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EFFECT OF URBAN INNOVATION ON LAND FINANCE DEPENDENCE: EVIDENCE FROM 233 CHINESE CITIES

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Abstract. Unlike most studies on urban innovation, which focus on the effects of land-use policies, this study investigates the effect of urban innovation (UI) on land finance dependence (LFD). In China, innovation-related policies are intended to create a shared business environment where new entrepreneurs can contribute to achieving sustainable economic growth. This study analyzes the spatiotemporal dynamics of LFD and UI from 2005 to 2019 using the spatial autocorrelation model and dynamic spatial Durbin model. It finds a positive spatial association between LFD and UI throughout the studied regions during the study period. It also reveals a significant inhibitory effect of UI on LFD and a negative impact on the LFD of neighbouring cities. Moreover, the inhibitory effects will increase over time. Lastly, this study shows varied impacts of UI on LFD in different regions, especially in eastern China. Important policy recommendations for high-quality development in China are provided.

Keywords: urban innovation, land finance dependence, spatial Durbin model, land-use policies, different regions, high-quality development.

Introduction

Land finance is an essential economic driver that not only generates a staggering amount of financial support for urban infrastructure (Zhong et al., 2019) but also serves as a solid base for governments to invite investment (Wang & Hou, 2021). According to the Treasury Department, China's land transfer income saw rapid growth, rising from 0.59 billion yuan in 2005 to 7.25 billion yuan in 2019 and accounting for over 70% of the government's budget revenue. However, given limited land resources, heavy dependence on land finance may lead to a high debt risk (Gyourko et al., 2022) and inefficient land use (Wei et al., 2017; Zhong et al., 2022), and hinder population growth (Liu et al., 2022). At the 19th Chinese National Congress of the Chinese Communist Party, President Xi Jinping proposed to accelerate the financial coordination between the central and local governments. Although this policy has prevented unrestrained urban sprawl, land finance dependence remains high. Only by changing the rigid development pattern of obtaining income sources can the country maintain its economic growth momentum and effectively transition into a phase of high-quality development (Han et al., 2022; Wang & Zhang, 2022). This study examines the multifaceted factors influencing land finance dependence (LFD), particularly the role of urban innovation (UI) in reducing such dependence. The relevant literature focuses mainly on the factors influencing LFD, and the effects of UI.

What is the cause of China's heavy dependence on land finance? Previous studies agree on the connection between government policies and land expansion in cities (Niu et al., 2022). Researchers concur that the 1994 tax-sharing reform laid the basis for land finance (Xu, 2019) and broadened the gap between local government income and expenditure. Under the institutional setting, the essence of this reform was the decentralization of fiscal responsibilities, presenting a phenomenon where the local revenue sharply decreased while the local expenditure increased. Faced with the pressure of budget deficits, local governments urgently need to increase their revenues to compensate for these deficits. A land market system monopolized by local governments is also an indispensable institutional factor. With economic development, the increased demand for construction land

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and the shortage of land resources has become a principal contradiction in China (Fan et al., 2020). Given limited land resources, local governments must decide how to relieve this pressure effectively through other means.

One possible solution to reduce LFD is to foster UI. When governments face fiscal pressure, two typical channels may offset the deficit (Guo, 2008; Wu et al., 2015): increasing nonbudgetary income, which mainly consists of land transfer premiums, or enhancing local economic development to boost budgetary tax revenue. An increase in the former may effectively reduce local government's reliance on the latter. The effects of UI on economic development have been studied extensively. Some scholars believe that new products and technologies can stimulate residential demand and consumption (Cao et al., 2020; Liu et al., 2021), thereby promoting local economic growth. In addition, the evolution of the industrial structure will improve resource use efficiency (Petrariu et al., 2013; Zhu et al., 2019) and thereby increase firm profitability and taxpaying capacity. As a catalyst, UI has sparked transformation and growth in the economy and society, which has the potential to boost government budgetary tax revenue and inhibit dependence on land finance.

However, few studies have explored the impact of urban innovation-related policies on land resources, which could alleviate this problem. As virtual platforms for businesses, cities have gradually become the central factor and unit of analysis for innovation (Florida et al., 2017; Martin & Sunley, 2008). Moreover, the central government has adopted an innovation-oriented development policy (State Council of China, 2016) that emphasizes the crucial role of innovation in raising social productivity. This policy is intended to create a shared business environment for new entrepreneurs and facilitate the establishment of new businesses to achieve sustainable economic growth for China. The potential long-term revenue from increased UI can alleviate financial crises within the government and change the traditional thinking of paying off debt through land transfers.

Relevant research on innovation related to land has tended to focus on topics such as land sprawl and marketization (Cheng et al., 2022; Tan et al., 2021). However, the impact of UI on land resources remains underexplored. This study has three main contributions. First, it places UI and LFD in the same analytical framework and explains the possible links between the two. Second, it considers the spatial spillover effects of LFD and UI using spatial econometric models to examine their relationship. Finally, it reveals regional differences at the city level, which are more accurate and credible than those shown in provincial-level studies.

The remainder of the study is structured subsequently. In Section 1, we provide the theoretical background and hypotheses. Section 2 presents the empirical data and methodology. In Section 3 we describe the spatial distribution of UI and LFD and analyze the impact of UI on land financing. Finally, we summarize our findings and offer policy recommendations.

1. Theoretical background and hypothesis

According to "Tobler's First Law" (Tobler, 1970), UI is typically accompanied by a knowledge spillover effect, a process of spreading knowledge (through certain methods) among organizations or enterprises (Xie et al., 2021). Because most economic activities occur in cities, increasing focus has been placed on the connection between regions. However, China has a vast landmass and a significant UI development gap. Meanwhile, this differentiation has led to increasingly close inter-regional ties because knowledge more easily flows locally than distantly (Marshall, 1920). Specifically, a positive spatial correlation exists among neighbouring cities in terms of UI. Several studies have confirmed the spatial correlation of innovation across different scopes (Peng et al., 2021; Shang et al., 2022; Tan et al., 2021). For example, at the company level, once innovation has been developed, information concerning its operations may quickly be known to rival firms (Mansfield, 1985).

