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How Does Land Misallocation Weaken Economic Resilience? Evidence from China

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Abstract

Drawing on evidence from China's land market, this study systematically investigates the impact of land misallocation on economic resilience and reveals the underlying mechanism that operates by suppressing technological advancement. A theoretical model of economic resilience is developed, incorporating technology and factor allocation. Empirical analysis is conducted using a panel dataset of 95 Chinese cities (2011-2024) through spatial econometric and mediation models. The findings indicate that land misallocation significantly reduces local economic resilience and exhibits negative spatial spillover effects. The core mechanism is identified as follows: subsidies via low-priced industrial land delay the market exit of low-efficiency firms, hindering the reallocation of production factors to more productive sectors. This suppression of technological progress ultimately weakens a region's capacity to withstand external shocks. Based on the findings, policy implications include optimizing land supply structure, accelerating fiscal system reform, and strengthening policy coordination.

Keywords: land misallocation; economic resilience; technological level; factor allocation

1. Introduction

At the present stage, the world economic situation is experiencing significant fluctuations. Under the influence of trade frictions and geopolitical games, how to enhance regional economic resilience has increasingly become a focal point of current research. Economic resilience is not only an important manifestation of high-quality economic development but also reflects the resistance and recovery capacity of an economic system when facing exogenous shocks. Existing research has indicated that the mobility efficiency and optimal allocation of production factors are central to economic resilience [1]. However, most studies have primarily focused on the allocation of mobile factors such as labor and capital, while overlooking the critical role of land as a key factor [2]. Particularly in developing countries like China, the land factor can often be subject to supply regulation by the government. Therefore, in practice, as an important lever for local governments to regulate the economy, the allocation efficiency of land may have a more profound impact on regional economic resilience. China's factor marketization reform has long prioritized labor and capital factors, while the marketization process for the land factor has been relatively lagging. It was not until 2020 that the Chinese government formally included the land factor within the scope of market-oriented reforms for the first time and proposed measures such as allowing cross-regional trading of land supply quotas. However, the optimization of land factor allocation still faces numerous challenges. Consequently, this study aims to build upon the theory of factor misallocation and use the Chinese land market as a sample to analyze how land factor misallocation affects regional economic resilience.

Early theoretical research focusing on the impact of factor misallocation on regional economies, such as the classic model by Hsieh & Klenow (2009), primarily concentrated on the analysis of how labor and capital factors affect Total Factor Productivity (TFP) [3], paying little attention to the economic effects arising from the distorted allocation of the land factor. However, within the context

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of China's unique land system—where local governments can determine the supply quantity and price of land for different uses—the land factor, conversely, becomes a crucial lever for regional economic regulation. Local governments can dictate the allocation of land factors across different uses and industries, and the particularity of local governments' objective functions may lead to structural distortions in land factor allocation [4]. The root of this distortion can be traced back to China's Tax-sharing Reform—due to the mismatch between "fiscal authority" and "administrative responsibility," land conveyance revenue has become a core source of local government fiscal revenue. In 2022, the total revenue from land transfers and related taxes in China exceeded 10 trillion-yuan, accounting for 9.1% of GDP. In some cities, fiscal revenue reliance on the land factor even exceeded 90%. To attract investment, Chinese local governments commonly adopt a "Price Scissors Gap" strategy, involving the low-price supply of industrial land and the high-price supply of commercial land, forming an implicit subsidy for industrial land [5]. However, this subsidy mechanism may allow inefficient enterprises to delay market exit due to cost advantages, thereby creating a "crowding-out effect" on efficient enterprises and inhibiting industrial upgrading and innovation [6]. In the long run, this land misallocation not only reduces the efficiency of resource allocation but may also weaken the regional economy's ability to cope with external shocks, thus negatively impacting economic resilience. Therefore, this research focuses on the underlying mechanism of this price misallocation of the land factor across different supply uses on regional economic resilience.

In recent years, research by Chinese scholars has gradually begun to pay attention to the economic effects of land misallocation [7]. However, these studies mostly concentrate on the impact of land misallocation on economic growth or industrial structure, seldom touching upon economic resilience. Some scholars point out that land misallocation may indirectly affect economic resilience by suppressing enterprise TFP, crowding out R&D investment, or exacerbating local government debt risks [8], but this mechanism has not yet been systematically tested. Furthermore, existing research is divided on the industrial agglomeration effects of land misallocation: on one hand, the lower price of industrial land within land price misallocation can promote the expansion of industrial scale, benefiting economic growth; on the other hand, this land price misallocation may also lead to inefficient enterprises remaining in the market, forming "inefficient agglomeration," ultimately impairing long-term economic resilience [9]. Regional economic resilience draws from the concepts in physics and ecology of a system's capacity to change, adapt, and transform in the face of external pressure and disturbance, leading to its definition in regional economics as the developmental capacity of a region to resist risk shocks and navigate uncertainty [10]. Following the 2008 "Subprime Mortgage Crisis", research on economic resilience gradually became a hotspot in academia. Early literature emphasized the role of industrial structure diversification in promoting economic resilience, while recent studies have focused more on the impact of innovation capacity and production efficiency on economic resilience [11]. However, most of these studies have overlooked the critical role of local governments in land resource allocation. In China, the degree of administrative intervention in the land factor is far higher than that for labor and capital. Its misallocation may systematically impact regional economic resilience through channels such as affecting industrial upgrading, enterprise innovation, and fiscal stability. Regrettably, there is currently a lack of empirical research directly exploring the relationship between land misallocation and economic resilience, let alone addressing the spatial correlation and mechanism of action between them.

This study aims to systematically investigate the intrinsic relationship between land misallocation and economic resilience and its underlying mechanism, with its marginal contributions being twofold. First, it is among the first attempts to integrate land misallocation and economic resilience into a unified analytical framework, empirically examining their causal linkage. Second, it unveils the mechanism through which price distortions in the land factor undermine economic resilience by hindering technological advancement, a pathway empirically substantiated through spatial econometric and mediation models. This theoretical and empirical approach—developed

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through a model integrating technology and factor allocation and applied to a panel dataset of 95 cities (2011–2024)—enables an in-depth analysis of the pathways through which land misallocation affects firm productivity, factor mobility, and technological progress, while also verifying its spatial spillover effects and nonlinear impacts. Consequently, this research not only addresses a notable gap in the existing literature but also provides a theoretical foundation and policy insights for optimizing land resource allocation and enhancing regional economic resilience.

