AN EXAMINATION OF THE INTERPLAY BETWEEN TOTAL FACTOR PRODUCTIVITY IN RETAIL SUB-INDUSTRIES IN CHINA MAINLAND

Pemeriksaan Interplay antara Jumlah Produktiviti Faktor dalam Sub-industri Runcit di Tanah Besar China

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ABSTRACT *This research employs a spatial econometrics approach to investigate the interdependencies and dynamics of total factor productivity (TFP) within retail sub-industries in China Mainland by utilizing statistical data from 2013 and 2018. By constructing an adjacency matrix based on industry similarity, the study examines the impact of various factors on the industrial characteristics of retail sub-industries. These factors include total assets and the average number of engaged persons. The findings reveal significant industrial interdependence, variations among sub-industries, and the presence of a distinct retail industry cluster, albeit in a diminishing state. The study also highlights the dominance of capital investment output over labor input and identifies a stage of increasing returns in production inputs. The implications underscore the need to consider mutual influences between neighboring industries when formulating relevant policies.*

Keywords: Industrial autocorrelation, Retail sub-industry; Spatial econometrics; total factor productivity (TFP)

ABSTRAK *Penyelidikan ini menggunakan pendekatan ekonometrik spatial untuk menyiasat saling bergantung dan dinamik produktiviti faktor keseluruhan (TFP) dalam sub-industri runcit di Tanah Besar China dengan menggunakan data statistik dari tahun 2013 dan 2018. Dengan membina matriks bersebelahan berdasarkan persamaan industri, kajian ini mengkaji kesan pelbagai faktor terhadap ciri-ciri industri sub-industri runcit. Faktor-faktor ini termasuk jumlah aset dan purata bilangan orang yang terlibat. Penemuan ini mendedahkan saling bergantung industri yang ketara, variasi dalam kalangan sub-industri, dan kehadiran kluster industri runcit yang berbeza, walaupun dalam keadaan yang semakin berkurangan. Kajian ini juga menekankan dominasi output pelaburan modal berbanding input buruh dan mengenal pasti tahap peningkatan pulangan dalam input pengeluaran. Implikasinya menekankan keperluan untuk mempertimbangkan pengaruh bersama antara industri jiran ketika merumuskan dasar yang berkaitan.*

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Kata kunci: *Autokorelasi industri, sub-industri runcit; Ekonometrik spatial; produktiviti faktor keseluruhan (TFP)*

1. Introduction

Total Factor Productivity (TFP) stands as a crucial metric reflecting economic growth quality, technological advancements, and enhanced management efficiency within regions or nations (Ngo et al., 2020). China Mainland's economic evolution demands a transition from a factor-intensive investment model to one propelled by Total Factor Productivity (Wang M. et al., 2021). As the consumption habits of Chinese residents continue to escalate, the demand for retail goods among consumers becomes increasingly apparent. Amidst the rapid advancements in the new retail sector, China Mainland's chain retail industry finds itself at a pivotal juncture for transformation and enhancement. This context raises pertinent questions: Are there correlations and interactions among total factor productivity within the retail industry? What roles do production factors, such as capital and labor, play in shaping these dynamics? This article aims to employ spatial econometrics methods to meticulously analyze the correlations and interactions of total factor productivity within the retail industry. In the contemporary landscape of economic globalization and regional integration, spatial dependence between economies emerges as an undeniable reality, necessitating a consideration of spatial spillover effects. Spatial econometrics, rooted in the first law of geography (Tobler, 2004), postulates that economic phenomena within specific regions exhibit inherent correlations with economic occurrences in adjacent regions, elucidating varying degrees of spatial correlation and differentiation (Anselin, 1988). Therefore, our study posits the existence of a correlation between the total factor productivity of segmented industries within the retail sector and that of neighboring industries. Importantly, we hypothesize that this correlation diminishes as industry dissimilarity grows. Based on this foundational assumption, this research embarks on a comprehensive exploration of the mutual influence of total factor productivity within China Mainland's retail industry.

2. Literature Review

In current research, the spatial econometric economic model has emerged as a robust approach for capturing the interrelationships between input and output factors in geographical space. Built upon the Cobb-Douglas production function theory, this model incorporates geospatial factors and additional independent variables specific to the research context. To effectively express spatial interactions in regression models, the establishment of a weight matrix is crucial (Anselin, 1995). The exploration of spatial econometric methods to analyze interrelationships among input and output factors in geographical space has been a focus of extensive research.