A related topic is the dependence on land finance. Assuming that local governments are rational, they will make reasonable decisions and avoid risks. Given the pressure on officials regarding promotion and performance evaluation by superior governments, China's unique performance evaluation mechanism exposes local governments' land finances to competition or cooperation, especially across geographically adjacent regions (Wang et al., 2021; Zeng, 2019). These local governments must ensure a greater economic growth rate than their peers to attract investment; that is, their actions may depend on and affect government actions in nearby areas (Liu et al., 2018; Wu et al., 2015). Consequently, governments have a strong incentive to pursue land finance and implement similar land transfer strategies. Given the dependence on land finance, which is a comprehensive indicator that effectively measures the extent to which a government relies on revenue from land sales to maintain normal operations (Lu et al., 2019; Mo, 2018; Tang et al., 2014), how will changing the LFD of a region affect the LFD of neighbouring regions? Does land finance dependence in Chinese cities exhibit a positive spatial correlation? Accordingly, we propose

Hypothesis 1: Both urban innovation and land finance dependence have positive spatial correlations in Chinese cities.

Local governments, acting as "rational men", are inclined to pursue the most profitable option. Under the institutional setting of tax-sharing reform, the essence of this reform was the decentralization of fiscal responsibilities, presenting a phenomenon where the local revenue sharply decreased while the local expenditure increased. Local governments typically have two options for offsetting shortfalls when faced with growing fiscal pressure. The first is enhancing local economic development to boost budgetary tax revenues. The second is increasing non-budgetary income to increase the tax base, mainly land transfer premiums (Guo, 2008). During economic downturns, there is a higher availability of excessive land transfer. For instance, land sales revenues have been increasingly promoted to offset the impact of the 2008 financial crisis. However, this option leads to the depletion of the long-term development potential at the expense of land resources. The substitution of land resource consumption with technological innovation for economic growth leads to lower dependence on land finance, thus resulting in high-quality development (Cao et al., 2020; Su et al., 2022).

The relationship between economic growth and innovation is of significant interest to researchers. This topic originated in a study by Solow (1956), who pointed out the existence of a long-term relationship between economic growth and innovation. As a key driver of economic growth, UI indirectly boosts government revenue. First, according to the endogenous economic growth model, enterprises can continuously introduce new products, technologies, and services to stimulate market demand, expand the market scale, stimulate resident consumption, promote local economic growth, and increase local government tax revenue (Petrariu et al., 2013). Meanwhile, UI improves enterprise technology, progress, competitiveness, and the evolution of the industrial structure (Clark, 1940; Rostow, 1959) to improve resource use efficiency and thereby increase firm profitability and taxpaying capacity, which promotes the growth of local tax revenue. Consequently, the government gains more sources of fiscal revenue than simply relying on land transfer income, thus reducing dependence on land finance.

Combined with Hypothesis 1, it is natural to conclude that a city's dependence on land finance is not only decreased by the level of local UI but also by the UI of neighbouring cities. However, few studies have captured spillover effects using a spatial economic analysis with panel data. We propose two paths in which UI significantly restrains the LFD of surrounding cities: one is technology innovation flow into the neighbouring cities, which boosts government revenue and thereby restrains the dependence on land finance (UI → W × UI → W × LFD). However, officials' strategies may depend on and affect their peer governments' strategies. If city clusters lack UI, learning and competitive relationships between areas could lead to an increase in land transfer fees in both areas (UI → LFD → W × LFD). In addition, urban innovation takes time to spread after they are born in a cluster. Only when people understand and adopt the information about the innovation can the source of innovation diffusion increase (Rogers, 1962). Thus, we propose

Hypothesis 2: Urban innovation has a significant restraining effect on the dependence of a city and its surrounding cities on land finance, which is increasing over time.

Potential revenue incentives brought from UI in different regions may have different effects on the LFD. The impact of UI on LFD might have spatial heterogeneity, owing to uneven resource usage and economic growth across different areas. The industrial structure of the eastern region is dominated by tertiary industries, whereas the central and western regions are rich in natural resources and their innovation ability is weaker (Ai et al., 2022; Ke et al., 2021; Liu & Dong, 2021). The eastern regions are densely populated and have limited land area, resulting in scarce land resources; however, because they have better economic and technological conditions, the degree of land use and land prices are relatively high (Fan et al., 2020). Owing to excellent technological development and abundant scientific resources in the eastern region, the contribution of innovation brings a much higher local revenue than in the midwestern region (Liu & Fan, 2020). As a result, the rising level of technological innovation boosts resident consumption, continuously improves and upgrades the industrial structure, and increases local government revenues outside of land transfer fees. As such, UI may have a bigger impact on LFD in the eastern region than it does in other regions (Ke et al., 2021). Therefore, we propose

Hypothesis 3: Urban innovation has different effects on land finance dependence in different regions.

2. Data and methodology

2.1. Data

This study analyzes 233 prefecture-level cities from 2005 to 2019. Because of difficulties in obtaining data for four provinces (Xinjiang, Tibet, Qinghai, and Gansu), Hong Kong, Macao, and Taiwan, these areas are not included in the scope of the present research.

We use the share of land transfer fees in overall budget revenue (general budget revenue plus land transfer fees) to measure the dependent variable, land finance dependence (Lu et al., 2019; Mo, 2018), which reflects how heavily local governments rely on land finance. Prior studies have applied narrow and broad metrics to measure LFD; these metrics are divided into three categories comprising (1) only land transfer fees; (2) non-tax revenues, land transfer fees, and land-related taxes; and (3) the metrics appearing in (2) plus land debt, mortgage, and related financing income (Tang et al., 2014; Wei & Lu, 2021). We refer to the first category because land transfer fees are the main incentive for local governments, and other taxes and fees are less easily attributed to a particular land transfer (Fan et al., 2020).

This study selects the City and Industrial Innovation Index compiled by Fudan University as the independent variable measuring urban innovation (UI) (Kou & Liu, 2020), and the index in the subsequent year is computed using the growth rate, to increase the number of samples.