2. Theoretical Model and Analysis

2.1. Theoretical Model of How Factor Misallocation Affects Economic Resilience

Land misallocation arises because local governments, acting as monopolistic suppliers in the regional land market, determine the supply quantity and price of the land factor across different industries and uses. Its essence manifests as a non-positive relationship between the supply price of the land factor and its rate of return. That is, based on objective functions such as attracting investment or short-term GDP growth, local governments allocate a lower land supply price to industrial uses with lower factor returns compared to uses with higher factor returns. This misallocation, which essentially supplies the land factor at a lower price to less efficient industrial uses, constitutes a price subsidy mechanism implemented by local governments for certain industrial uses [12]. This price subsidy mechanism hinders the market exit of inefficient industries, thereby impeding technological advancement and improvements in production efficiency [13]. It is undeniable that efficiency gains and technological progress are crucial supports for regional economic resilience. Therefore, it can be simply inferred that land misallocation has a negative impact on regional economic resilience.

Next, it is necessary to model the mechanism through which land misallocation affects economic resilience and conduct an in-depth theoretical analysis of its impact pathways. First, a functional model between production factors and economic resilience needs to be constructed. Economic resilience is defined as the economy's resistance and recovery capacity in the face of short-term exogenous shocks. While such short-term shocks affect factor returns and total economic output, they evidently do not cause significant changes in the technological level in the short term. Therefore, drawing on the model of Loupias and Wigniolle (2013), an economic resilience function that incorporates both the technological level and production factors is constructed as follows [14]:

$$RES = f(G) = f\left\{\sum_i \left[{T_i}^{1-\eta}\left(K_i^{\alpha} \cdot N_i^{\beta} \cdot L_i^{\gamma}\right)^{\eta}\right]\right\} \quad (1)$$

Here, regional economic resilience (*RES*) is expressed as a function of total regional economic output (*G*), which is the aggregation of output values of economic entities (firm *i*) within the region. Assume the output of firm i follows a Cobb-Douglas form, expressed as a function of the average technological level (*T*) and the production factors: capital (*K*), labor (*N*), and land (*L*). η is the contribution rate of production factors to economic output, hence (1-η) is the contribution rate of the technological level. α, β, and γ are the elasticity coefficients among the production factors. Economic resilience represents the resistance and recovery capacity of the regional economy to exogenous shocks. Based on Equation (1), if short-term shocks act uniformly on production factors, then the variation in output across firms under risk shocks depends primarily on the technological level. Overall regional economic resilience is the aggregated representation of these firm-level output differences under exogenous shocks. Therefore, regions with advanced technology and a higher contribution rate from technology would exhibit lower fluctuations in economic output, consequently demonstrating higher regional economic resilience – existing research has also found a significant positive correlation between economic resilience and TFP [15], confirming the above theoretical analysis.

However, using Equation (1) for comparative analysis of economic resilience across regions introduces significant bias. This is because Equation (1) simplifies regional economic output as a functional model of the aggregate firms' output. In the process of transforming firms' output into total regional economic output, the technological level cannot be simply arithmetically averaged. That is, differences in technological levels between regions cannot be simply represented by the average difference in firm technological levels. This is because firms with different technological levels have varying market shares in different regions. Therefore, the overall regional technological level requires a weighted average of firm technological levels.

Olley and Pakes (1996) constructed a weighted model of regional economic efficiency level (i.e., technological level) [16]. In this model, if inefficient firms have high market shares, it indicates that production factors are not allocated to the most efficient firms, thereby pulling down the overall regional technological level. Following the Olley-Pakes model, this research also constructs a functional relationship between regional economic resilience (*RES*) and the weighted regional technological level:

$$RES = f(G) = f\left(\sum_i \theta_{ij} T_i\right) = f\left\{\bar{T} + \sum_i\left[\left(\theta_{ij} - \bar{\theta}_j\right)\left(T_i - \bar{T}\right)\right]\right\} \quad (2)$$

Here, T_i is the productivity (technological level) of firm *i*, and θ_{ij} is the factor share of firm *i* in industry *j* within the region. $\bar{T}$ is the simple average productivity of firms in the region, and $\bar{\theta}_j$ is the simple average factor share of firms in industry *j* within the region. Therefore, it can be seen that regional economic output is not only related to the average technological level ($\bar{T}$) but also highly correlated with the allocation of production factors among industries with different technological levels $\sum_i\left[\left(\theta_{ij} - \bar{\theta}_j\right)\left(T_i - \bar{T}\right)\right]$. Research on regional economic resilience primarily focuses on the impact of short-term exogenous shocks on the economic level. Therefore, within a short-term horizon, technological levels between regions do not change significantly, making factor allocation a key influencing factor for regional economic resilience. The model in Equation (2) reveals that, under the general research assumption of technological neutrality, differences in factor allocation structures between regions affect their respective technological levels, thereby influencing regional economic resilience.

2.2. The Underlying Mechanism of Land Misallocation on Economic Resilience

The above model identified the mechanism through which factor allocation affects the technological level and consequently regional economic resilience. Next, the analysis focuses more specifically on the underlying mechanism of land factor allocation on economic resilience. To incorporate land, other production factors, and the technological level into a unified analytical framework, a dual model is constructed based on the analytical conclusion of Hansen and Prescott (2002) that "technological progress in the land factor is much slower than in the capital factor" [17]. Assume there are two firms in the region, *A* and *B*: firm *A*'s primary input factors are land and labor, while firm *B*'s primary input factors are capital and labor. Consequently, firm *B*'s technological level leads that of firm *A*, and the overall technological level of the region depends primarily on firm *B*'s technological progress.

Based on the above assumptions, the output functions for firms *A* and *B*, following the Cobb-Douglas form, are constructed:

$$\begin{cases} Y_A(L,N) = L^{\alpha} {N_A}^{1-\alpha} \\ Y_B(K,N) = (TK)^{\alpha} {N_B}^{1-\alpha} \end{cases} \quad (3)$$

Here, *Y* is the output function of the input factors. The total output of firm *A* (Y_A) is a function of the land factor (*L*) and the labor factor (N_A). The total output of firm *B* (Y_B) is a function of the technological level (*T*), the capital factor (*K*), and the labor factor (N_B). This research primarily analyses the relationship between the land factor and the technological level, so the labor factor is assumed to be exogenous, with a consistent elasticity coefficient (1-α) in the output function, and it can flow freely between firms *A* and *B*.