However, within the realm of retail industries, particularly concerning Total Factor Productivity (TFP), the literature presents a complex landscape that demands nuanced analysis. This section delves into the nuanced world of spatial econometrics, emphasizing its application in understanding TFP dynamics within retail industries.

Central to spatial econometrics is the choice of a weight matrix, a decision that profoundly influences empirical outcomes. Various weight matrices, such as distance-based or contiguity-based, introduce different spatial dynamics into the analysis. Understanding these nuances is pivotal; for instance, a distance-based matrix might emphasize geographical spread, while a contiguity-based matrix could underscore immediate neighbors. This choice resonates deeply in empirical studies, shaping the interpretation of results and influencing real-world applications. The weight matrix can be constructed using various methods, with the simplest approach utilizing spatial proximity and spatial distance matrices (Schneider et al., 2007). However, scholars argue that geographical distance alone may not fully account for spatial spillovers. Alternative approaches have been proposed, such as defining weight matrices based on economic aggregates or regional trade flows, as done by Giacomini et al (2004) and Beck et al (2008), respectively. These methods have gained wide usage. Recognizing the limitations of a uniform interaction intensity assumption in weight matrices, Li (2010) further developed spatial weight matrices that consider both geographical and socio-economic characteristics from distinct perspectives. Several scholars have contributed methodologies to spatial econometrics, each with its unique strengths and limitations. An in-depth analysis of these methods reveals their nuanced applications. For instance, Anselin's work provides a foundational understanding of spatial autocorrelation, laying the groundwork for subsequent advancements. Exploring diverse methodologies such as spatial lag models and spatial error models not only broadens the methodological toolkit but also sheds light on the intricacies of TFP relationships within retail sectors. Lesage (2014) emphasizes the sensitivity of estimation and inference in spatial regression models to the specification of weight matrices. To ensure the robustness of model estimation, it is recommended to employ relatively simpler spatial weight matrices. These studies offer valuable insights and serve as references for the matrix setting in the present article.

Integration of empirical studies into a cohesive narrative unveils critical patterns. Research by Feldman et al (2010) highlighted the spatial dependencies in retail TFP, indicating an industry landscape intertwined with geographical proximity. Conversely, Lynch et al (2002)'s findings, emphasizing the significance of market-based weight matrices, challenge traditional methodologies. These studies, in conjunction, establish a comprehensive understanding of the interplay between spatial dynamics and retail TFP. The existing literature emphasizes not just technical nuances but also the broader implications of spatial econometrics. The choice of a specific weight matrix profoundly shapes the interpretation of empirical findings, showcasing the pivotal role spatial relationships play in understanding retail TFP.

Furthermore, the nuanced understanding of methodologies allows for an enriched exploration of TFP dynamics, offering valuable insights into policy-making and strategic decisions within the retail industry. Overall, the spatial weight matrices employed in the existing literature on spatial econometrics primarily utilize proximity matrices, spatial distance matrices, economic characteristic matrices, and nested matrices. Proximity matrices have found extended applications. For example, Zhang et al (2023) constructed pure geographical adjacency matrices and pure administrative adjacency matrices to analyze the mutual influence of infrastructure public expenditure between prefecture-level cities and regions. Xie et al (2011) utilized a proximity matrix based on whether a three-digit industrial industry belongs to the same two-digit industry to investigate wage agglomeration and interaction in China Mainland's industrial sector. Regardless of the matrix setting, it is crucial to consider the non-independence of the data.

In summary, this literature review delves into the intricate world of spatial econometrics, emphasizing its application in unraveling the complexities of Total Factor Productivity within retail sectors. By understanding the significance of weight matrices, delving into methodological intricacies, integrating empirical findings, and exploring broader implications, this review provides a comprehensive foundation for the current research, bridging the gap between spatial econometric methodologies and the intricate dynamics of retail TFP.

3. Research Methods and Data Sources

3.1 Basic model of production function

The Cobb-Douglas production function, a fundamental tool in economics, is applied in this study to capture the relationship between TFP, capital, and labor inputs. This choice is justified by the capacity of the Cobb-Douglas function to provide insights into production processes and TFP variations. It allows for a quantitative exploration of how changes in capital and labor inputs influence TFP within the retail industry.