Based on an extensive literature review, we select the following four indicators related to LFD as control variables: financial and administrative power imbalances (PPI), land marketization level (LML), government capital competition (ADI), and land urbanization level (UOL). PPI is measured as the ratio of fiscal revenue to fiscal expenditure (Tang et al., 2014). The LML is measured based on the proportion of land bidding, auctions, and hanging out in land transfers (Mou & Qian, 2018). The ADI is calculated using foreign investment per capita in the region (Head & Ries, 1996). The UOL is measured as the proportion of built-up area to the total land area within the jurisdiction

Table 1. Variable selection and statistics

Variables	Definition	Data source	Unit	Mean	Std. Dev.	Min	Max
Dependent variable							
LFD	The share of land transfer fees in the overall revenue budget	Data from 2005–2017 are from the China City Statistical Yearbook (2006–2018); Data from 2018–2019 from China Land Market Network	2,844	0.346	0.141	0.001	0.921
Independent variable							
UI	Urban Innovation Index	FIND Report on City and Industrial Innovation in China	2,844	9.418	45.624	0.006	849.057
Control variable							
PPI	The proportion of fiscal revenue to fiscal expenditure	China City Statistical Yearbook (2006–2020)	2,844	0.513	0.223	0.065	1.541
LML	The proportion of land bidding, auction and hanging out in the land transfers	Land data from 2005–2017 are from the China City Statistical Yearbook (2006–2018); Land data from 2018–2019 from the China Land Market Network	2,844	0.631	0.288	0.001	1.000
ADI	Utilized foreign investment per capita	China City Statistical Yearbook (2006–2020)	2,844	165.611	288.626	0.074	2646.680
UOL	The proportion of built-up area in the total land area within the jurisdiction	China City Statistical Yearbook (2006–2020)	2,844	0.016	0.035	0.000	0.462

Note: Std. means standard deviation. *N* means number of observations.

(Ye & Wu, 2014). The details are presented in Table 1. Before importing the model, we logarithmized the metrics.

2.2. Methodology

2.2.1. Global Moran's I index

Global spatial autocorrelation is used to inspect the spatial dependence of the selected variables (Getis & Ord, 2010; Stone, 2014). The likeness in attribute values among geographically close or adjacent places is indicated by this index (ranging from –1 to 1). A low value denotes a geographically negative correspondence, whereas a high value denotes a spatially positive correlation. There is no spatial association if the value equals 0. The formula is as follows:

$$Moran's\, I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i - \bar{Y}\right)\left(Y_j - \bar{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}}; \quad (1)$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2. \quad (2)$$

where: n represents the count of cities; W_{ij} denotes the matrix of inverse distance spatial weight; Y_i and Y_j denote the land finance dependence of cities i and j; $\bar{Y}$ is the mean value, and S^2 is the variance.

2.2.2. Spatial econometric models

Theoretical and empirical analyses indicate that local governments' UI has significant indirect spatial effects that can influence local governments' interactions. To address this issue, we analyze the impact of UI on LFD using spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SMD) (Anselin, 1988). An SEM implies that the disturbance term is spatially dependent. By contrast, an SLM combines the space component and lag period of the explanatory variable representing the effect of the component on others. An SDM, which combines spatial elements and explanatory variables, can, in certain cases, be simplified to an SLM or SEM.

According to the theoretical assumptions in Section 1, a higher LFD worsens UI. A one-year delay can reduce a possible endogeneity problem in LFD; therefore, we include the explanatory variable's one-stage lag term in the dynamic spatial Durbin model (DSDM). The formula is as follows:

$$\begin{aligned} \ln LFD_{i,t} &= \alpha + \varphi \ln LFD_{i,t-1} + \lambda\left(W_{ij} \times \ln LFD_{i,t}\right) + \\ &\theta\left(W_{ij} \times \ln LFD_{i,t-1}\right) + \rho_1 UIL_{i,t} + \rho_2 (W_{ij} \times UIL_{i,t}) + \\ &\delta X_{i,t} + \mu_i + \gamma_i + \varepsilon_{i,t}, \end{aligned} \quad (3)$$

where: $LFD_{i,t}$ denotes the land finance dependence of the i^{th} region during the t^{th} year; $UIL_{i,t}$ denotes the urban innovation of the i^{th} region in the t^{th} year; $X_{i,t}$ denotes a set of control factors (PPI, LML, ADI, UOL); α represents the constant term; φ represents the time lag term coefficient; λ stands for the spatial lag term coefficient; θ represents the time and spatial lag term coefficient; ρ_1 stands for the coefficients of *UIL*; ρ_2 stands for the spatial lag term coefficients of *UIL*; δ is the control variable coefficient; μ_i, γ_i represent the unobserved spatial and temporal effects; $\varepsilon_{i,t}$ stands for the error term, and W_{ij} represents the spatial weight matrix.

Tests must be conducted to determine which model fits best (Elhorst, 2010). Several tests (such as the Lagrange multiplier test) are used to determine whether the model incorporates spatial interactions (Anselin, 1988).

The likelihood ratio (LR) test is also performed to determine whether the SDM can be streamlined to an SLM or SEM. Moreover, the fixed and random effects are chosen simultaneously using the Hausman test.

3. Results and discussion

3.1. Test based on a spatial model

3.1.1. Spatial autocorrelation test

To determine whether there was a spatial association between Chinese prefecture-level cities, the Global Moran's I indicator (GMI) was used. Table 2 shows GMI of LFD and the independent variable UI calculated using the Geoda software with W (inverse distance space weight matrix). All values from 2005 to 2019 were close to the 1% significance level and demonstrated a positive spatial association between LFD and UI throughout the regions. In light of this, Hypothesis 1 indicates that UI and LFD have a positive spatial correlation.

3.1.2. Model selection test

We found a spatial association between LFD and UI among cities and determined the most appropriate model using spatial econometric tests. Our findings are summarized in According to the Hausman test results, the SDM incorporating both spatial and time-fixed effects should be utilized, meaning that the hypothesis of random effects is rejected with a significance level of 1%.

Both the SLM and SEM results for the LM test were significant at the 1% level (Table 3). No spatial lag effect was disproved, thereby demonstrating spatial dependence within the data and highlighting that spatial panel models more suitable fit for estimation. Again, Hypothesis 1 holds. Both null hypotheses were significant in the LR and Wald tests at the 1% level, thus rejecting the assumption that the SDM can be simplified and confirming that the SDM is the best option for this study. According to the Hausman test results, the SDM incorporating both spatial and time-fixed effects should be utilized, meaning that the hypothesis of random effects is rejected with a significance level of 1%.