After defining the output functions in Equation (3), the profit functions are calculated based on the cost of input factors. The labor factor is exogenous, so the labor cost for both firms *A* and *B* is the exogenously given per capita income level (*W*). The land factor cost should be the land supply price. However, due to land price misallocation, the land price allocated to firm *A* by the local government

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is lower than the market equilibrium price (p). Existing research models often interpret land price misallocation as a subsidy mechanism [18], so the land factor cost is the difference between the market equilibrium land price (p) and the land price subsidy (ε). The capital factor cost is also exogenous, denoted as r. Based on the above analysis, the profit functions for firms A and B are constructed as follows:

$$\begin{cases} \Pi_A = L^\alpha[(1-\phi)N]^{1-\alpha} - (p-\varepsilon)L - W[(1-\phi)N] \\ \Pi_B = (TK)^\alpha(\phi N)^{1-\alpha} - rK - W(\phi N) \end{cases} \quad (4)$$

Here, $\Pi_{A/B}$ is the profit level of firms A and B; N is the total labor factor for firms A and B, and ϕ represents the proportion of the labor factor allocated to firm B, so $N_A = (1-\phi)N$ and $N_B = \phi$N. This research aims to analyze the underlying mechanism of land price misallocation on the technological level. In Equation (4), ε represents the land misallocation coefficient and T represents the technological level coefficient. Therefore, the focus is on analyzing the correlation function between ε and T. Assuming the total input of production factors between firms A and B is fixed (i.e., L, K, and N in Equation (4) are fixed variables), and given that the labor cost (W) and capital cost (r) are exogenous variables, the main variables affecting the difference in profit levels (Π) between firms A and B are the land factor cost (p - ε) and the allocation ratio of the labor factor (ϕ). Since the labor factor can flow freely between firms A and B, in equilibrium, the per capita profit levels of firm A and firm B should be equal, leading to Equation (5):

$$\begin{cases} \varepsilon = p + \dfrac{WN(1-\phi) - L^\alpha N^{1-\alpha}(1-\phi)^{1-\alpha}}{L} \\ T = \dfrac{K(W\phi N + rK)^{\frac{1}{\alpha}}}{(\phi N)^{\frac{1-\alpha}{\alpha}}} \end{cases} \quad (5)$$

This implies an inverse relationship between the land price misallocation coefficient (ε) and the labor factor allocation ratio (ϕ). This indicates that land price subsidies favoring firm A lead to the agglomeration of the labor factor towards firm A, resulting in an outflow of the labor factor from firm B. Simultaneously, Equation (5) suggests a positive relationship between the labor factor allocation ratio (ϕ) and the technological level coefficient (T). This can be understood as the agglomeration of the labor factor towards the capital-intensive firm B leading to an improvement in the regional technological level. Therefore, the above analysis can be simply deduced as follows: an increase in the land factor price misallocation coefficient (ε) leads to a decrease in the regional technological level coefficient (T). According to Equation (1), the technological level (T) is a positive function of economic resilience (*RES*). Thus, it indirectly demonstrates that the subsidy mechanism of land prices for inefficient firms reduces the optimization of overall regional production efficiency, thereby affecting overall regional economic resilience.

Based on the above theoretical model analysis, the following research hypothesis is proposed: Land misallocation hinders the progress of the regional technological level, thereby affecting the performance of economic resilience. That is, the differentiated land supply methods used by local governments, allocating lower land prices to industries with lower returns, are detrimental to the improvement of the regional technological level and consequently reduce regional economic resilience.

3. Research Design and Methodology

3.1. Key Variable Operationalization

To empirically test and analyze the mechanism through which land misallocation affects economic resilience, it is first necessary to operationalize these two primary research variables.

3.1.1. Operationalization of Land Misallocation

Land misallocation refers to the price distortion of land supply across different uses within a region, which severs the relationship between the supply price of the land factor and its factor value,

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creating a misallocation at the price level. Facing budgetary constraints and fiscal deficit pressures, local governments typically choose to offer substantial price discounts on industrial land in exchange for short-term industrial development, while simultaneously supplying commercial land at higher prices to generate revenue to offset the cost of industrial land price subsidies. Although this price subsidy mechanism for the land factor can alleviate the fiscal constraints of local governments acting as land operators and provide effective growth momentum for regional economic development, this model of using commercial land to “cross-subsidize” industrial land distorts the market price of the land factor and is detrimental to the optimal allocation of land resources from a long-term perspective.

Therefore, existing studies generally use the degree of relative price distortion between different land uses to measure land misallocation [8]. This approach can reflect both the degree of land factor misallocation and the preferences and tendencies of different local governments in the land market, making it more suitable for the reality of local government monopolistic supply in the land market following the Tax-sharing Reform. Based on this analysis, the distortive difference between the supply prices of industrial and commercial land is the most effective measure of land misallocation. Consequently, this study selects this most effective measurement model as the research variable for the land misallocation coefficient:

$$Land\ Misallocation\ Coefficient = \frac{Average\ Price\ of\ Commercial\ Land}{Average\ Price\ of\ Industrial\ Land} \quad (6)$$

3.1.2. Operationalization of Economic Resilience

Currently, in theoretical circles, measurement models for regional economic resilience are mainly divided into two types: Multi-dimensional Indicator System Evaluation Models and Single-variable Shock Econometric Models. First, from the perspective of Multi-dimensional Indicator System Evaluation Models, economic resilience is a composite concept encompassing economic vulnerability, reorganization capacity, and adaptive capacity. Therefore, a multi-dimensional indicator system should be constructed to comprehensively measure regional economic resilience. For example, Brakman et al. (2015) used GDP, social capital accumulation, and non-economic indicators such as population density, ecological environment, public services, and infrastructure to measure urban economic resilience levels [19]; Zhang and Tian (2024) constructed an urban resilience evaluation system for China using the Analytic Hierarchy Process (AHP) based on aspects like per capita GDP, fiscal revenue, FDI, and household savings [20]. However, due to the inherent subjectivity in indicator selection and the significant variation in weights assigned to different indicators within the resilience evaluation system, the evaluation results of different measurement models cannot be compared horizontally, leading to their infrequent use in empirical research. Second, from the perspective of Single-variable Shock Econometric Models, economic resilience is viewed as the fluctuation of one or more regional economic variables in the face of exogenous shocks. For instance, selecting economic output or employment rate as the single variable and using the amplitude of its fluctuation during an exogenous shock as the measure of regional economic resilience. This Single-variable Shock Econometric Model effectively overcomes the shortcomings of Multi-dimensional Indicator System Evaluation Models and is increasingly adopted in complex empirical analyses. For example, Martin (2012) used employment as the single variable, characterizing regional economic resilience by describing the difference between the change in regional employment during the shock period and the change rate of employment at the national level [21].