This section recognizes the limitations associated with the dataset, provides a rationale for variable selection, and underscores the relevance of the Cobb-Douglas production function in addressing the research questions. Clarity and systematic organization are prioritized to enhance the understanding of the research methodology. The Cobb-Douglas production function is a widely recognized method for assessing the contributions of factor inputs to economic growth. Assuming two inputs, capital (K) and labor (L), and considering technological progress as an exogenous variable, the industrial added value (IAV) of the retail industry during the period t is given by the following equation:

$$IAV = ATA_{it}^{a} EPY_{it}^{b} e \qquad (1)$$

Among them, IAV represents the added value of the i industry during the period t. TA refers to the capital factor investment of the i industry during the period t. EPY refers to the input of labor factors of the i industry during the period t. e is a Hicks-neutral productivity term for technological progress that grows at a constant rate.

To facilitate estimation, Equation (1) is logarithmically transformed, resulting in a linear correlation and the elimination of the variance effect. The transformed equation is as follows:

$$LnIAV = LnA + LnTA_{it}^{a} + LnEPY_{it}^{b} + Lne \qquad (2)$$

Equation (2) establishes a stable functional relationship between the total factor productivity of retail industry segments and the main factors, capital and labor, under the assumption of unchanged technology.

The research sample used in this study consists of the four-digit retail industry in China Mainland. As the economic census in Mainland China is conducted every five years, only two cross-sectional data points from 2013 and 2018 are available for comparative analysis. This study relies on cross-sectional data collected in 2013 and 2018. It's essential to acknowledge the limitations posed by the utilization of only two data points. Cross-sectional data provides a snapshot view, making it challenging to capture dynamic changes comprehensively. However, these two points in time were chosen due to their relevance to industry classification systems, providing a suitable basis for comparison in line with the research objectives. The limitation of the dataset is recognized, and efforts are made to mitigate it through robust statistical analysis. The total assets (TA) measured in ten thousand yuan and the number of employees at the end of the year (EPY) is employed to represent the capital and labor input factors, respectively. These two variables are used as explanatory variables in the economic model measuring retail output. Two key variables, "total assets (TA)" and "number of employees at the end of the year (EPY)," are employed as proxies for capital and labor input factors, respectively. These choices stem from their pertinence to the measurement of Total Factor Productivity (TFP) within the retail industry. The inclusion of "TA" is rooted in the substantial capital requirements characteristic of the retail sector. Investments in assets influence the ability to deliver services, and consequently, TFP. "EPY" reflects labor input, and its relevance emerges from the labor-intensive nature of the retail industry, where the quality and quantity of the workforce significantly impact productivity. While these variables are chosen, it is crucial to acknowledge that the concept of TFP often extends beyond capital and labor inputs. The focus here remains consistent with the objectives of this study. The industry value added (IAV) is used as the dependent variable. The data for this study mainly comes from the "China Economic Census Yearbook - 2013" and "China Economic Census Yearbook - 2018."

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3.2 Spatial autocorrelation test model

To examine the presence of spatial correlation in regional economic output, Moran's I is employed. The formula for Moran's I is given by:

$$Moran's \quad I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \qquad (3)$$

Among them, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y})^2$, $\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$, Y_i represents the observation value of the i region, n represents the total number of regions, and W_{ij} represents the spatial weight matrix.

Generally, industries with similar economic activities tend to influence each other. Assessing the similarity of economic activities between industries is essential when analyzing the mutual impact of total factor productivity. The National Economic Industry Classification categorizes industries based on the homogeneity of economic activities and identifies their industry nature according to the primary economic activities of the units. The industry codes indirectly represent the similarity between industries. A common approach to measuring industry similarity is to determine the degree of similarity or "distance" between four-digit sub-industries based on whether they belong to the same three-digit industry (Xie L. et al., 2011).

The elements in elements in the i row and j column of the adjacent matrix W_{ij} are as:

$$W_{ij} = \begin{cases} 1 \text{When industry i and industry j belong to the same three digit industry} \\ 0 \text{When industry i and industry j do not belong to the same three digit industry} \end{cases}$$

The "China Economic Census Yearbook - 2013" and "China Economic Census Yearbook - 2018" correspond to the GB/T4754-2011 and GB/T4754-2017 editions of the National Economic Industry Classification, respectively. For this study, the two cross-sectional datasets are used to identify the four-digit sub-industries within the retail industry. These industry classifications are based on the homogeneity of production activities, which aligns with the research objectives of this study. Employing the aforementioned matrix construction method, two adjacency matrices are formed for each industry.