Table 2. Global spatial autocorrelation test

Year	Land finance dependence			Urban innovation		
	Moran's I	*z*-value	*p*-value	Moran's I	*z*-value	*p*-value
2005	0.441	16.274	0.000	0.105	4.020	0.010
2006	0.363	13.418	0.000	0.111	4.220	0.001
2007	0.281	10.432	0.000	0.012	0.809	0.418
2008	0.258	9.594	0.000	0.119	4.501	0.001
2009	0.310	11.486	0.000	0.153	5.762	0.001
2010	0.331	12.265	0.000	0.165	6.195	0.001
2011	0.261	9.747	0.000	0.182	6.831	0.001
2012	0.189	7.081	0.000	0.186	6.973	0.001
2013	0.292	10.854	0.000	0.193	7.215	0.001
2014	0.335	12.421	0.000	0.195	7.292	0.001
2015	0.233	8.672	0.000	0.205	7.669	0.001
2016	0.248	9.228	0.000	0.215	8.035	0.001
2017	0.356	13.159	0.000			
2018	0.373	13.792	0.000			
2019	0.407	15.067	0.000			

Table 3. Spatial econometric model tests results

Factors	Statistics	Factors	Statistics
LM test spatial lag	11.715***	LM test spatial error	0.040
	(0.00)		(0.841)
Robust LM test spatial lag	17.439***	Robust LM test spatial error	5.764**
	(0.00)		(0.02)
LR test spatial lag	23.29***	LR test spatial error	14.56***
	(0.00)		(0.00)
Wald spatial lag	25.39***	Wald spatial error	15.59***
	(0.00)		(0.01)
Hausman	16.460***		
	(0.00)		

Note: 1. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. 2. The coefficients' *p*-values are enclosed in parentheses.

3.1.3. Spatiotemporal analysis of LFD and UI

Land finance dependence: from a temporal perspective, China's LFD exhibited an oscillating upward trend from 2005 to 2019, which is typical of speculative funds. Specifically, three inflexions occurred in 2008, 2012, and 2016 (Figure 1). After 2008, LFD steadily increased, reaching 0.4176 in 2010. From 2010 to 2012, LFD showed a second negative growth of five per cent point. After experiencing a brief up-and-down period, LFD increased steadily, reaching 0.4483 in 2019.

To explore the spatiotemporal patterns of LFD, three representative years of LFD, namely, 2005, 2012 and 2019, were selected (Figure 2). We used the upper quartile value in 2005 (0.20) and the median values in 2012 (0.35) and 2019 (0.45) as criteria for developing the grading scale using ArcGIS10.8. Cities with high LFD (the darkest figure, above 45%) increased from 48 in 2005 to 118 in 2019, mostly located to the east of the "Hu line."

Anselin (1995) divides the local indicator of spatial autocorrelation (LISA). In this scheme "High-High" represents instances where higher values are found in proximity to neighbouring units with similarly higher values, signifying positive spatial autocorrelation. Conversely, "Low-Low" represents situations where lower values are clustered around neighbouring units exhibiting lower values, which also indicates positive spatial autocorrelation. For increased visual-spatial clustering, we synchronously drew a clustering map of LISA, which showed the following characteristics. In 2005, the low-low region (a spatial cluster with low values of LFD) was the largest among the different zones, with 42% of the cities exhibiting agglomeration, followed by the high-high region (a spatial cluster with high values of LFD). In 2019, the high-high areas became the largest, with a 47.7% share of agglomeration units. In the eastern coastal region, labour costs are high, but land resources are scarce, and inland cities are gradually transforming into sites with a high dependence on LFD. The distribution of the high-low and low-high types fell between that of the high-high and low-low types, and these two regional types exhibited significant variability with low levels of statistical significance.

The results showed the Yangtze Delta and the metropolitan agglomerations of Chengdu and Chongqing were the key locations of high-high regions. Low-low regions were primarily in northeastern China, a pattern consistent with economic growth and population distribution (Fan et al., 2020). Changes in the agglomeration pattern of LFD occurred mainly in Guangxi Province, evolving from low-low to high-low agglomeration, and finally to high-high agglomeration. The agglomeration types of LFD changed considerably in Chongqing Province.

Urban innovation: we found that from 2005 to 2019, UI capacity expanded from the eastern coastal region to the centre, which may be due to the impact of the 13th Five-Year Plan, which grouped innovative factors to create transregional innovation networks. Consequently, China's overall level of UIUI has increased since 2005. From a spatial perspective, UI is characterized by distinctive regional agglomeration, as is shown in Figure 3. Specifically, compared with other cities, cities on the eastern coast and developed industrial economy zones had higher levels of urban city innovation and showed the characteristics of spatial agglomeration. Overall, most cities remained at a low level of UI. In southwest China, Chongqing and Chengdu developed in the same direction, both showing a positive trend of high-quality development. However, the Chengdu–Chongqing region remained far from the state of the developed eastern regions in terms of overall strength and competitiveness.

The spatial agglomeration of UI had been continuously enhanced during the study period. In 2005, the high-high area (i.e., the neighbouring region of cities with high UI) had 27 cities centred on the Jing-Jin-Ji urban agglomeration and eastern seaboard. The breadth of high-high area increased to 40 units in 2019, including cities adjacent to the Yangtze River Delta urban agglomeration and Guangdong Province. In 2005, the low-low area, an aggregated region of units with low UI, comprised 24 cities centred in the southwest and northeast regions. The low-low region in 2019 showed a significant increase, spanning 10 cities, and the low-low region in the northeast expanded, whereas the low-low area in Guangxi Province disappeared. Overall, agglomeration due to UI increased during this period.

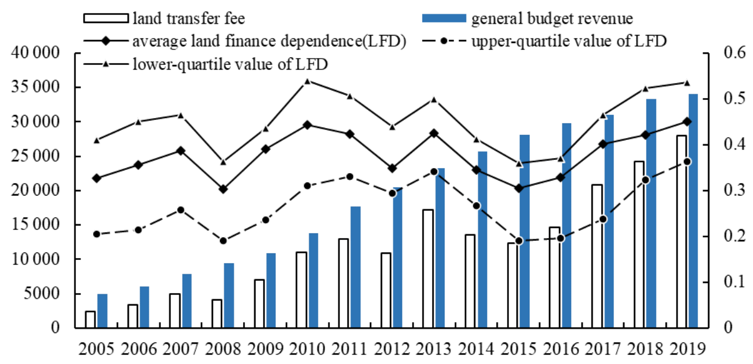

Figure 1. Average land finance dependence of 233 prefecture-level cities from 2005 to 2019