In the subsequent empirical analysis, to study the relationship between economic resilience and land misallocation and to construct a complex econometric model suitable for horizontal comparison, the Single-variable Shock Econometric Model is chosen as the measurement tool for economic resilience. The essence of this method lies in using the change rate of the overall economic variable under risk shock to calculate the counterfactual level of the regional economic variable. Then, the

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actual change rate of the regional economic variable is compared with the change rate of the economic variable under the counterfactual level. If the actual value is higher than the counterfactual level, it indicates stronger regional economic resilience; conversely, if the actual economic level is lower than the counterfactual level, it indicates relatively weaker regional economic resilience. Martin (2012) first used this counterfactual level method for measuring economic resilience [21]: $RES_i=(\Delta G_i/G_i)/(\Delta G_N/G_N)$, where G is the single economic variable (employment rate initially, later changed to economic output), i denotes the region, and N denotes the nation. Thus, regional economic resilience is expressed as the relative change rate of the regional economic fluctuation compared to the national economic fluctuation during the risk shock period. If $RES_i>1$, it indicates that the decline in the economic variable of city i in the face of the risk shock was less than the national average, suggesting relatively stronger economic resilience for city i. However, using 1 as the benchmark for economic resilience in Martin's (2012) original model can lead to issues due to inconsistent signs, which is not conducive to empirical econometric analysis with other variables [21]. Therefore, this research makes appropriate modifications and reconstructs the regional economic resilience measurement model:

$$\begin{cases} RES_i^t = \frac{[\Delta G_i^t - (\Delta G_i^t)^{exp}]}{|(\Delta G_i^t)^{exp}|} \\ (\Delta G_i^t)^{exp} = G_i^t \times (g_N^t / g_N^{t-1}) \times g_i^{t-1} \end{cases} \tag{7}$$

In Equation (7), RES^t_i represents the regional economic resilience of city i in period t. It is defined as the relative ratio between the actual economic level ΔG_i^t of city i and the expected counterfactual level $(\Delta G_i^t)^{exp}$: where G represents GDP, g_N represents the national average GDP growth rate, and g_i represents the GDP growth rate of city i. When an exogenous risk shock occurs, if the decline in the economic growth rate of city i is smaller than the decline in the national average economic growth rate, then $RES^t_i>0$ in Equation (7) indicates relatively stronger economic resilience in that region.

3.2. Research Methods

To test the impact of land misallocation on economic resilience, a linear regression empirical model needs to be constructed. However, land factor allocation may exhibit spatial autocorrelation across different regions. To address potential biases arising from spatial dependencies in traditional linear regression models, this research employs a spatial econometric model. Furthermore, to examine the mechanism through which land misallocation affects economic resilience, the mediation model proposed by Baron and Kenny (1986) will be utilized for empirical analysis [22].

3.2.1. Spatial Econometric Model

The foundation of the spatial econometric model is constructing a reasonable spatial weight matrix. However, in the subsequent empirical section, due to data availability constraints for land misallocation, the sample consists of 95 Chinese cities (including 4 ultra-large municipalities). Most sample cities are not geographically adjacent, making it impossible to use a traditional weight matrix based on geographical contiguity. Based on the premise that land misallocation affects economic resilience through its impact on technological levels, and given that technological achievements can flow across regions at low cost—primarily among regions with comparable economic development—this study, drawing on established research methodologies [23], constructs a spatial economic weight matrix based on inter-city GDP disparities. The matrix is formulated as follows:

$$W_{ij} = \begin{cases} 1/|GDP_i - GDP_j| \, (if \quad i \neq j) \\ 0(if \quad i = j) \end{cases} \tag{8}$$

In Equation (8), W_{ij} represents the spatial economic weight matrix, defined as the reciprocal of the absolute difference between the total economic output (GDP) of city i and city j. Therefore, when the economic aggregates of two sample cities are relatively close (i.e., the spatial economic distance is small), the spatial economic weight takes a larger value.

Once the spatial weight matrix is determined, Moran's I needs to be calculated to test for spatial autocorrelation of the core variables. If spatial autocorrelation exists, a spatial econometric model should be constructed. Current spatial econometric models mainly include the Spatial Error Model (SEM), the Spatial Autoregressive Model (SARM), and the Spatial Durbin Model (SDM). The SEM only includes an error term with spatial autocorrelation, indicating that the spatial effect of the dependent variable is the result of random shocks, and its spatial transmission occurs mainly through the error term rather than the independent variables. The SARM, also known as the Spatial Lag Model, includes the spatial lag term of the dependent variable in its model, indicating that the dependent variable can affect other regions through spatial interaction. The SDM simultaneously considers both of the above spatial transmission mechanisms – spatial effects can occur both in the spatial lag term of the dependent variable and in the error term caused by random shocks. Moreover, the SDM model also considers the spatial interaction of independent variables, meaning that the dependent variable in a given region is influenced not only by the independent variables in its own region but also by the independent variables in other regions, which is also expressed as the spatial spillover effect of the independent variables. The determination of the spatial econometric model can be tested sequentially according to the order OLS → SEM → SARM → SDM. The testing equation for the spatial econometric model is constructed as follows:

$$RES_{i,t} = \beta_0 + \rho \times \sum_{j=1}^{n} W_{i,j} \bullet RES_{j,t} + \beta_1 \times LMC_{it} + \beta_2 \times Controls_{it}$$
$$+\theta_1 \times \textstyle\sum_{j=1}^{n} W_{i,j} \bullet LMC_{j,t} + \theta_2 \times \sum_{j=1}^{n} W_{i,j} \bullet Controls_{j,t} + \varepsilon \quad (9)$$

In Equation (9), *RES* represents regional economic resilience, *LMC* is the land misallocation coefficient, *Controls* represents a series of control variables, W_{ij} is the spatial economic weight matrix, and ε is the error term. Additionally, ρ is the coefficient of the spatial lag term of the dependent variable, and θ is the coefficient of the spatial interaction term of the independent variables. When ρ=0 and all θ_i=0 (i=1, 2, ...), it indicates no spatial correlation among all variables, and Equation (9) becomes the classic OLS model. When the regression coefficients β_i of the independent variables, their interaction term coefficients θ_i and the dependent variable spatial lag term coefficient ρ satisfy $\theta_i = -\rho\beta_i$, it indicates that the spatial effect transmission occurs mainly through the error term, and Equation (9) becomes the Spatial Error Model (SEM). When $\rho \neq 0$ but all θ_i=0, the spatial interaction of independent variables does not exist, and only unidirectional spatial correlation of the dependent variable exists between regions; then Equation (9) becomes the Spatial Autoregressive Model (SARM). When $\rho \neq 0$ and $\theta_i \neq 0$, it indicates the simultaneous existence of spatial correlation effects from the dependent variable and spatial interaction effects from the independent variables; then Equation (9) is the Spatial Durbin Model (SDM).

When selecting among the above spatial econometric models, Lagrange Multiplier (LM) tests are usually conducted first to determine if spatial correlation exists in the model. Then, Likelihood Ratio (LR) tests are performed for the SEM, SARM, and SDM models. If both test results reject the null hypothesis, the SDM model should be selected. Simultaneously, Wald tests are conducted to determine whether the SDM degenerates into SEM or SARM. If the SDM is ultimately chosen, the lag term of the dependent variable (or the spatial interaction term of the lagged dependent variable) can be added during the empirical regression process, turning the SDM into a Dynamic Spatial Durbin Model.

