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The Impact of Fixed Assets Investment on The Growth of Primary, Secondary and Tertiary Industries: A Case Study of Liaoning, China

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ABSTRACT

This research examines panel data from 14 cities in Liaoning Province from 2003 to 2024 to investigate the impact of fixed assets investment on the development of primary, secondary, and tertiary industries. It further analyzes the heterogeneous characteristics of industrial development across these cities. First, panel regression model was constructed. The Hausman test indicated the appropriateness of a fixed effects specification, and time effect were subsequently introduced to establish a two-way fixed effects model. The results demonstrate that investments in agriculture and forestry significantly promote the primary industry, while investments in manufacturing and construction drive the growth of the secondary industry. For the tertiary industry, investments in information services, environmental governance, and social welfare exert a significant positive impact. Subsequently, a city feature matrix was constructed by extracting the sensitivity of urban fixed effects and time effects, combined with indicators such as the coefficient of variation, trend slope, and dominant frequency amplitude. The Fuzzy C-Means clustering method was then applied to classify the 14 cities in Liaoning. The clustering results reveal that the primary and secondary industries display three structural types, whereas the tertiary industry displays two. Notably, Shenyang and Dalian exhibit prominent characteristics as core growth poles in regional industrial development These findings reveal differentiated pathways for urban industrial evolution in Liaoning Province, providing a valuable reference for optimizing regional industrial layouts and formulating targeted fixed assets investment policies.

Keywords: Fixed Assets Investment, Two-way Fixed Effects Model, Industrial Development, Fuzzy C-Means Clustering, Urban Heterogeneity

INTRODUCTION

Fixed assets investment is widely regarded as the key driving force for economic growth, industrial restructuring and regional development. As one of China's traditional industrial bases, Liaoning Province has undergone a transformation from a resource-based and manufacturing-oriented economy to a diversified industrial system. The research of Wang, Qi,&Shu (2020) shows that there is a significant dynamic interaction between China's fixed assets investment and the evolution of industrial structure; Heinrich, T., Yang, J.,&Dai, S. (2020) pointed out that investment driven development has always been an important force driving China's structural transformation.

Recently, Yang, Z. (2025) found that investment related capital inflows continue to have a significant impact on industrialization and regional economic performance. Fixed assets investment has different impacts on the industrial promotion and evolution of cities (Wang et al., 2020). Clustering techniques are increasingly being applied to regional economic classification and industrial structure research. Yuan, H. (2022) used fuzzy clustering method to optimize regional industrial structure and emphasized the importance of considering heterogeneous development models. Compared with traditional hard clustering methods, Fuzzy C-Means clustering allows each observation to belong to multiple groups simultaneously, thus enabling a more accurate representation of regional economic systems (Lin, Y.,&Chen, S. 2020). In addition, recent methodological studies have also demonstrated the effectiveness of FCM in identifying complex patterns in multidimensional datasets (Wang et al., 2023; Mallik et al., 2025). The statistical reliability of clustering results is increasingly receiving attention, especially in terms of clustering validity and classification stability (Dalmaijer, E. S., Nord et al., 2020). Current research mainly focuses on investment efficiency, industrial upgrading, and industrial structure optimization, with less attention paid to the differences in investment effects between different cities and industries within the province (Cheng, H. 2025).

Therefore, this study uses a two-way fixed effects panel model to examine the impact of fixed assets investment on the primary, secondary and tertiary industries in Liaoning Province. Subsequently, fixed effects and time sensitivity at the city level are extracted to characterize long-term structural differences and their response to time shocks. Using indicators such as coefficient of variation, trend slope, and dominant frequency amplitude, the Fuzzy C-Means clustering framework was employed to classify 14 cities in Liaoning Province. It reveals how fixed assets investment affects industrial development in Liaoning, and provides basis for differentiated urban development.

Research Objectives

This research takes 14 cities in Liaoning Province as the research object, and the research time range is from 2003 to 2024. It constructs a panel data-set to analyse regional economic differences and their evolution characteristics from the dimension of fixed assets investment on the primary industry agriculture, the secondary industry manufacturing industry and the tertiary industry service industry. Specific objects include:

1. The role of fixed assets investment in Liaoning. The added value of different industries in Liaoning is the dependent variable, and fixed assets investment is the explanatory variable.

2. Characteristics of urban heterogeneity. Extracting the sensitivity of fixed effects and time effects in each city through a two-way fixed effects model, reflecting the development foundation and prospects of different cities.