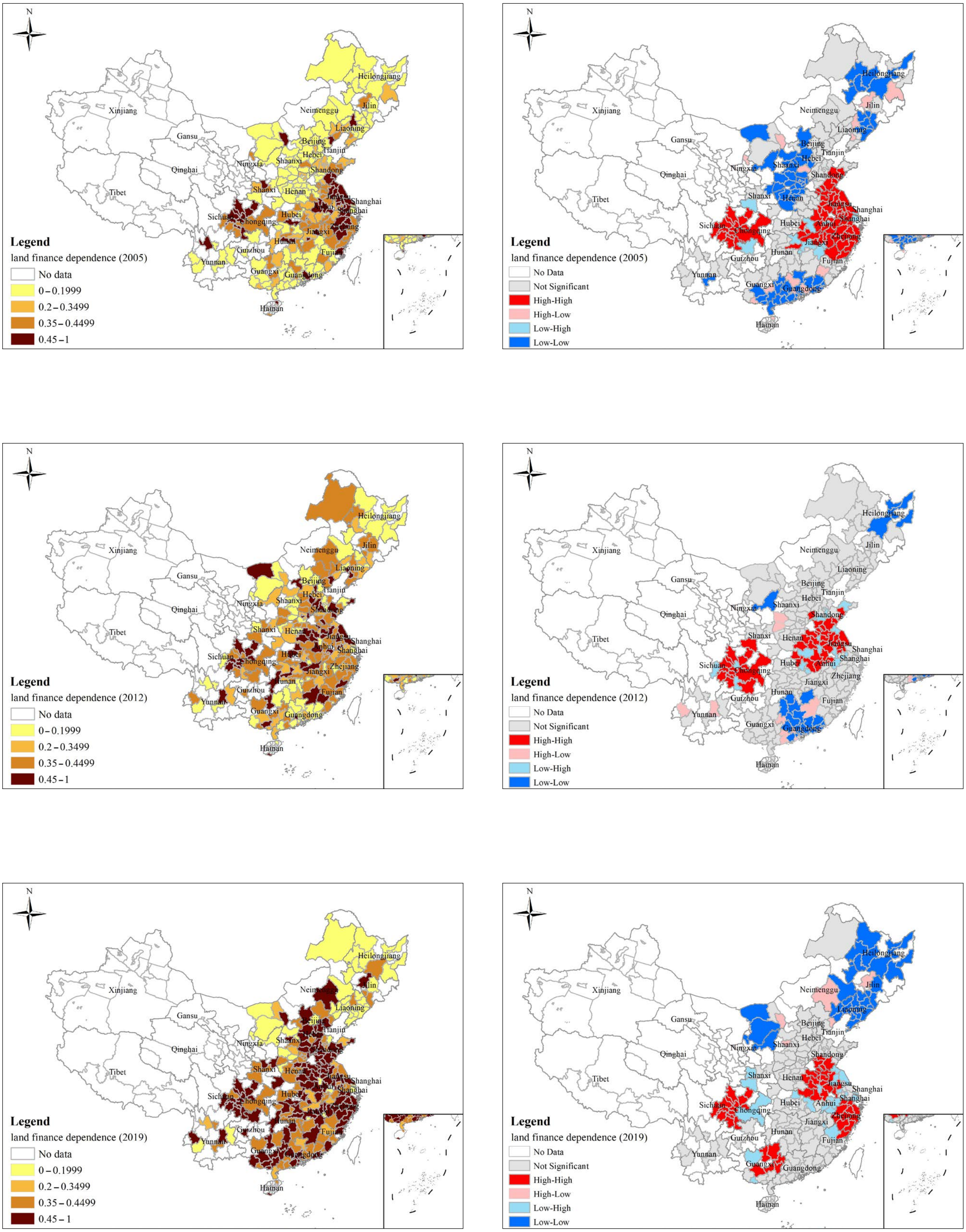

Figure 2. Spatiotemporal pattern and spatial agglomeration pattern of LFD in China (2005, 2012, 2019)