3.2.2. Mediation Model

If the spatial econometric model confirms that land misallocation has a significant impact on economic resilience, the mechanism between them needs further testing and analysis. The theoretical research section found that land misallocation affects regional economic resilience by influencing the technological level. The analysis of such a pathway is typically empirically tested using the mediation model, which can be described using the following system of equations through the stepwise method:

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$$\begin{cases} Function1: & Y = \alpha X + \gamma_1 CVs + \varepsilon_1 \\ Function2: & M = \beta X + \gamma_2 CVs + \varepsilon_2 \\ Function3: & Y = \alpha' X + \lambda M + \gamma_3 CVs + \varepsilon_3 \end{cases} \quad (10)$$

In the three equations of (10), Y represents the explained variable, X is the core explanatory variable, M is the mediating variable, and CVs and ε represent control variables and residual terms, respectively.

Step 1: Calculate the regression coefficient α in Function 1 to test whether the core independent variable X has a significant relationship with the explained variable Y. If α is not significant, the mediation effect does not hold.

Step 2: Calculate the regression coefficient β in Function 2 to test whether the explanatory variable X has a significant impact on the mediating variable M.

Step 3: Calculate the regression coefficients α' and λ in Function 3. If both β from Function 2 and λ from Function 3 are significant, it indicates that the mediation effect exists. If α' in Function 3 is also significant, it indicates a partial mediation effect. If α' is not significant, it indicates a complete mediation effect. However, if either β or λ is not significant, the Sobel test is needed to determine the significance of the mediation effect. When the mediation effect exists, the ratio ($\beta \cdot \lambda / \alpha$) is referred to as the proportion of the mediation effect [22].

4. Empirical Analysis

4.1. Sample and Data

In the empirical analysis section, the spatial econometric model is first used to test the impact of land misallocation on regional economic resilience. Subsequently, the mediation model is employed to examine the underlying mechanism and pathway: whether land misallocation affects regional economic resilience by inhibiting technological innovation. Accordingly, the following main research variables are constructed:

(1) Explained Variable: Regional Economic Resilience (*RES*). According to the theoretical model in Equation (7), this is derived using the Single-variable Shock Econometric Model and counterfactual levels to calculate the fluctuation differences in economic variables across regions.

(2) Core Explanatory Variable: Land Misallocation Coefficient (*LMC*). Land structural misallocation refers to the distortion in the supply price of the land factor across different uses within a region, severing the relationship between the supply price and the factor value of land. In the empirical test, the ratio of commercial land supply price to industrial land supply price is selected as the measurement equation for the land misallocation coefficient.

(3) Mediating Variable: Technological Level (*Patent*). For the operationalization of the technological level variable, existing research offers two perspectives: “technology input” and “technology output”. From the “technology input” perspective, regional R&D expenditure or the number of R&D personnel are used as proxy variables. From the “technology output” perspective, the number of patent applications or grants are used as proxies [24]. Following the research design of Tan et al. (2023), this research selects the “number of patents granted” as the proxy variable for regional technological level in the empirical test [25].

(4) Control Variables. (I) Degree of Openness (*Open*): The proportion of foreign investment in total economic output. Regions with a higher degree of openness are more susceptible to exogenous risk shocks, but stronger industrial diversity can also enhance urban economic resilience. This research uses the share of foreign investment in city GDP as the proxy for the degree of openness. (II) Urbanization Rate (*Urban*): The proportion of urban population in the city’s permanent resident population. Urbanization development can lead to the agglomeration of production factors and promote industrial structure upgrading and diversification, thereby significantly impacting regional economic resilience. (III) Income Index (*Income*): Per capita disposable income of urban residents. Preliminary empirical analysis results show that the income level of urban residents has a positive impact on regional economic resilience; that is, regions with higher per capita disposable income tend

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to have relatively stronger economic resilience. Therefore, this variable continues to be used as a control variable in subsequent empirical tests and is logarithmically transformed in the empirical analysis model. (IV) Market Scale (*Market*): Total retail sales of consumer goods. Studies have found that regions with relatively larger market scale have a stronger ability to withstand risk shocks [26]. Therefore, market scale may have a significant impact on regional economic resilience. In this empirical test, the total retail sales of consumer goods have been chosen as the proxy variable for market scale and included as a control variable in the testing model. This variable is also logarithmically transformed in the empirical analysis model.

Table 1. Variable Definitions and Descriptive Statistics.

Variables	Definitions	Min	Max	Mean	Std. Dev.
RES	Regional Economic Resilience	-15.82	75.66	0.37	3.69
LMC	Land Misallocation Coefficient	0.48	366.95	16.51	27.17
Patient	Number of Patents Granted: Total (unit)	10.00	367541.00	21712.88	35806.72
Open	Openness to the Global Economy: Share of Foreign Investment in Gross Output	0.03	937.98	87.85	347.49
Urban	Urbanization Rate (%): Urban Population as a Percentage of Total Resident Population	42.49	98.17	67.61	12.43
Income	Income Index: Per Capita Disposable Income of Urban Households (in thousand-yuan)	0.2	81.53	45.82	18.91
Market	Market Scale: Total Retail Sales of Consumer Goods (in billion-yuan)	10.02	1807.93	248.97	260.47

Based on a 14-year panel dataset from 2011 to 2024 covering 95 Chinese cities (including 91 prefecture-level cities and 4 municipalities directly under the central government), this research employs an empirical sample for analysis. Table 1 presents the descriptive statistics for all variables. Data for economic resilience and land misallocation are calculated from publicly available information in the *China Land and Resources Statistical Yearbook* and the WIND database. Data for other variables, including foreign direct investment, urbanization rate, disposable income per capita, total retail sales of consumer goods, and the number of patents granted, are sourced from the WIND database.

4.2. Empirical Testing and Result Analysis

Before conducting the empirical analysis, the spatial autocorrelation of the explained variable needs to be tested. Using the spatial economic weight matrix W_{ij} constructed in Equation (8) above, Moran's I is calculated as follows:

$$Moran's \quad I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(V_i - \overline{V}\right)\left(V_j - \overline{V}\right)}{S^2 \cdot \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (11)$$

In Equation (11), S^2 represents the sample variance, n is the total number of samples, and V represents the explained variable being tested for spatial autocorrelation. Since the subsequent empirical analysis includes mediation effect tests, the spatial autocorrelation of the mediating variable also needs to be tested. Table 2 reports the Moran's I test results for regional economic resilience (*RES*) and technological level (ln*Patent*).