3.3 Spatial econometric economic model and estimation

This study primarily employs the spatial lag model (SLM) and spatial error model (SEM) to conduct correlation analysis. The estimation of SLM and SEM involves the use of ordinary least squares (OLS).

However, OLS estimation alone may not suffice, and it is necessary to employ the maximum likelihood method (ML) for more accurate estimation. The SLM and SEM models are both widely used in spatial econometric analysis to account for spatial dependence and spatial heterogeneity. These models consider the spatial interactions and spillover effects among neighboring regions, allowing for a more comprehensive understanding of the factors influencing total factor productivity in the retail industry. Estimating SLM and SEM involves incorporating spatial weight matrices and estimating the spatial autocorrelation parameters. The OLS method is a common approach for estimation, but it may not fully capture the complexities of spatial dependence. Therefore, the maximum likelihood method (ML) is utilized to enhance the estimation accuracy and account for potential spatial heterogeneity. By employing ML estimation in addition to OLS, this study aims to provide more robust and reliable estimates of the parameters in the SLM and SEM models. ML estimation takes into account the spatial dependence and potential spatial heterogeneity, ensuring a more comprehensive analysis of the interactions and correlations of total factor productivity in the retail industry.

4. Results and Analysis

4.1 General Descriptive Statistical Analysis of Total Factor Productivity by Industry in China Mainland's Retail Industry

Table 1 presents the descriptive statistics of logarithmically transformed variables, including retail sector output (lnIAV), total assets (lnTA), and year-end employment (lnEPY), in Chinese Mainland for the years 2013 and 2018. The largest difference among variables between the two cross-sections is observed in the number of employees at the end of the year (lnEPY). The dependent variable, industry output (lnIAV), follows as the second-largest in terms of industry differences. Total assets (lnTA) also exhibit significant industry variations. These findings indicate that the retail industry output and its influencing factors in the Chinese Mainland exhibit a distribution trend characterized by noticeable industry heterogeneity, with the heterogeneity being more pronounced in 2013 compared to 2018.

Table 1.

Descriptive Statistics of China Mainland's Retail Sub-industrial TFP

	2013			2018		
Variable	lnIAV	lnTA	lnEPY	lnIAV	lnTA	lnEPY
Minimum	10.1533	9.9543	7.0094	11.2611	11.3953	8.0784
Maximum	18.4860	17.6668	14.0938	19.5509	18.8678	14.4060
Mean	14.8717	14.4863	11.2841	15.4692	15.2246	11.5213
Standard deviation	1.6758	1.5478	1.4368	1.7020	1.6209	1.4612
Coefficient of variation	0.1127	0.1068	0.1273	0.1100	0.1065	0.1268

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Descriptive statistics provide insights into the distribution and dispersion of the variables. The minimum and maximum values illustrate the range of variation, while the mean indicates the average level. The standard deviation measures the degree of dispersion around the mean, and the coefficient of variation offers a relative measure of dispersion, enabling comparisons across variables. These statistics reveal the industry-specific characteristics of the retail sub-industrial total factor productivity (TFP) in China Mainland, emphasizing the importance of considering industry heterogeneity when analyzing the mutual interactions and factors influencing TFP in the retail sector.

4.2 Spatial autocorrelation test

To examine the correlation between retail sub-sectors in the Chinese Mainland across two cross-sections, an assessment of interdependence is conducted. Assuming the absence of spatial autocorrelation, Moran's index is calculated using the industry proximity matrix. The matrix is permuted 999 times using the repeated random arrangement method, and a standard normal statistic is constructed. The Moran's index measures the global spatial correlation characteristics for each variable, considering both univariate and bivariate spatial autocorrelation. This analysis allows for an assessment of the spatial autocorrelation effect within each variable and the spatial correlation characteristics between the variables themselves.

Table 2 presents the results of Moran's index for both single and double variables, indicating the spatial correlation between retail sub-sectors in the Chinese Mainland for the years 2013 and 2018. The results reveal the spatial correlation characteristics of each variable. The Moran's index measures the degree of spatial clustering or dispersion, where a value close to 1 indicates a strong positive spatial correlation, while a value close to -1 indicates a strong negative spatial correlation. The p-value represents the statistical significance of the Moran's index, indicating the likelihood of observing such a spatial pattern by chance.

