Will Platform Economy Improve Resource Allocation?

—An Empirical Study Based on Provincial Panel Data in China

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Abstract. Amid the digital wave driving global industrial transformation, the platform economy, as a new organizational form in the digital era, is reshaping the paradigms of production factor allocation and regional economic development. This study overcomes the spatial limitations of traditional resource allocation research by analyzing China's provincial panel data from 2014 to 2019. Using a dynamic Spatial Durbin Model, we empirically examine how platform economy development affects resource allocation. The results show: (1) A significant positive spatial correlation exists between platform economy growth and resource allocation, indicating that platform economy development promotes geographically optimized resource distribution. (2) Platform economy expansion exhibits spillover effects, where improved resource allocation in one region may exacerbate imbalances in neighboring areas.

Keywords: Platform economy; Resource allocation; Spatial Durbin Model

1 Introduction

The April 2023 meeting of the Political Bureau of the CPC Central Committee reaffirmed the commitment to the "Two Unwavering Principles" and called for promoting the standardized development of platform enterprises while encouraging leading firms to pursue innovation. Amid the ongoing economic transformation characterized by structural adjustments and growth momentum shifts, the platform economy has emerged as a catalyst for high-quality development. By enhancing production efficiency [1], optimizing transaction mechanisms [2], and fostering mass entrepreneurship, this new economic model demonstrates significant potential in advancing China's development objectives.

As a digital-driven organizational form centered on platform enterprises, the platform economy integrates multi-market entities and resources through open, shared, and networked ecosystems. Its disruptive impact on traditional industries manifests in two dimensions: reconfiguring operational models through data-driven decision-making [3] and reshaping resource allocation patterns via algorithmic coordination [4]. However,

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existing research predominantly focuses on micro-level issues such as antitrust regulation and corporate governance [5], with limited exploration of its macroeconomic implications. Scholars have identified multi-tiered determinants of resource allocation, including policy interventions through industrial policies and regional development plans [6-7], as well as institutional factors such as tax efforts [8] and cross-border technology spillovers [9].

This knowledge gap persists in understanding how platform economy development spatially affects resource allocation efficiency—crucial for policymaking in China's transitional economy. Existing studies focus on micro-level impacts (e.g., industry digitization, supply chain upgrading), neglecting three key areas: standardized measurement of platform economy development, spatial interdependencies in resource allocation, and integration of macroeconomic mechanisms with platform operational traits [10]. To address these gaps, this study develops a multidimensional provincial platform economy index (spanning technological penetration, market integration, and value creation) to reduce single-indicator bias, and applies a dynamic Spatial Durbin Model to analyze spatial spillovers between platform economy growth and resource misallocation.

2 Platform Economy Development Index System

Drawing on existing research and considering data availability, this study constructs a comprehensive evaluation system for platform economy development, comprising two primary dimensions: platform infrastructure and transaction capacity. The hierarchical indicator system, detailed in Table 1, integrates three-level metrics that reflect China's platform economy characteristics.

Table 1. Development Indicator System for the Platform Economy.

	Secondary Indicator	Tertiary Indicator	Unit	Variable
Platform Infrastructure Level	Platform Hardware Development Level	Number of Internet Broadband Access Ports	10,000 units	Netport
		Number of Domain Names	10,000 units	Netnum
	Telecommunication Capability and Service Level	Telephone Penetration Rate	sets/100 people	Tcover
		Mobile Telephone Switchboard Capacity	10,000 units	Tcapacity
		Total Telecommunication Business Volume	100 million yuan	Tvolume
Platform Transaction Level	E-commerce Development Level	E-commerce Sales	100 million yuan	Ebuss
		E-commerce Procurement	100 million yuan	Epurch
		Number of Enterprises with E-commerce Transactions	units	Enumber
	Platform-based Products	Number of Express Parcels per Internet User	pieces/person	Econsumer

Synthesized provincial indices (see Table 2) demonstrate significant growth from 2014 to 2019, with persistent regional disparities. Eastern provinces consistently outperformed central and western regions. In 2019, Guangdong led the rankings, followed by Beijing, Jiangsu, Zhejiang, and Shandong, underscoring the alignment between platform economy maturity and regional economic development levels.

Table 2. Composite Index of Provincial Platform Economic Development in China (2014-2019).