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Table 2. Spatial Autocorrelation Test (Moran's I).

Variables	2014	2015	2016	2017	2018	2019	2020	2021	2022
RES	0.026 (0.763)	0.126*** (3.192)	0.102** (3.331)	0.043 (-0.718)	0.127*** (3.128)	0.090** (3.418)	-0.045 (-1.082)	0.016** (3.150)	0.026 (0.732)
ln*Patient*	0.222*** (4.629)	0.258*** (5.356)	0.294*** (6.056)	0.344*** (7.038)	0.351*** (7.165)	0.321*** (6.566)	0.355*** (7.240)	0.382*** (7.790)	0.386*** (7.886)

Note: Reported values are Moran's I statistics. Z-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

In Table 2, Moran's I for regional economic resilience (*RES*) is significant in over half of the sample years, with Z-statistics generally greater than 1.96. Overall, this indicates positive spatial autocorrelation in regional economic resilience. Simultaneously, Moran's I for technological level (ln*Patent*) is also significant at the 1% level, indicating that the technology factor exhibits significant cross-regional influence among different regions with similar economic levels. Since both the explained variable and the mediating variable exhibit spatial autocorrelation, a spatial econometric model should be used for regression testing. Given that the empirical test sample is panel data, stationarity tests for the main variables are required before spatial econometric regression. Panel unit root tests using the LLC and IPS methods showed that some variables are non-stationary. However, the results of Kao and Pedroni cointegration tests for the research model indicate that the model variables satisfy a cointegration relationship, allowing for the establishment of a panel regression model.

Table 3. Model Specification Tests for Spatial Econometric Models.

Test Method	Test Statistic	Statistic Value	P-value
LM Test	Moran's I	0.144	0.886
	Robust LM-lag	8.363***	0.004
	Robust LM-error	8.394***	0.004
LR Test	LR-SDM/SEM	9.39*	0.094
	LR-SDM/SARM	9.42*	0.094
Wald Test	Wald-SDM/SEM	9.22***	0.006
	Wald-SDM/SARM	9.39**	0.045

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

Next, the selection of the spatial econometric model needs to be confirmed. Table 3 reports the test results for the spatial panel models. The LM test statistics are all significant at the 1% level, indicating that spatial econometric models can be used for regression analysis. Based on the Hausman test, the fixed effects model is selected. Spatial econometric tests for the SEM, SARM, and SDM models are conducted separately, and the results of the three models are presented in Table 4. Subsequently, LR tests are performed for the two null hypotheses related to the three models. The statistics are all significant at the 10% level, indicating rejection of the null hypotheses and suggesting that the SDM model cannot degenerate into the SEM or SARM (LR test results are detailed in Table 3). Simultaneously, the Wald test statistics are also significant at the 5% level, further confirming that the SDM model is superior to the SEM and SARM.

Table 4 reports the empirical test results for several econometric models. Column (1) reports the results of the non-spatial OLS regression, showing that the coefficient for the core explanatory variable, the land misallocation coefficient (*LMC*), is significantly negative. However, the low R^2 of the econometric model indicates weak explanatory power. Columns (2) to (4) report the spatial econometric regression results for SEM, SARM, and SDM, respectively. Based on the LR and Wald tests, the SDM model is selected as the optimal choice. Since economic resilience not only has spatial correlation but might also be influenced by its own past values in the time dimension, Column (5) reports the test results for a Dynamic Spatial Durbin Model that includes the one-period lagged term of the dependent variable (*RES*).

Table 4. Empirical Results.

Variables	（1） **OLS**	（2） **SEM**	（3） **SARM**	（4） **SDM**	（5） **Dynamic-SDM**
L.RES					-0.109*** (0.023)
LMC	-0.006*** (0.002)	-0.008* (0.004)	-0.006*** (0.002)	-0.006*** (0.002)	-0.009** (0.004)
Open	-0.003 (0.003)	-0.004 (0.008)	-0.003 (0.003)	-0.001 (0.003)	0.007 (0.006)
Urban	1.676* (1.386)	1.736* (7.663)	1.796* (4.983)	1.545* (5.239)	1.964 (7.268)
ln*Income*	0.791*** (0.224)	0.431 (0.366)	0.504** (0.261)	-0.194 (2.645)	-3.047 (6.303)
ln*Market*	-0.536*** (0.208)	-0.462** (0.208)	-0.454** (0.193)	-0.459*** (0.170)	-0.374* (0.412)
W. *RES*			0.254** (0.111)	0.247** (0.113)	0.251** (0.109)
W. *LMC*				0.021* (0.016)	0.027 (0.025)
Log-L		-219.961	-224.368	-198..054	-198.185
R^2	0.112	0.354	0.429	0.573	0.565

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

The results in Table 4 show that all econometric models indicate a significant negative effect of the land misallocation coefficient (*LMC*) on regional economic resilience (*RES*). That is, cities with more severe distortions in land supply prices have relatively lower economic resilience. This is consistent with the conclusions of the theoretical analysis: when local governments supply industrial land at lower prices and commercial land at higher prices, this non-market-based, differentiated land supply price misallocation reduces the region's economic resilience.

Furthermore, comparing the goodness-of-fit of the several spatial econometric models using the Log-Likelihood (Log-L) and R-squared values shows that the SDM model has a better fit and relatively stronger explanatory power. The static Spatial Durbin Model also has more significant regression coefficients compared to the dynamic version. Therefore, the results of the static SDM model presented in Column (4) are ultimately selected as the basis for empirical analysis. In this model, not only is the coefficient for the land misallocation coefficient (*LMC*) significant, but its spatial interaction term ($W \times LMC$) is also significant, yet the signs of the two are completely opposite. This indicates that urban economic resilience is not only negatively affected by land misallocation within its own region but also potentially positively affected by land misallocation in economically similar cities. This can be understood as the "industrial crowding-out" effect of land misallocation: distorted allocation of the land factor crowds out high-quality industries from the local region, adversely affecting the local economic resilience. However, when these industries relocate to economically similar regions, it may conversely enhance the economic resilience of those other regions.

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Table 5. Direct, Indirect, and Total Effects of the SDM.