Table 2.
Moran's Index for Single and Double Variable Spatial Correlation

		2013		2018	
	Variable	moran'I	p-value	moran'I	p-value
Univariate	lnIAV	0.3980	0.0010	0.3354	0.0020
	lnTA	0.3375	0.0020	0.2925	0.0040
	lnEPY	0.4051	0.0010	0.3571	0.0010
Bavaria	lnIAV/lnTA	0.3682	0.0020	0.3111	0.0020
	lnIAV/lnEPY	0.3937	0.0020	0.3372	0.0010

The analysis demonstrates significant spatial correlation for all variables in both cross-sections, indicating the presence of spatial dependence among retail sub-sectors in the Chinese Mainland. Additionally, the bivariate analysis examines the spatial correlation between pairs of variables, revealing their interrelationships. These findings contribute to a better understanding of the spatial autocorrelation effects and spatial correlation characteristics within and between the variables in the study.

Moran's index of single variables, namely lnIAV, lnTA, and lnEPY, demonstrates significant positive autocorrelation in the retail sub-industry in Chinese Mainland, passing the 1% significance test. The magnitude of autocorrelation follows the order lnEPY > lnIAV > lnTA. Comparing the industry correlation between 2013 and 2018, it is observed that the industry correlation weakened in 2018 due to the refinement of industry classification and clearer categorization of retail industry segments.V Furthermore, calculating the bivariate Moran's index using lnIAV as the central variable and lnTA and lnEPY as surrounding variables, it is found that lnTA and lnEPY exhibit positive correlations with lnIAV within the industry and pass the 1% significance test. The magnitude of the correlation is lnIAV/lnEPY > lnIAV/lnTA. Similar to the univariate analysis, the bivariate industry correlation also weakened in 2018 compared to 2013.

In conclusion, the industry correlation of retail total factor productivity in the Chinese Mainland demonstrates a declining trend. This suggests that the distribution of retail total factor productivity is not purely random but exhibits strong positive autocorrelation (industry dependence), with noticeable industry agglomeration. The assumptions stated in the introduction are valid, indicating a correlation between the output of retail industry segments and the total factor productivity of neighboring industries, which decreases as industry similarity weakens. Figure 1 illustrates Moran's index scatter plot, displaying the industry correlation degree of total factor productivity within the subcategories of the retail industry. The left side represents 2013, while the right side represents 2018. The scatter plot is divided into four quadrants, with the first and third quadrants indicating high-value clustering (H-H) and low-value clustering (L-L), respectively. This implies that industries with high total factor productivity are surrounded by similarly high-performing industries, and the same applies to industries with low total factor productivity. This indicates a positive correlation, with H-H and L-L types dominating. However, compared to 2013, the agglomeration situation has weakened in 2018. The second and fourth quadrants display a negative correlation, where high total factor productivity industries are surrounded by low-performing industries, and vice versa. The number of retail subcategories distributed in the second and fourth quadrants is relatively small.

The quantitative analysis presented above provides evidence of industry agglomeration in the total factor productivity of retail sub-industries in the Chinese Mainland. It demonstrates strong industry correlation and significant industry differences. Therefore, it is both reasonable and feasible to employ spatial econometric methods for analyzing the correlation among small categories of total factor productivity in the retail industry and other industries (Figure 1).