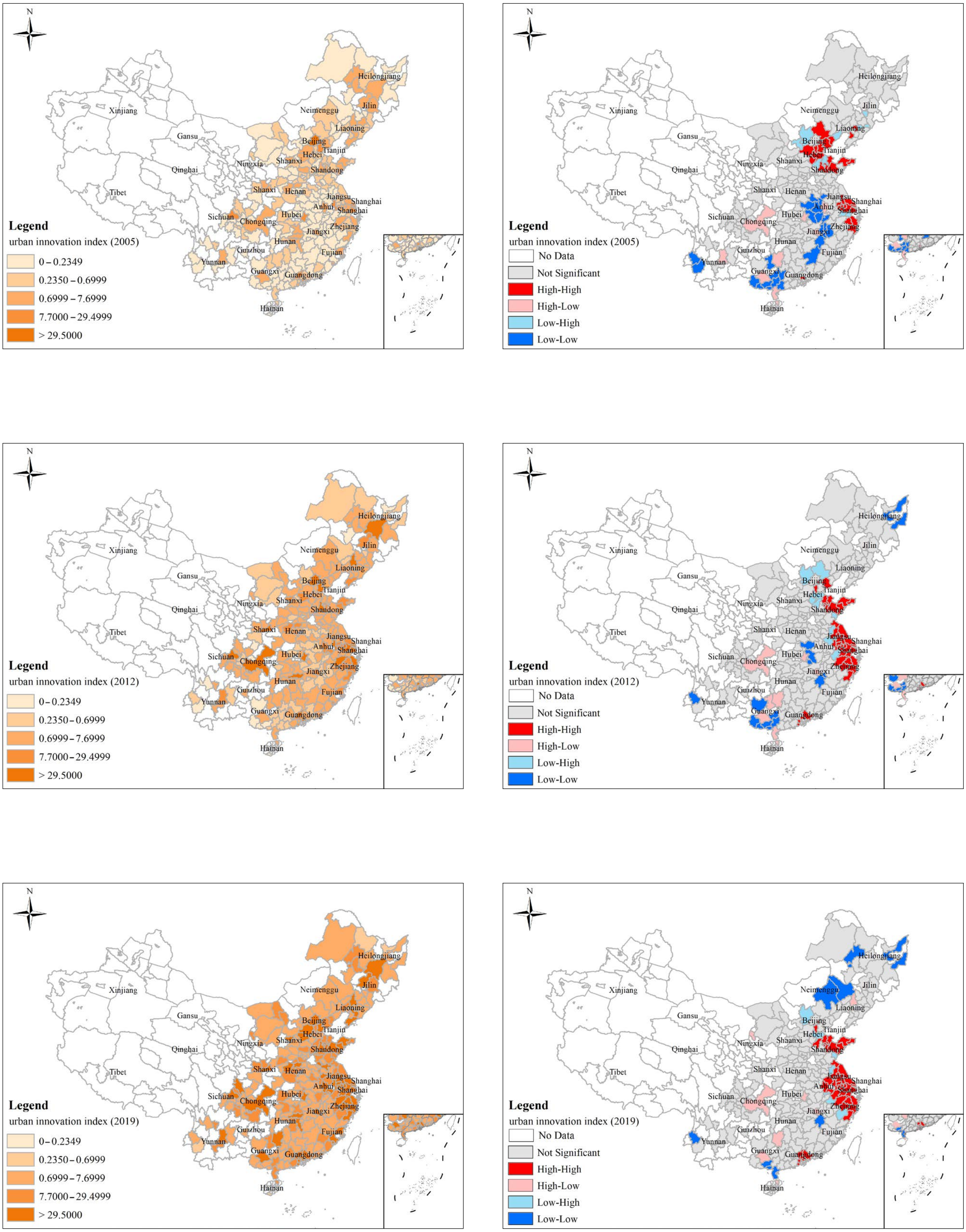

Figure 3. Spatiotemporal and spatial agglomeration patterns of UI in China (2005, 2019)

3.2. Regression results of UI on LFD in China

The global spatial autocorrelation analysis shown in Table 2 supports the spatial agglomeration of both LFD and UI. The results in Table 3 also demonstrate the accuracy of the selected spatial econometric models. Regression analysis was carried out using Stata 16 software to analyze the spatial spillover effects of UI on LFD. As presented in Table 4, we found that the model (4) had the best fitting specification for this investigation, according to an integrated examination of the estimated values of R^2 (0.1314), which was more significant than the estimates in the models (1)–(3). Therefore, the study that followed centred on the findings from model (4).

According to the one-stage time-lag coefficient (LFD_{t-1}), LFD in Chinese prefecture-level cities remained relevant over time. LFD exhibited significant short-term inertia dependence and continued to increase in the year after the city depended heavily on land finance. In particular, an average increase of 1% in LFD would lead to an increase of 0.340% the following year, which is consistent with the rapid industrialization and urbanization in China (Han et al., 2022). In terms of the spatial aspect, the spatial lag coefficient (W × LFD) was statistically significant at the 1% level, indicating that a rise of 1% in LFD in local regions would simultaneously result in a 0.825% upsurge in neighbouring regions. This result and GMI in Table 2 both support the spatial dependence of LFD at the prefecture level in Chinese cities. To be specific, a 1% growth in LFD in one region was linked with a 0.825% growth in LFD in neighbouring regions. The estimates for temporal and spatial lags (W × LFD_{t-1}) were significant at the 1% level in both the temporal and spatial dimensions: an average increase of 1% in UI within one region would result in a 0.284% decrease in UI in neighbouring regions the

Table 4. SDM estimated regression results

Factors	Model (1) Static Spatial Durbin model (Time-Fixed Effects)	Model (2) Dynamic Spatial Durbin model (Time-Fixed Effects)	Model (3) Dynamic Spatial Durbin model (Spatial-Fixed Effects)	Model (4) Dynamic Spatial Durbin model (Spatial-and Time-Fixed Effects)
LFD_{t-1}	–	0.722***	–	0.340***
		(–38.99)		(17.67)
W × LFD	0.562***	3.095***	0.833***	0.825***
	(5.76)	(82.87)	(–22.54)	(–22.36)
W × LFD_{t-1}	–	–	0.077	–0.284***
			(–1.06)	(–3.85)
UIL	–0.109***	–0.083**	–0.083**	–0.043*
	(–4.08)	(–3.14)	(–3.07)	(–2.02)
W × UIL	–0.015	0.227**	–0.241**	–0.259**
	(0.10)	(–2.56)	(–2.56)	(–2.83)
PPI	–0.278***	–0.016	–0.238***	0.100*
	(–5.75)	(–0.33)	(–4.82)	(–1.71)
W × PPI	1.189**	1.396***	0.146	0.0917
	(2.94)	(5.05)	(0.49)	(0.32)
ADI	0.028***	0.074***	0.031***	0.013
	(2.35)	(5.99)	(2.48)	(1.06)
W × ADI	0.019	–1.935***	0.073	0.099
	(0.20)	(–24.81)	(0.87)	(1.21)
UOL	0.060*	0.066*	0.091*	0.099**
	(1.83)	(1.81)	(2.45)	(–2.72)
W × UOL	1.474***	1.793***	1.497***	1.355***
	(3.69)	(4.32)	(3.46)	(3.21)
LML	–0.003	0.009	–0.001	0.008
	(–0.22)	(0.56)	(–0.07)	(0.49)
W × LML	–0.198*	0.498***	–0.101*	–0.100*
	(–1.91)	(8.53)	(–1.69)	(–1.71)
R^2	0.0026	0.0067	0.0781	0.1314
N	2844	2607	2607	2607

Note: 1. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. 2. The z values for the coefficients are in parentheses.

Table 5. Decomposition results of the DSDM

Factors	Short term			Long term		
	Direct impacts	Indirect impacts	Total impacts	Direct impacts	Indirect impacts	Total impacts
UIL	−0.049**	−1.748***	−1.796***	−0.074*	−2.714**	−2.788**
	(−1.91)	(−2.91)	(−3.01)	(−1.90)	(−1.98)	(−2.03)
PPI	−0.178***	−0.266	−0.443	−0.269***	−0.437	−0.706
	(−3.90)	(−0.17)	(−0.28)	(−3.90)	(−0.17)	(−0.27)
ADI	0.016	0.639	0.655	0.024	0.975	0.999
	(−1.34)	(−1.51)	(−1.55)	(1.33)	(1.23)	(1.26)
UOL	0.135***	8.582***	8.717***	0.206***	13.369*	13.576*
	(3.35)	(2.70)	(−2.73)	(3.16)	(1.86)	(1.88)
LML	0.007	−0.561*	−0.554*	0.010	−0.873	−0.863
	(−0.46)	(−1.74)	(−1.73)	(−0.46)	(−1.31)	(−1.30)

Note: 1. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. 2. The z-values associated with the coefficients are provided within parentheses.

following year. The finding suggests that an enhancement in UI tended to inhibit an increase in LFD in neighbouring regions the following year.