Variables	Direct Effect	Indirect Effect	Total Effect
LMC	-0.006*** (0.002)	0.002* (0.001)	-0.008*** (0.003)
Open	-0.003 (0.002)	-0.001 (0.001)	-0.004 (0.003)
Urban	1.864* (1.013)	0.655 (0.522)	2.519* (1.407)
ln*Income*	0.492* (0.358)	0.153** (0.109)	0.645** (0.319)
ln*Market*	-0.464** (0.197)	-0.174 (0.135)	-0.638** (0.302)

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

For the spatial spillover effects of the explanatory variables, the partial differential method of Lesage and Pace (2014) can be used to decompose the impact of independent variables on the dependent variable in the spatial econometric model into direct effects, indirect effects, and total effects [27]. The direct effect reflects the average impact of an independent variable on the dependent variable within the same region. The indirect effect (also known as the spatial spillover effect) reflects the impact of an independent variable on the dependent variable in other regions. The total effect expresses the average impact of an independent variable on the dependent variable across all regions. Table 5 reports the measurement results for the direct effects, spatial spillover effects, and total effects of each independent variable. The spatial spillover effect coefficient for *LMC* is significantly positive at the 10% level, indicating that land misallocation in a given region has a certain positive effect on the economic resilience of other economically similar regions. Meanwhile, the total effect coefficient for *LMC* is significantly negative, indicating that land misallocation has an adverse effect on the economic resilience of the overall region.

4.3. Robustness Tests

The essence of economic resilience is the relative differential state of regional economic fluctuations in the face of exogenous shocks, and these differences might also influence local government decisions regarding land supply, potentially leading to endogeneity issues in the econometric model. Simultaneously, the essence of land misallocation is a price subsidy for specific industries through the low-price supply of industrial land. Existing research has found that price subsidies can have an “inverted U-shaped” impact on industrial development and economic growth [28]. Therefore, it is also necessary to test whether there is a non-linear relationship between land misallocation and regional economic resilience. Since land misallocation affects regional economic resilience, economic resilience might, in turn, influence land supply decisions. To test for model endogeneity, the one-period lag of the dependent variable is typically introduced to construct a System Generalized Method of Moments (SYS-GMM) model. The test results for the System GMM are reported in Table 6 below. However, traditional GMM estimation is primarily applied in non-spatial linear regression models. To simultaneously control for endogeneity and spatial correlation, Han and Phillips (2006) combined the Dynamic Spatial Autoregressive Model (DSARM) with System GMM (implemented in Stata using the *spregdpd* command) [29]. This spatial GMM method was later extended to the Spatial Durbin Model. Table 6 also reports the test results using this Dynamic Spatial Durbin GMM method.

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Table 6. Results of Robustness Tests.

Variables	(1) SYS-GMM	(2) SYS-GMM	(3) Han-Phillips GMM	(4) Han-Phillips GMM
L.RES	-0.094*** (0.002)	-0.092*** (0.002)	-0.093*** (0.034)	-0.089*** (0.034)
LMC	-0.017** (0.013)	-0.017** (0.008)	-0.010* (0.009)	-0.010* (0.008)
LMC^2		0.003 (0.002)		0.009 (0.000)
Open	-0.005 (0.003)	-0.005 (0.003)	0.003 (0.014)	0.003 (0.014)
Urban	10.052*** (2.141)	10.052*** (2.141)	10.505*** (14.471)	10.505*** (4.545)
ln*Income*	2.308*** (0.481)	2.308*** (0.481)	1.921 (2.848)	1.921 (2.848)
ln*Market*	-3.577*** (0.134)	-3.575*** (0.134)	-3.432*** (1.309)	-3.432*** (1.412)
W. *LMC*			0.001 (0.000)	0.001 (0.000)
Log-L			-199.082	-191.908
Sargan[P]	37.333 [0.318]	37.334 [0.318]	95.457 [0.440]	95.457 [0.440]

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

Columns (1) and (3) in Table 6 report the test results for System GMM and Dynamic Spatial Durbin GMM (Han-Phillips GMM), respectively. The Hansen test indicates the validity of the instruments. The results from both testing methods show that the coefficient for *LMC* is significantly negative, supporting the conclusion from the baseline tests that land misallocation has a negative impact on regional economic resilience. To test for a non-linear relationship in the core independent variable, a squared term of *LMC* was also added to the models, presented in columns (2) and (4) of Table 6. The results show that the coefficient for the squared term (LMC^2) is not significant, thus failing to provide evidence for a non-linear effect of land factor misallocation on regional economic resilience.

4.4. Empirical Examination of the Underlying Mechanism via Mediation Model

Theoretical research found that land misallocation significantly affects regional economic resilience through the “technological level”. Price misallocation in land supply across different uses delays the exit of technologically backward enterprises and hinders the flow of production factors from low-efficiency to high-efficiency sectors. This manifests as land misallocation impeding regional technological development, thereby negatively impacting economic resilience. Next, a mediation model is constructed to empirically test whether the “technological level” is the pathway through which land misallocation affects economic resilience.

First, the total effect of land misallocation on economic resilience is tested. Second, the significance of the relationship between the land misallocation coefficient and the mediating variable is tested. Finally, the mediating variable is added to the total effect model, and the significance of the mediation effect is tested. Since the Spatial Durbin Model was chosen for the total effect test of the land misallocation coefficient on economic resilience, spatial econometric models are also required for the mediation effect tests, simply represented as follows:

$$\begin{cases} Function1: & RES_{i,t} = \rho_1 \times W_{i,j}RES_{j,t} + \alpha \times LMC + \theta_1 \times W_{i,j}IndVariables_{j,t} + \varepsilon_1 \\ Function2: & M_{i,t} = \rho_2 \times W_{i,j}M_{j,t} + \beta \times LMC + \theta_2 \times W_{i,j}IndVariables_{j,t} + \varepsilon_2 \\ Function3: & RES_{i,t} = \rho_3 \times W_{i,j}RES_{j,t} + \alpha' \times LMC + \lambda \times M_{i,t} + \theta_3 \times W_{i,j}IndVariables_{j,t} + \varepsilon_3 \end{cases} \tag{12}$$

In the three equations of (12), *RES* is the dependent variable, *LMC* is the core independent variable, *M* is the mediating variable (proxy for technological level), *W* is the spatial economic weight matrix, and $W_{i,j}$ $IndVariables_{j,t}$ represents the spatial interaction terms for all independent variables. First, coefficient α in Function 1 primarily measures the significance of the total effect of the core independent variable on the dependent variable. Second, coefficient β in Function 2 tests whether the core independent variable has a significant effect on the mediating variable. Third, coefficient λ is calculated in Function 3. If both β and λ are significant, it indicates the existence of a mediation effect. If either coefficient is insignificant, the Sobel test is needed to determine the significance of the mediation effect.

Table 7. Empirical Results of Mediation Tests.