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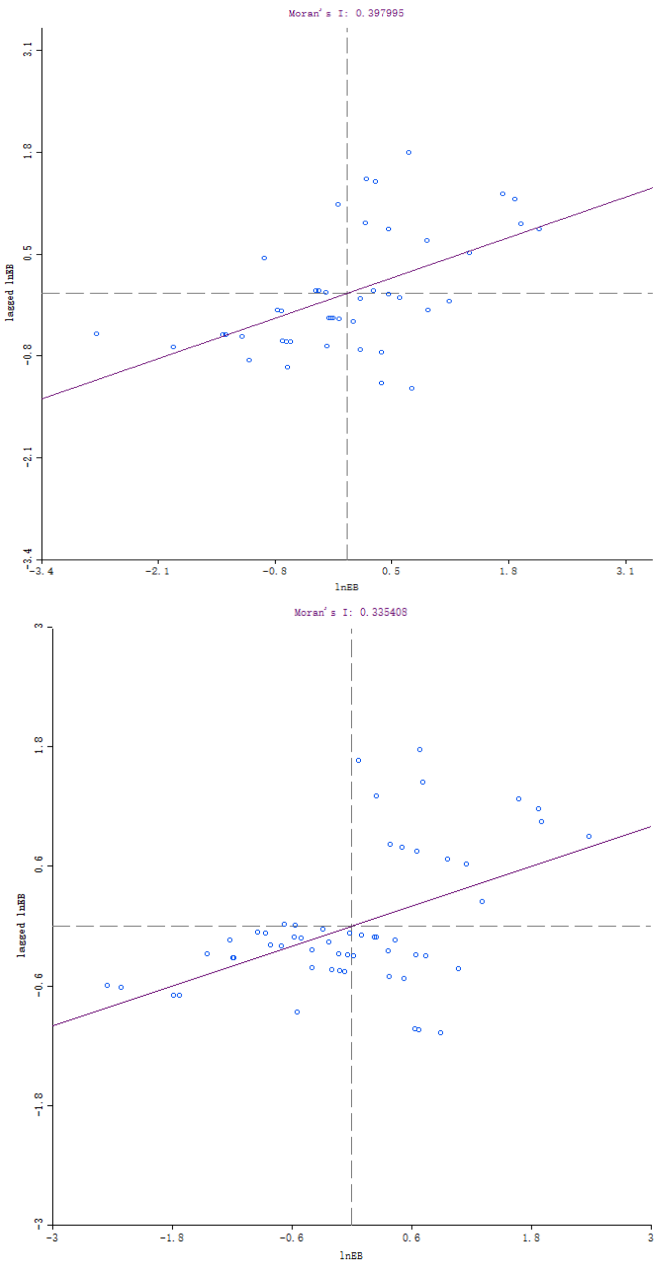

Figure 1. *Moran's, I scatter plots of China Mainland's Retail Sub-industrial TFP*

4.3 Spatial econometric estimation and analysis

In this section, this study proceeds with the spatial econometric estimation and analysis. Building upon the Moran's I index calculated for the entire region, this study utilizes the least squares (OLS) method to estimate the total factor productivity of the retail industry in the Chinese Mainland. To further illustrate the industry autocorrelation, two Lagrange multiplier (LM) tests and their corresponding robust forms (Robust LM) are conducted.

Table 3.
Tests of LM

Spatial Dependency Test	2013 MI/DF	2013 Statistical value	2013 p-value	2018 MI/DF	2018 Statistical value	2018 p-value
Moran's I(error)	0.0127	0.4867***	0.0626	0.2144	3.0204*	0.0025
LM (lag)	1	5.0531**	0.0246	1	3.9031**	0.0482
Robust LM (lag)	1	5.1333**	0.0235	1	2.2662	0.1322
LM (error)	1	0.0134	0.908	1	6.126**	0.0133
Robust LM (error)	1	0.0936	0.7596	1	4.4891**	0.0341
LM(SARMA)	2	5.1467***	0.0763	2	8.3922**	0.0151

Note: *** indicates passing the significance test at the 1% level, ** at the 5% level, and * at the 10% level.

The LM tests assess spatial dependency and provide insights into the industry autocorrelation. The Moran's I (error) test examines the spatial autocorrelation in the error term and reveals a statistically significant value in 2018. The LM (lag) test and Robust LM (lag) test examine the spatial lag autocorrelation and yield significant results in both 2013 and 2018. The LM (error) and Robust LM (error) tests explore the spatial error autocorrelation, with the latter test showing significant results in 2018. The LM (SARMA) test examines spatial autocorrelation with a spatial simultaneous autoregressive moving average (SARMA) model, revealing significant results in both 2013 and 2018. These tests provide evidence of spatial dependency and significant industry autocorrelation in the total factor productivity of the retail industry in the Chinese Mainland. The results support the need to consider spatial effects when analyzing and modeling the retail industry's total factor productivity.

Based on the results presented in Table 3, it is evident that Moran's I (error) test exhibits significant industry dependence (correlation) in the classical regression errors. Further analysis involves the Lagrange multiplier error and lag tests, along with their corresponding robustness tests. In 2013, LM (lag) and Robust LM (lag) passed the 5% significance test, whereas LM (error) and Robust LM (error) failed the 10% significance test. In 2018, LM (lag), LM (error), and Robust LM (error) pass the 5% significance test, while Robust LM (lag) fails the 10% significance test. According to Anselin's criterion, it can be deduced that the industry agglomeration analysis of the total factor productivity of the retail industry in Chinese Mainland in 2013 is more suitable for the spatial lag model (SLM). On the other hand, the spatial error model (SEM) is more appropriate for the industry cluster analysis of the total factor productivity of the retail industry in the Chinese Mainland in 2018. This indicates that the total factor productivity of the retail industry in the Chinese Mainland in 2013 exhibits endogenous spatial lag, whereby the total factor productivity of neighboring industries significantly impacts the total factor productivity of the focal industry.