Province	Platform Economic Development Index			Province	Platform Economic Development Index		
	2014	2017	2019		2014	2017	2019
Beijing	33.13	44.41	53.17	Henan	12.14	19.16	27.75
Tianjin	7.04	9.17	12.03	Hubei	9.75	14.54	21.00
Hebei	11.09	17.95	22.30	Hunan	7.95	13.66	21.73
Shanxi	6.08	8.18	12.99	Guangdong	44.84	51.18	84.47
Inner Mongolia	6.79	9.25	12.00	Guangxi	4.84	10.69	16.87
Liaoning	11.54	13.49	17.68	Hainan	4.76	6.37	8.83
Jilin	5.92	8.76	10.18	Chongqing	7.27	12.69	17.45
Heilongjiang	7.71	8.76	10.89	Sichuan	13.48	22.36	32.41
Shanghai	25.68	31.35	39.26	Guizhou	4.45	8.15	13.90
Jiangsu	26.89	32.00	47.52	Yunnan	5.78	8.42	14.47
Zhejiang	27.19	35.66	45.25	Shaanxi	7.63	11.71	16.61
Anhui	9.09	14.39	22.00	Gansu	3.08	6.72	9.46
Fujian	14.74	29.02	31.58	Qinghai	3.04	4.22	5.78
Jiangxi	3.80	8.76	15.09	Ningxia	4.05	5.20	5.95
Shandong	22.57	33.89	40.10	Xinjiang	6.28	7.24	10.92

3 Research Design

3.1 Model Specification

The analysis begins with spatial autocorrelation testing using Moran's I index, which quantifies spatial dependence among variables. The calculation follows:

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

Where n denotes the number of provinces, $x_i$represents the variable value for province$i$, $\bar{x}$ is the variable mean, and W_{ij} defines the economic-distance spatial weight matrix.

Given the identified spatial dependence, we employ a dynamic Spatial Durbin Model (SDM) to account for both temporal inertia and cross-regional spillovers. Building on Lesage and Pace's [5] framework, the model incorporates first-order lag terms to address path dependency in resource misallocation:

$$\tau_{kit} = \alpha_0 + \beta_{kj}\tau_{ki,t-1} + \rho_j \sum_j^N W_{ij}\,\tau_{kit} + \rho_i \sum_j^N W_{ij}\,platform_{it} + \lambda X_{it} + +\mu_i + v_t + \xi_{it} \quad (2)$$

$$\tau_{lit} = \alpha_0 + \beta_{lj}\tau_{li,t-1} + \rho_j \sum_j^N W_{ij}\,\tau_{lit} + \rho_i \sum_j^N W_{ij}\,platform_{it} + \lambda X_{it} + +\mu_i + v_t + \xi_{it} \quad (3)$$

Here, τ_{kit} and τ_{lit} denote capital and labor misallocation indices for province i in year t, with lagged terms $\tau_{ki,t-1}$and$\tau_{mi,t-1}$capturing temporal persistence. The spatial weight matrix W_{ij} is constructed based on interprovincial economic disparities:

$$W_{ij} = \frac{1}{|\bar{Y_i} - \bar{Y_j}|}(i \neq j), W_{ij} = 0(i = j) \quad (4)$$

Where $\bar{Y}$ represents per capita GDP in 2000, ensuring closer economic ties between provinces with smaller developmental gaps.

3.2 Data Sources

The study covers 30 Chinese provinces (excluding Tibet, Hong Kong, Macau, and Taiwan) from 2014 to 2019. Data originates from the China Statistical Yearbook, China Population and Employment Statistical Yearbook. Variable Operationalization

Independent Variables: In this study, we chose Resource Misallocation Indices as the dependent variables. Following Chen and Hu [4], capital (τ_{kit}) and labor (τ_{lit}) misallocation indices are derived through:

$$\gamma_{Ki} = \frac{1}{1+\tau_{Ki}}, \gamma_{Li} = \frac{1}{1+\tau_{Li}} \quad (5)$$

Where γ_{Ki} and γ_{Li} measure deviations from optimal allocation. The operationalized metrics are:

$$\widehat{\gamma_{Ki}} = \left(\frac{K_i}{K}\right) / \left(\frac{s_i \beta_{Ki}}{\beta_K}\right), \quad \widehat{\gamma_{Li}} = \left(\frac{L_i}{L}\right) / \left(\frac{s_i \beta_{Li}}{\beta_L}\right) \quad (6)$$

Here, $s_i = \frac{y_i}{Y}$ indicates provincial GDP share, $\beta_K$and $\beta_L$represent national capital/labor elasticities, and $\frac{K_i}{K}$ and $\frac{L_i}{L}$ denote actual resource usage shares.

Dependent Variable: The platform economy development index ($platform_{it}$) is constructed as detailed in Section 3.

Control Variables: Drawing on established literature, control variables include technological investment, urbanization rate, financial development, and human capital (descriptive statistics in Table 3).

Table 3. Variable Descriptions and Descriptive Statistics.

Variable Attribute	Variable	Variable Description	Full Sample		
			Mean	Max	Min
Independent Variable	τ_k	Measurement Results	0.307	1.793	0.002
	τ_l	Measurement Results	0.349	1.726	0.007
Dependent Variable	Platform	Constructed Index (platform)	17.395	84.47	3.04
Control Variables	Open	Ratio of Total Import-Export Volume to Regional GDP	0.25	1.22	0.01

	Population	Logarithm of Regional Total Population	8.239	12.503	6.368
	Human	Average Years of Education in Regional Population	25.338	44.594	12.404
	Rgdp	Regional Per Capita GDP	10.92	12.01	10.17

Continued Table 3. Variable Descriptions and Descriptive Statistics.