3. Urban classification and clustering characteristics. Using the Fuzzy C-Means clustering method, 14 cities in Liaoning Province were classified to identify city categories under different industrial development models, providing a basis for differentiated urban development.

LITERATURE REVIEWS

Review of Fixed Assets Investment and Panel Data

Qin, D.,&Song, H. (2009) studied how to improve the structure of fixed assets investment and optimize resource allocation through empirical model quantification. At the same time, negative impacts exist in resource misallocation and policy distortion. Ruan, L. (2020) studied the impact of instability on investment decisions and explored the relationship between fixed asset accounting treatment and investment efficiency through a framework of real options. Croissant, Y.,&Millo, G. (2019) demonstrated the efficiency and flexibility of R in panel data analysis through case studies covering fixed effects, random effects, and various diagnostic tool implementation methods.

Imai, K.,&Kim, I. S. (2021) analysed the limitations of the two-way fixed effects regression model in panel data causal inference, particularly the bias that may arise when the treatment effect changes over time. The two-way fixed effects and difference method estimates have significant effects when studied for multi processing effect analysis. It also provides new tools for complex policy evaluation issues (De Chaisemartin, C., et al., 2022).

Review of Cluster Analysis

Frades, I.,&Matthiesen, R. (2010) elaborated on the main technical routes, levels, K-means, and the impact of the model itself on clustering analysis. Kim, H., Hwang, S. J.,&Yoon, W. (2023) analyzed the impact of organizational diversity on innovation capability in industrial clusters and found that diversity in clusters can promote knowledge exchange and technological innovation. The study provides a new perspective for formulating policies to promote innovation in industrial clusters and emphasizes the importance of organizational heterogeneity.

This discovery provides new theoretical support for optimizing cluster innovation policies, while highlighting the critical significance of organizational differentiation in the innovation ecosystem. Dalmaijer, E. S., Nord, C. L.,&Astle, D. E. (2022) focused on the issue of statistical testing power in cluster analysis and constructed an analytical framework for evaluating the effectiveness of clustering methods. This study systematically examined the impact of sample size, effect magnitude, and algorithm type on the robustness of clustering results, laying a methodological foundation for enhancing the scientific reliability of clustering analysis. Sari, I. et al. (2021) focused on online education scenarios and empirically compared the performance of two algorithms. They found that K-Means had an advantage in large sample situations due to its computational efficiency, while fuzzy C-Means exhibited higher accuracy and adaptability in handling grouping tasks with transitional relationships.

METHODOLOGY

Panel Data and Two-way Fixed Effects Model

For the analysis of panel data effects, fixed effects and random effects models are the foundation. The fixed effects model assumes that unobservable effects of individuals are related to explanatory variables, and eliminates individual effects by introducing dummy variables or subtracting data. Wang&Tan's (2023) study suggests that changes in rural land construction have promoted the development of rural secondary and tertiary industries. There is a possibility of using fixed effects models to control for regional heterogeneity.

Two-way Fixed Effects model is an extension of the fixed effects model that effectively integrates individual and temporal fixed effects. This approach improves model interpretability while mitigating dual heterogeneity. De Chaisemartin&d'Hautfoeuille (2020) pointed out that the two-way fixed effects model has strong advantages in dealing with heterogeneous treatment effects, especially in policy evaluation and causal inference.

$$y_{it} = \alpha + u_i + \lambda_t + \beta X_{it} + \epsilon_{it} \tag{1}$$

Where:

y_{it}: The dependent variable of the i-th individual during period t;α: Overall intercept;u_i: Individual fixed effects capture specific characteristics of individuals that are independent of time;λ_t: Fixed time effect, capturing time specific features that are not related to individuals; X_{it}: Independent variable matrix (explanatory variable); β: The coefficient of the independent variable; ϵ_{it}: Random error term.

Li, Z. et al. (2020) used a two-way fixed effects model to analyse the relationship between urban construction land expansion and economic growth in Liaoning Province, eliminating potential individual and temporal interference factors Wooldridge (2021) proposed that two-way fixed effects and double difference models are suitable for panel data with individual and temporal dimensions.

The two-way fixed effects model is applicable to fields such as economic growth, industrial investment, and policy evaluation, and can handle the analysis of multiple regions and time points in Liaoning. It is particularly applicable to the analysis of the time and individual dimensions of fixed assets investment in the three industries of Liaoning.