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However, in 2018, the total factor productivity of the retail industry in the Chinese Mainland displays industry error autocorrelation, suggesting the presence of additional factors beyond capital and labor that influence the total factor productivity of the retail industry. This finding aligns with the earlier analysis, which indicated a weakened industry correlation among the subcategories of the retail industry's total factor productivity.

Table 4.
Estimation results of SLM and SEM

Variable	2013				2018			
	SLM				SEM			
	β	Std E	z-value	p-value	β	Std E	z-value	p-value
C	-1.2402	0.5393	-2.2995**	0.0215	0.2132	0.4362	0.4889***	0.0625
lnTA	1.0062	0.1006	9.9995*	0.0000	0.9012	0.1108	8.1309*	0.0000
lnEPY	0.0372	0.1115	0.3338***	0.0739	0.1333	0.1260	1.0579**	0.0290
ρ/λ	0.0750	0.0347	2.1624**	0.0306	0.3727	0.1439	2.5902*	0.0096
statistical test	DF	Statistical value	p-value		DF	Statistical value	p-value	
R^2		0.9789				0.9722		
Log L		-0.3294				-9.8915		
LR	1	4.7375**	0.0295		1	4.9872**	0.0255	
AIC		8.6588				25.7831		
SC		15.8855				31.8591		

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

Next, we will compare the estimation results of the spatial lag model (SLM) from 2013 with the spatial error model (SEM) results from 2018 to analyze the economic implications of the estimated parameters. Based on Table 4, it is evident that the elasticity coefficients of all variables, including the constant term CONSTANT, pass the significance test, at least at the 10% level. The elasticity coefficient of total factor productivity of the retail industry in the Chinese Mainland concerning capital investment (TA) is the largest. This indicates that capital investment plays a crucial role in determining the total factor productivity of the retail industry, highlighting the industry's strong reliance on capital and the need for substantial investments to ensure sales turnover. However, compared to 2013, the coefficient decreases by 0.105 in 2018, indicating a significant reduction in the impact of capital on total factor productivity. Nevertheless, capital remains a significant driver of the interaction among small industries within the retail sector. The elasticity coefficient of total factor productivity with respect to labor input (EPY) is considerably smaller than that of capital input (TA).

This suggests that the quality and quantity of employees have minimal influence on the retail industry's development, which aligns with the practical situation. However, the elasticity coefficient of labor input exhibits a significant increase from 0.0372 in 2013 to 0.1333 in 2018. With advancements in technology, economic growth, and changes in consumer consumption patterns, the retail industry has become increasingly dependent on human resources. The combined elasticity coefficient of capital and labor input is 1.0434 in 2013 and 1.0345 in 2018, indicating that the retail industry in the Chinese Mainland continues to experience increasing returns to scale.

In 2013, the spatial lag regression coefficient ϱ (0.0750) is positive, indicating a spillover effect from neighboring industries on the total factor productivity of the retail industry. Similarly, in 2018, the spatial error regression coefficient λ (0.3727) was positive and passed the significance test at least at the 5% level. This highlights an enhanced spillover effect from nearby industries on the total factor productivity of the retail industry, indicating a strong interplay among industries in terms of total factor productivity. Furthermore, the CONSTANT regression coefficient, representing the constant term, changes from -1.2402 in 2013 to 0.2132 in 2018 and remains significant, at least at the 10% level. Other uncertain factors, such as industrial-technological progress, marketization degree, per capita disposable income, consumption patterns, and demand, have shifted from having a negative effect on the total factor productivity of the retail industry in the Chinese Mainland to having a positive effect.

These findings shed light on the factors influencing the total factor productivity of the retail industry, capturing the spatial spillover effects and highlighting the changing dynamics over time. They provide valuable insights for policymakers and industry stakeholders in understanding the determinants of total factor productivity and formulating appropriate strategies for enhancing productivity in the retail sector.

