, R. E. (2010). Total factor productivity growth in agriculture: The role of technological capital. *Handbook of Agricultural Economics, 4*, 3769-3822. https://doi.org/10.1016/S1574-0072(09)04072-9

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis, 3*, 153-169. https://doi.org/10.1007/BF00158774

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325-332. https://doi.org/10.1007/BF01205442

Bertinelli, L., & Black, D. (2004). Urbanization and growth. *Journal of Urban Economics, 56*(1), 80-96. https://doi.org/10.1016/J.JUE.2004.03.003

Brenner, N. (2013). Theses on urbanization. *Public Culture, 25*(1), 85-114. https://doi.org/10.1215/08992363-1890477

Burgess, R., & Venables, A. J. (2004). *Towards a microeconomics of growth.* Retrieved from https://www.lse.ac.uk/economics/Assets/Documents/personal-pages/robin-burgess/microeconomics-of-growth.pdf

Chen, M., Liu, W., Lu, D., Chen, H., & Ye, C. (2018). Progress of China's new-type urbanization construction since 2014: A preliminary assessment. *Cities, 78*, 180-193. https://doi.org/10.1016/J.CITIES.2018.02.012

Chen, M., Ye, C., Lu, D., Sui, Y., & Guo, S. (2019). Cognition and construction of the theoretical connotations of new urbanization with Chinese characteristics. *Journal of Geographical Sciences, 29*, 1681-1698. https://doi.org/10.1007/s11442-019-1685-z

Driffield, N. (2001). The impact on domestic productivity of inward investment in the UK. *The Manchester School, 69*(1), 103-119. https://doi.org/10.1111/1467-9957.00237

Fang, C. (2022). On integrated urban and rural development. *Journal of Geographical Sciences, 32*(8), 1411-1426. https://doi.org/10.1007/s11442-022-2003-8

Henderson, J. V. (2005). Urbanization and growth. *Handbook of Economic Growth, 1*, 1543-1591. https://doi.org/10.1016/S1574-0684(05)01024-5

Henderson, V. (2003). The urbanization process and economic growth: The so-what question. *Journal of Economic Growth, 8*, 47-71. https://doi.org/10.1023/A:1022860800744

Karras, G. (2010). Land and population growth in the Solow growth model: Some empirical evidence. *Economics Letters, 109*(2), 66-68. https://doi.org/10.1016/j.econlet.2010.08.019

Kumar, A., & Kober, B. (2012). Urbanization, human capital, and cross-country productivity differences. *Economics Letters, 117*(1), 14-17. https://doi.org/10.1016/J.ECONLET.2012.04.072

Landes, D. S. (2003). *The unbound Prometheus: technological change and industrial development in Western Europe from 1750 to the present*: Cambridge University Press. https://doi.org/10.1017/CBO9780511819957.

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics.* New York: Chapman and Hall, CRC.

Li, G., & Wang, L. (2023). Study of regional variations and convergence in ecological resilience of Chinese cities. *Ecological Indicators, 154*, 110667. https://doi.org/10.1016/j.ecolind.2023.110667

Liang, Q., & Wang, W. (2022). Trade openness, public human capital and total factor productivity. *Statistics & Decision, 38*(10), 136-140. https://doi.org/10.13546/j.cnki.tjyjc.2022.10.027

Liang, W., & Yang, M. (2019). Urbanization, economic growth and environmental pollution: Evidence from China. *Sustainable Computing: Informatics and Systems, 21*, 1-9. https://doi.org/10.1016/J.SUSCOM.2018.11.007

Lipsey, R. G., & Carlaw, K. I. (2004). Total factor productivity and the measurement of technological change. *Canadian Journal of Economics/Revue canadienne d'économique, 37*(4), 1118-1150. https://doi.org/10.1111/j.0008-4085.2004.00263.x

Liu, Y., Ouyang, Y., & Cai, H. (2021). Evaluation of China's agricultural green TFP and its spatiotemporal evolution characteristics. *Quantitative Economic and Technological Economic Research, 38*(05), 39-56. https://doi.org/10.13653/j.cnki.jqte.2021.05.003

Sargent, T. C., & Rodriguez, E. R. (2001). *Labour or total factor productivity: Do we need to choose?* Ottawa, ON, Canada: Department of Finance.

Van Ark, B. (2014). *Total factor productivity: Lessons from the past and directions for the future (No. 271).* NBB Working Paper.

Wang, X.-R., Hui, E. C.-M., Choguill, C., & Jia, S.-H. (2015). The new urbanization policy in China: Which way forward? *Habitat International, 47*, 279-284. https://doi.org/10.1016/J.HABITATINT.2015.02.001

Wang, Y., Li, S., & Jiang, Y. (2022). Can transportation infrastructure construction improve the urban green development efficiency? Evidence from China. *Sustainability, 14*(21), 14231. https://doi.org/10.3390/su142114231

Williamson, J. G. (1988). Migration and urbanization. *Handbook of Development Economics, 1*, 425-465. https://doi.org/10.1016/S1573-4471(88)01014-9

Yu, B. (2021). Ecological effects of new-type urbanization in China. *Renewable and Sustainable Energy Reviews, 135*, 110239. https://doi.org/10.1016/j.rser.2020.110239

Yu, J., Zhang, R., & Gong, X. (2022). How does digital finance affect green total factor productivity: Characteristic of dynamics, identification of mechanism and spatial effects. *Modern Economic Science, 44*(6), 42-56.

Zhou, Y., & Li, S. (2023). Can the innovative-city-pilot policy promote urban innovation? An empirical analysis from China. *Journal of Urban Affairs, 45*(9), 1679-1697. https://doi.org/10.1080/07352166.2021.1969243