Because the spillover effect coefficient is significant, the SDM does not directly explain the impacts of UI and the control variables. Therefore, the effects of each variable on LFD were further divided into direct, indirect, and total impacts (Peng et al., 2021). In particular, the coefficient for direct effect encapsulates the influence of factors on the LFD of the local regions; the indirect effect coefficient shows the impact of changing an explanatory variable on LFD in neighbouring cities, and the total effect coefficient demonstrates the impact of variables on LFD. Moreover, they may be divided into long-term (far-reaching implications) and short-term (instant impact) impacts developed by the time-lag effect of the DSDM. The results are summarized in Table 5.

In terms of UIL, we observed a similar impact on LFD in local and neighbouring regions over the short and long durations; all estimates were statistically negative and passed the significance test at the 1% level. In addition, the coefficients associated with the long-term impact estimates surpassed those related to the short-term impacts, suggesting that UI within a local region and its surrounding regions would have a negative impact on LFD in the initial phase, with the inhibiting effects increasing over time. Owing to China's large geographical spread, urban innovation takes time to disseminate after being born in a cluster. Only when people understand and adopt information about innovation can the sources of innovation diffusion increase (Rogers, 1962). Local governments can rely on existing businesses to make money and not keep thinking about making money from land resources. Thus, the reliance of manufacturing firms on financial assistance from local government experiences decreases accordingly. Regarding direct impacts, an increase of 1% in the UI could lead to a reduction of 0.049% in LFD. Compared with the main effect coefficient (UI → LFD), there was barely any difference in size; the small difference was the feedback effect (UI → W × LFD → LFD). Regarding the indirect effects, an increase of 1% in UI could cause a reduction of 1.748% in LFD; this result captures how UI in a region impacts that in neighbouring regions (UI → W × LFD) and the spatial spillover effect in UI (UI → W × UI → W × LFD).

Regarding the decomposition results of the control variables, the direct effect coefficients of PPI are significantly negative at the 1% significance level. One possible reason is that the scope of authority and expenditure allocation responsibility is unequal for local governments, and monopolized land transfer fees become a rational choice for local governments to obtain capital reserves, thus resulting in a heavy LFD. The direct, indirect, and total effect coefficients of UOL indicate that continued urban sprawl is likely to increase LFD. The indirect effect and the total effect coefficients of LML were both significantly negative and passed the 10% significance level, which means that compared with bidding, auction, and listing transfers, negotiated transfers are a way for the government to negotiate with land users, and they have a significant positive effect on LFD. As a result, Hypothesis 2, according to which, UI inhibits LFD in the local region and neighbouring regions, is correct.

3.3. Regression results of UI on LFD by regions

To test whether the driving force of China's LFD varies by geographical region, Table 6 compares the spatial regression results for the four regions.

For the temporal dimension, the temporal relevance of LFD was found in all regions. More precisely, a 1% growth in the UIL within one year would correspondingly result in increases of 0.257%, 0.278%, 0.411%, and 0.388% in the four regions. However, eastern China showed a weaker spatial aggregation effect on UI compared with other regions. The findings revealed that a 1% rise in LFD correlated with a 0.190% growth in LFD among neighbouring eastern regions. In comparison, the corresponding

Table 6. SDM estimation on LFD by region

	Eastern-Region	Northeast-Region	Western-Region	Central-Region
LFD_{t-1}	0.257***	0.278***	0.411***	0.388***
	(7.83)	(5.03)	(9.89)	(11.33)
W × LFD	0.190***	0.444***	0.656***	0.672***
	(23.36)	(4.10)	(9.47)	(10.63)
W × LFD_{t-1}	0.051	0.097	0.020	–0.332***
	(0.46)	(0.61)	(0.14)	(–2.95)
UI	–0.231***	–0.043	0.042	–0.002
	(–3.71)	(–0.38)	(0.82)	(–0.06)
W × UI	0.127	0.235	–0.376***	–0.308***
	(1.17)	(1.47)	(–2.74)	(–2.88)
PPI	–0.220**	–0.300	–0.207**	–0.109
	(–2.00)	(–0.38)	(–2.27)	(–1.59)
W × PPI	–0.299	1.079***	0.694**	–0.107
	(–0.62)	(3.26)	(2.12)	(–0.35)
ADI	–0.008	0.052**	0.001	–0.013
	(–0.22)	(1.98)	(0.03)	(–0.57)
W × ADI	0.040	–0.168***	–0.181*	0.467***
	(–0.22)	(–2.47)	(–1.69)	(3.00)
UOL	0.030	0.130	0.040	0.191***
	(0.46)	(1.42)	(0.39)	(3.66)
W × UOL	0.379	–1.338**	1.303**	0.604
	(0.99)	(–2.47)	(2.20)	(1.50)
LML	–0.053	0.004	0.019	0.041
	(–1.61)	(0.06)	(0.77)	(1.46)
W × LML	0.020	0.113	0.080	–0.306***
	(0.28)	(0.77)	(1.11)	(–3.31)
Log-likelihood	–516.8013	–92.1858	–223.1922	–67.4248
R^2	0.0665	0.3301	0.2192	0.2909
The number of obs.	924	308	561	814

Note: 1. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. 2. The z values for the coefficients are in parentheses.

estimated spatial spillover effects in the other regions were 0.444%, 0.656%, and 0.672%. In general, the evolution of LFD in these four regions showed temporal inertia and spatial spillover effects.

More importantly, the comparative analysis of the impact decomposition in the four regions yielded several valuable insights. Given that economically developed regions, particularly the East Coast, tend to attract more attention for political positions, intergovernmental competition in UI is generally much more intense in eastern cities. Adjacent cities face a loss of innovation factors and a lack of enthusiasm for innovation activities (Peng et al., 2021), which is consistent with the Matthew effect. This is illustrated in Figure 4. Additionally, well-performing innovative cities in the East can more effectively absorb relevant resources for innovation. Consequently, the inhibiting impact on the local region's level of UI was stronger than that on neighbouring regions in the previous year, compared to other regions. A potential explanation for the lack of significance in the estimates for temporal and spatial lags in Midwest Chinese is that these cities possess relatively lower innovation capacities. Many of them are still in the process of exploring ways to incentivize early UI, and the manifestation of the Matthew effect has not yet become visible. The impact of LFD in the Midwest is not solely influenced by technology, industrial structure, and economic level, other factors such as foreign investment also indirectly contribute to its effect. These factors may meddle with the correlation between LFD and UI. Therefore, solely promoting UI cannot effectively curtail LFD in the Midwest. Therefore, Hypothesis 3, which states that the LFD in various regions receives different inhibition from UI, is true.