Variable Attribute	Variable	Variable Description	Full Sample		
			Mean	Max	Min
	market	Ratio of Non-state-controlled Industrial Enterprises to Above-scale Industrial Enterprises	0.896	0.982	0.72
	Istruct	Share of Tertiary Industry in GDP	0.492	0.835	0.354
	Gov	Ratio of Fiscal Expenditure to GDP	0.26	0.63	0.12

3.3 Empirical Analysis

Table 4 shows the Moran's test results between the dependent variable and the core explanatory variable. The test indicates that the core explanatory variable and the eight control variables are statistically significant and exhibit strong spatial autocorrelation. We conduct a Hausman test on the capital misallocation coefficient and the labor misallocation coefficient; the p-values are 0.0000 and 0.0032 respectively, and they pass the significance test at the 1% level, so fixed effects are chosen. In the LR test, the two p-values are 0.0037 and 0.0066, both below 0.01, indicating that the spatial Durbin model can be used.

Table 4. Moran Test Results.

Variable	Moran's I
platform	0.248**
open	0.288**
population	0.152
human	0.383***
rgdp	0.462***
market	0.425***
istruct	0.085
gov	0.570***

Note: The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively (same below).

The regression results shown in Table 5 and Table 6.

Table 5. Benchmark Regression Results.

	(1)	(2)
	τ_k	τ_l
$L.\tau_k$ $L.\tau_l$	1.2719***	2.292***
	(0.000)	(0.000)
$W.\tau_k$ $W.\tau_l$	-0.1988	3.878***

	(0.233)	(0.000)
platform	0.0724	-0.081*

Continued Table 5. Benchmark Regression Results

	(1)	(2)
	(0.314)	(0.075)
W×platform	-0.873***	1.3223***
	(0.000)	(0.000)
Spatialrho	0.7170***	1.234***
	(0.000)	(0.000)
Controls	YES	YES
Year FE	YES	YES
Province FE	YES	YES

Table 6. Effect Decomposition Results.

	τ_k			τ_l		
	Direct	Indirect	Total	Direct	Indirect	Total
platform	-0.3638**	0.106	-0.258	-0.092	0.161	0.069
	(0.038)	(0.864)	(0.683)	(0.489)	(0.623)	(0.864)

The spatial Durbin model results reveal that both the one-period lagged capital and labor misallocation indices are statistically significant at the 1% level, confirming a time lag effect in resource optimization. Spatial spillover effects are evident, with positive spatial autocorrelation coefficients of 0.717 (capital) and 1.234 (labor), both significant at 1%, indicating that provinces with efficient resource allocation positively influence neighboring regions through capital spillovers and labor mobility. The platform economy's spatial lag term (W×platform) demonstrates divergent impacts: a coefficient of -0.873 for capital misallocation (1% significant) suggests local platform economy development improves neighboring regions' capital allocation, while a coefficient of 1.322 for labor misallocation (1% significant) highlights its exacerbating effect on labor misallocation in adjacent areas. Dynamic effects analysis shows negative direct effects for both capital and labor misallocation, underscoring the platform economy's role in mitigating local resource misallocation, though positive (albeit insignificant) indirect effects imply potential aggravation of neighboring regions' imbalances. Total effects (-0.258 for capital, +0.069 for labor) further reveal that platform economies enhance capital matching but hinder labor matching, driven by mechanisms where economically developed provinces attract capital and labor from neighbors through higher returns and infrastructure advantages, improving their own efficiency at the cost of widening regional resource allocation disparities.

4 Conclusions and Recommendations

The platform economy demonstrates a positive spatial correlation with resource allocation efficiency, quantified by Moran's Index, indicating its capacity to optimize resource distribution. While enhancing market transparency and liquidity to reduce misallocation at the macro level, it generates dual spatial spillover effects: positive local impacts but negative spillovers on neighboring regions due to talent and capital concentration in hubs. This underscores the necessity for coordinated strategies to balance regional development.

Based on the research and analysis results, the following suggestions are put forward: First, Narrow regional disparities in platform economy development through targeted policies addressing infrastructure, talent, and capital gaps. Second, Prioritize attracting innovative talent, venture capital, and R&D resources through incentive-driven entrepreneurship policies. Third, Establish unified regulatory frameworks and cross-regional cooperation mechanisms to reduce interprovincial barriers. Fourth, Expand 5G, AI, and industrial internet infrastructure to support platform innovation. Fifth, Leverage innovation-driven strategies to optimize economic structures and ensure long-term viability.

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