5. Conclusion and Policy Recommendations

This study assumes the presence of industry correlation in the total factor productivity of different subcategories within the retail industry and employs spatial econometric methods to validate this assumption. The key conclusions derived from the analysis are as follows:

(1) The calculation results of Moran's I index confirm the effectiveness and feasibility of the industry matrix constructed in this study. The retail industry in Chinese Mainland exhibits a strong positive autocorrelation (industry correlation) in terms of total factor productivity. The industry distribution and agglomeration characteristics are highly pronounced, displaying a clear clustering phenomenon albeit with a weakening trend.

(2) The Lagrange multiplier (LM) test and its robust form (Robust LM) test support the applicability of the spatial lag model (SLM) for the endogenous spatial lag interaction of total factor productivity in the retail industry in 2013.

In 2018, the industry demonstrated error autocorrelation, fitting the spatial error model (SEM).

(3) The contribution of capital investment to the total factor productivity of the retail industry in the Chinese Mainland is significantly greater than that of labor investment. However, the impact of capital factors is diminishing over time, while the contribution of labor factors is gradually increasing. The combined elasticity coefficients of capital and labor exceed 1, indicating an increasing return to scale stage.

(4) The positive spatial lag regression coefficient ϱ (0.0750) in 2013 and the positive spatial error regression coefficient λ (0.3727) in 2018 indicate the growing prominence of spillover effects from neighboring industries on the total factor productivity of the retail industry in the Chinese Mainland.

Regarding policy implications, given the evident agglomeration and interaction of total factor productivity within the retail industry, it is essential to consider inter-industry relationships when formulating industrial development policies. The mutual influence of total factor productivity among subcategories should not be overlooked. Furthermore, efforts should focus on accelerating the collaborative development of the retail value chain, breaking down existing segmentation barriers, and leveraging competitive advantages and core competitiveness across subcategories. Establishing resource linkages through industrial value chain cooperation can facilitate rapid response and in-depth development through shared value networks. Additionally, initiatives such as business process reengineering, optimization, and the establishment of customer relationship management systems are necessary. The implementation and application of the Internet of Things (IoT) in the retail industry should be expedited to enhance enterprise informatization and improve service quality. Building stable strategic networks through the IoT allows for quick market information acquisition and information sharing, strengthening communication between enterprise departments, suppliers, and customers, and promoting the utilization of network technology to enhance traditional retail industry practices.

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7. REFERENCES

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Kluwer Academic Publishers.

Anselin, L., & Florax, R. J. G. M. (1995). New directions in spatial econometrics: Introduction. In L. Anselin & R. J. G. M. Florax (Eds.), *New directions in spatial econometrics* (pp. 3–18). Springer. https://doi.org/10.1007/978-3-642-79877-1_1

Beck, N., Gleditsch, K. S., & Beardsley, K. (2008). Space is more than geography: Using spatial econometrics in the study of political economy. *International Studies Quarterly, 50*(1), 27–44. https://doi.org/10.1111/j.1468-2478.2006.00391.x

Feldman, M. P., & Kogler, D. F. (2010). Stylized facts in the geography of innovation. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the economics of innovation* (Vol. 1, pp. 381–410). Elsevier. https://doi.org/10.1016/s0169-7218(10)01008-7

Lynch, J. P., & Law, K. H. (2002). Market-based control of linear structural systems. *Earthquake Engineering & Structural Dynamics, 31*(10), 1855–1877. https://doi.org/10.1002/eqe.193

Ngo, M. N., & Nguyen, L. D. (2020). Economic growth, total factor productivity, and institution quality in low-middle income countries in Asia. *The Journal of Asian Finance, Economics and Business, 7*(7), 251–260. https://doi.org/10.13106/jafeb.2020.vol7.no7.251

Tobler, W. (2004). On the first law of geography: A reply. *Annals of the Association of American Geographers, 94*(2), 304–310. https://doi.org/10.1111/j.1467-8306.2004.09402009.x

Wang, M., Xu, M., & Ma, S. (2021). The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. *Structural Change and Economic Dynamics, 59*, 427–441. https://doi.org/10.1016/j.strueco.2022.02.006

Xie, L., Zhang, J., & Liu, X. (2011). Wage agglomeration and interaction in China's industrial industry. *World Economy, (7)*, 3–26.

Zhang, C., Liu, T., Li, J., Wang, X., Yang, Y., & Zhang, Y. (2023). Economic growth target, government expenditure behavior, and cities' ecological efficiency Evidence from 284 cities in China. *Land, 12*(1), 182. https://doi.org/10.3390/land12010182