Variables	**(1)** *RES*	**(2)** ln*Patient*	**(3)** *RES*
LMC	-0.006*** (0.002)	-0.002* (0.002)	-0.005*** (0.001)
ln*Patient*			0.572 (0.235)
Open	-0.001 (0.003)	-0.004** (0.001)	-0.001 (0.003)
Urban	1.545* (5.239)	0.185 (0.648)	1.653* (1.031)
ln*Income*	-0.194 (2.645)	0.863** (0.258)	-0.123 (0.403)
ln*Market*	-0.459*** (0.170)	-0.212** (0.092)	-0.405** (0.139)
W.*RES*	0.247** (0.113)		0.195*** (0.096)
W. ln*Patient*		0.411** (0.039)	
W. *LMC*	0.021* (0.016)	0.872** (0.407)	0.013* (0.019)
R^2	0.573	0.821	0.792
Sobel Z [P Value]			1.542 [0.188]

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

First, following the setting in existing research [25], the number of patents granted (ln*Patent*) is selected as the proxy variable for the regional technological level. The mediation effect test results are reported in Table 7. The results in column (2) show that the coefficient of *LMC* on ln*Patent* is significantly negative, indicating that land misallocation hinders the progress of the regional technological level, verifying the research hypothesis proposed in the theoretical analysis.

However, the results in column (3) of Table 7 show that the coefficient for ln*Patent* is not significant, failing to prove that ln*Patent* can serve as a mediating variable through which land misallocation affects economic resilience. The empirical results ultimately also failed the Sobel test, indicating that the mediation effect using the number of patents granted (ln*Patent*) is not established.

Currently, patent applications in China include three types: invention patents, utility model patents, and design patents. Research finds significant differences in the impact of different patent types on the technological level. Invention patents require relatively higher technological levels and are more difficult to obtain, while utility model and design patents have lower technological requirements and are easier to acquire. Therefore, following the patent weighting standard of Zhang et al. (2023) [30], invention patents are classified as high-weight patents (denoted as *Invention*), while utility model and design patents are classified as low-weight patents (denoted as *Design*). The number of patents granted is then disaggregated by high and low weights, and the mediation test is conducted again. The results are presented in Table 8.

Table 8. Mediation Tests with Disaggregated Patent Variables.

Variables	(1) *RES*	(3) ln*Invention*	(3) *RES*	(4) ln*Design*	(3) *RES*
LMC	-0.006*** (0.002)	-0.002* (0.004)	-0.007*** (0.002)	0.001 (0.000)	-0.006*** (0.002)
ln*Invention*			0.112* (0.235)		
ln*Design*					-0.135 (0.096)
Open	-0.001 (0.003)	0.002 (0.002)	-0.003 (0.003)	0.001 (0.001)	-0.003 (0.003)
Urban	1.545* (5.239)	2.322** (1.185)	1.674* (0.982)	2.782*** (0.929)	2.182* (1.143)
ln*Income*	-0.194 (2.645)	2.157*** (0.319)	0.262 (0.265)	0.856*** (0.186)	0.706** (0.289)
ln*Market*	-0.459*** (0.170)	-0.482*** (0.165)	-0.566** (0.217)	0.623*** (0.123)	-0.349** (0.156)
W.*RES*	0.247** (0.113)		0.241** (0.111)		0.254** (0.112)
W. ln*Invention*		0.332*** (0.039)			
W. ln*Design*				0.221** (0.071)	
W. *LMC*	0.021* (0.016)	1.417** (0.039)	0.027** (0.026)	0.002 (0.002)	0.024 (0.025)
R^2	0.573	0.665	0.256	0.608	0.338
Sobel Z [P Value]			1.795 [0.073]		0.345 [0.730]

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

Columns (1) to (3) in Table 8 report the test results using invention patents (*Invention*) as the mediating variable. Columns (4) to (6) report the results using utility model and design patents (*Design*) as the mediating variable. Using *Design* as the mediating variable failed the Sobel test, indicating the mediation effect is not established. However, in column (2), the coefficient of the land misallocation coefficient (*LMC*) on the number of invention patents granted (*Invention*) is significantly negative, again proving the negative effect of land misallocation on the regional technological level. In column (3), both the coefficients for *LMC* and *Invention* are significant and passed the Sobel test, indicating a partial mediation effect for *Invention*. Since invention patents (*Invention*) require a higher technological level, they serve as a better proxy for "technological level" compared to the total number of patents granted (ln*Patent*). The above empirical test results confirm the research hypothesis proposed by the theoretical study: land misallocation reduces regional economic resilience by hindering the progress of the regional technological level.

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5. Conclusions and Policy Implications

Through theoretical analysis and empirical testing, this research systematically investigates the underlying mechanism of land misallocation on economic resilience, arriving at the following core conclusions:

(1) Land misallocation significantly inhibits regional economic resilience. The research finds that the "Price Scissors Gap" strategy employed by local governments—supplying industrial land at lower prices and commercial land at higher prices—leads to land factor misallocation, thereby reducing regional economic resilience. Simultaneously, the negative impact of land misallocation on regional economic resilience exhibits spatial spillover effects.

(2) Land misallocation indirectly weakens economic resilience by hindering technological progress. Using invention patents as the core proxy for regional technological level and employing the mediation model for empirical testing reveals that land misallocation significantly inhibits regional technological progress and further weakens economic resilience. This indicates that land misallocation, by "crowding out" efficient enterprises and delaying the exit of inefficient ones, hinders the flow of production factors to high-productivity sectors, ultimately reducing the region's capacity to cope with shocks.

(3) The agglomeration effect induced by land misallocation is characterized by "diseconomies of scale." While the policy of low-price industrial land supply can foster initial clustering, empirical results confirm that this price misallocation enables the survival of low-efficiency enterprises, creating a pattern of "ineffective agglomeration." This ultimately suppresses TFP and hinders the upgrading of the industrial structure, which is detrimental to the enhancement of long-term economic resilience.

The above research conclusions indicate that land misallocation is a significant bottleneck currently constraining China's high-quality economic development, as it weakens regional economic resilience by inhibiting technological progress, among other channels. In the future, further market-oriented reforms of production factors are needed to shift land resource allocation from "administrative dominance" to "efficiency priority," providing institutional guarantees for building a more resilient modern economic system. Accordingly, this research proposes the following policy implications to alleviate land misallocation and enhance regional economic resilience: First, optimize the land supply structure under the New Urbanization context. Implement a "population-land-fund linkage" mechanism, dynamically matching land supply prices with labor mobility directions and industrial demands to avoid inefficient allocation of land resources. Second, accelerate the fiscal transformation of local governments and build a diversified fiscal revenue system. Reduce local governments' reliance on land conveyance revenue and supplement fiscal revenue through long-term tax categories such as property taxes and resource taxes. Third, strengthen policy coordination between land supply and industrial upgrading. Link land policies with innovation policies, granting land use priority or price preferences to high-technology enterprises to incentivize productivity improvements. For instance, include R&D investment or patent output clauses in land supply agreements, forming a "technology-oriented" land supply incentive mechanism.

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