The PPI for each region was consistent with the theoretical prediction of a negative correlation. The scope of authority and responsibility for the distribution of expenditures is unequal for governments, and monopolized land transfer has become a rational choice for officials to

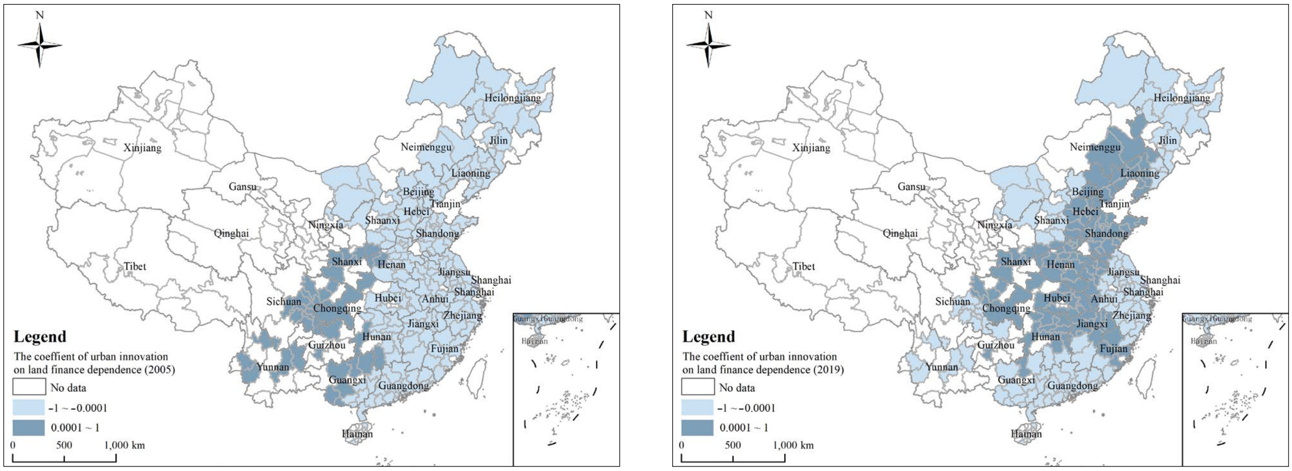

Figure 4. Relationship between LFD and UI in 233 prefecture-level cities

secure capital reserves. The ADI was barely positive in the northeast region. Foreign investment is mainly focused on secondary industries that require a large amount of land development. This is closely related to Northeast China's strong industrial base, but its agriculture and tertiary industries are relatively underdeveloped. Similarly, the UOL in the central region was significantly positive, whereas the urbanization level in the other regions was not significant. This may be because the urban expansion rate in the central region is not overexploited. Governments tend to exploit land resources from urban renewal to achieve economic development.

Conclusions

The 1994 tax-sharing reform laid the basis for land finance (Xu, 2019) and broadened the gap between local government income and expenditure. Faced with the pressure of budget deficits, local governments urgently need to increase their revenues to compensate for these deficits. Data show that China's land transfer income saw rapid growth, with a rise from 0.59 billion yuan in 2005 to 7.25 billion yuan in 2019, accounting for over 70% of the government's budget revenue. This situation may also lead to a high debt risk, inefficient land use, and the loss and conversion of agricultural land (Du et al., 2016; Funk et al., 2014; Gyourko et al., 2022). Policies relevant to innovation may have the potential to inhibit local governments' LFD. Such policies are intended to create a shared business environment for new entrepreneurs facilitate the establishment of new businesses, and thereby contribute to achieving sustainable economic growth in China. The potential long-term revenue from increased UI can alleviate the financial crisis within the government and change the traditional thinking of paying off debt through land concessions. This study analyzed the spatiotemporal dynamics of LFD and UI from 2005 to 2019; below are its key findings.

First, LFD and UI exhibited positive spatial associations throughout the studied regions in China during the study period. LFD exhibited an oscillating upward trend, reaching 0.4483 in 2019. The spillover effect of neighbouring cities positively affected rising LFD. Second, UI significantly inhibited the LFD and had a negative impact on the LFD of neighbouring cities. Moreover, the coefficients of the long-term effect estimates exceeded those of the short-term effects, indicating that UI had a negative impact on LFD, with inhibiting effects increasing over time. Third, UI had varied implications for LFD in different regions, especially in eastern China, because cities in the eastern region with strong innovation performance possess a higher capacity to effectively incorporate and utilize innovation resources.

We offer the following policy recommendations for building a model to inhibit LFD. Considering time trends, technological innovation has the greatest stimulating effect on economic growth and its level is likely to rise further. Local governments should provide in-depth guidance regarding the strategic direction of economic development and establish policies to accelerate UI. Industrial cooperation should be encouraged to provide support to less-developed regions. This can be done by building mechanisms for regional networking UI and talent tracking and further implementing new technologies and industries through the industrial transfer of innovation resources to promote economic development and reduce dependence on land finance. Although resource consumption can stimulate economic growth, it is less stable and less sustainable. For cities that do not yet have pillar industries and do not rely heavily on land finance, such as those in the western region, land concessions and the promotion of investment are appropriate strategies to attract enterprises and talent to settle in, and lay the foundation for talent in innovative cities at a later stage. In addition to taxes related to land concessions and economic growth, local governments can levy other taxes such as property taxes. These measures could help cities achieve sustainable development, reduce their dependence on land revenues for urban development, and create better living environments and lifestyles.

This study highlights the important role of UI in solving the pressure of land resources, but it has a few limitations. First, given the unavailability of indicators for land-related taxes, future studies may conduct empirical analysis by including more revenue sources aside from land transfer. Second, UI was calculated using a constructed index system (Kou & Liu, 2020), and a more comprehensive evaluation of the index system needs to be established. Third, we proposed only a simple theoretical explanation; a more systematic discussion would enrich our understanding of how UI affects LFD.

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