Fuzzy C-Means Clustering Analysis and Industrial Impacts

Cluster analysis belongs to unsupervised learning methods and is suitable for summarizing and collecting characteristic information of datasets. Hejdukov á et al. (2020) mentioned the structural differentiation of cluster analysis in EU countries at the level of 4.0 industrial development, emphasizing the advantages of cluster analysis in multidimensional data analysis.

For the main types of cluster analysis, K-means clustering with uniform data distribution, hierarchical clustering with gradual merging and splitting, and principal component clustering suitable for high-dimensional data. The Fuzzy C-Means Cluster used in this article is suitable for classifying datasets with complex or fuzzy boundaries. The specific clustering model is:

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$$J_m = \sum_{i=1}^{n} \sum_{j-1}^{c} u_{ij}^{m} \left\| x_i - v_j \right\|^2 \tag{2}$$

Where：

J_m: Objective function, total clustering error; n: Number of samples; c: Number of clusters; u_{ij}^{m}: The degree to which city i belongs to category j; x_i: The i city number; v_j: The j cluster center; $\left\| x_i - v_j \right\|^2$: Euclidean distance squared, the difference between cities and cluster centers.

In the research of Liaoning Province, Fuzzy C-Means clustering analysis can be used to identify the industrial development characteristics of 14 cities and classify them as key development areas for different industries. Ge et al. (2022) identified the industrial development patterns of different regions through clustering analysis when studying the integration of different industries in rural areas, providing a scientific basis for coordinated regional economic development. Sanguinet&Rodr í guez Puello (2022) emphasized the role of the tertiary industry as a regional economic engine, and combined cluster analysis to reveal the differences in industrial development among different regions in Brazil.

The application of cluster analysis can not only reveal regional differences, but also provide scientific support for the formulation of industrial policies, which has important theoretical and practical significance.

Data Sources

Data in Two-ways Fixed Effects Model

Based on the panel data of cities in Liaoning Province from 2003 to 2024, this paper aims at the differences of fixed assets investment in different cities, establishes fixed assets investment targets suitable for different industries, and distinguishes the development characteristics of each city.

Table 1: Fixed Assets Investment Variables of The Three Industries in Liaoning

Primary Industry	Variables (unit: million yuan)	Abbreviation	Source
Dependent Variable	Primary industry GDP	gdp1	China National Bureau of Statistics
	Agriculture, forestry and water conservancy	agrifw	Liaoning Statistical Yearbook
	Agriculture, forestry, animal husbandry and fishery	agrian	Liaoning Statistical Yearbook
Secondary Industry			
Dependent Variable	Secondary industry GDP	gdp2	China National Bureau of Statistics
	Mining	mine	Liaoning Statistical Yearbook
	Manufacturing	manu	Liaoning Statistical Yearbook
	Production and supply of electricity, gas, and water	elec	Liaoning Statistical Yearbook
	Construction	constr	Liaoning Statistical Yearbook
Tertiary Industry			
Dependent Variable	Tertiary industry GDP	gdp3	China National Bureau of Statistics
	Transportation, storage and postal services	trp	Liaoning Statistical Yearbook
	Information transmission, computer services, and software industry	ei	Liaoning Statistical Yearbook
	Wholesale and retail	sales	Liaoning Statistical Yearbook
	Accommodation and catering	acco	Liaoning Statistical Yearbook
	Finance	fin	Liaoning Statistical Yearbook

	Real estate	hous	Liaoning Statistical Yearbook
	Scientific research, technical services, and geological exploration industry	scie	Liaoning Statistical Yearbook
	Water conservancy, environment and public facilities management	envi	Liaoning Statistical Yearbook
	Education expenditure	edu	Liaoning Statistical Yearbook
	Health, social security, and social welfare industries	welf	Liaoning Statistical Yearbook

Data in Fuzzy C-Means Cluster Analysis

The data collection for cluster analysis first requires the ability to distinguish relevant data from different cities in Liaoning Province. The selection of clustering analysis data includes:

Table 2: Cluster Analysis Variables

Variables	Abbr.	Function	Source
Individual Fixed Effects	fe_i	$\mu_i = \overline{y_i} - \beta \overline{X_i}$	Front Panel Data Analysis
Time Effect to City Sensitivity	$Stfe_i$	$\gamma_i = \frac{\partial GDP_{it}}{\partial \lambda_t}$	Front Panel Data Analysis
Trend Slope	Ts_i	$\mathrm{Ts_i} = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(y_i - \bar{y})}{\sum_{i=1}^{n}(t_i - \bar{t})^2}$	Author's Calculation
Coefficient of Variation	CV_i	$\mathrm{CV_i} = \frac{\sigma}{\mu}$	Author's Calculation
Main Frequency Amplitude	A_{Hi}	$f_{Hi} = \frac{arg\ max_k \lvert X[k] \rvert}{N} f_s$; $A_{Hi} = max_k \lvert X[k] \rvert$	Author's Calculation

1. Add individual fixed effects and time fixed effects. In order to cluster analysis, the original panel data ratio of fixed assets investment is compressed, and the mean value of each variable is used as the clustering variable.
2. Divide the data into three industry segments. The fixed effects and time effects extracted from the panel data analysis before adding clustering analysis. Lee, L. F.,&Yu, J. (2010) Time effects represent the economic trends of different years. And fixed effects consider the unique economic and industrial structure of each city.
3. Introducing time effect to city sensitivity, variables with temporal concepts such as trend slope, coefficient of variation, and main amplitude frequency can describe the main information of panel data variables from different cities in Liaoning that have temporal effects.

EMPIRICAL ANALYSIS

Descriptive Statistics and Model Selection

Table 3 presents the descriptive statistical results of the main variables for 14 cities in Liaoning Province from 2003 to 2024. Overall, the added value of the three industries shows significant regional differences, with the average added value of the tertiary industry slightly higher than that of the secondary industry, and the average added value of the primary industry relatively lower, reflecting that Liaoning Province's industrial structure has gradually tilted towards the secondary and tertiary industries.

Fixed assets investment variables also have a large degree of dispersion, indicating that there are significant differences in investment scale between different cities. At the same time, most investment variables have high skewness and kurtosis, indicating that investment is mainly concentrated in a few cities with high levels of economic development, and there are certain agglomeration characteristics. Overall, the variables exhibit strong heterogeneity, providing a data foundation for the subsequent use of two-way fixed effects models and Fuzzy C-Means clustering analysis.

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Table 3: Descriptive Statistics of Fixed Assets Investment in Liaoning

Vars	Mean	Sd.	Median	Range	Skew	Kurtosis	Se.
gdp1	13314.237	10436.491	10673.480	57910.340	1.952	4.309	594.674
gdp2	69886.934	85019.452	39943.700	385121.000	2.311	4.419	4844.433
gdp3	72580.716	104649.004	37671.150	554211.530	2.650	6.336	5962.930
agrifor	2074.750	1635.241	1798.285	8554.190	0.934	0.645	93.177
agrian	2039.550	3527.564	1042.362	26735.540	4.101	20.328	201.002
mine	2428.287	3318.333	955.435	15281.915	1.761	2.353	189.080
manu	22964.832	35348.359	12557.110	231800.360	3.235	11.950	2014.160
elec	4733.589	6197.660	2568.500	47417.768	2.981	12.149	353.144
constr	889.253	2244.739	97.239	21435.176	5.214	34.815	127.906
trp	6149.604	20092.660	1512.343	235198.323	8.175	80.093	1144.886
ei	3465.618	7437.739	431.311	52940.830	3.404	13.142	423.804
sales	1817.581	3714.429	564.030	33496.030	4.683	27.758	211.649
acco	1511.433	3149.336	261.810	22882.414	3.393	13.276	179.450
fin	30815.438	237615.859	4.250	2816895.776	8.881	85.844	13539.420
scie	757.327	1779.318	121.725	13172.440	4.183	20.366	101.386
envi	6503.417	14926.355	2589.527	127299.510	5.728	37.365	850.508
edu	953.833	1552.176	356.784	9266.700	3.153	11.023	88.443
welf	1083.456	2825.935	250.188	30527.765	6.014	47.405	161.023

Source: Author's Calculations

In order to determine the panel model form of the impact of fixed assets investment on the economic growth of three industries in Liaoning Province, this paper first constructs the fixed effect model and the random effect model, and uses Hausman test to select the model. The null hypothesis of Hausman's test is that the random effects model is effective; The alternative hypothesis is that the fixed effects model is effective, meaning there is a correlation between individual effects and explanatory variables.

Table 4: Hausman Test for Fixed Effects/Random Effects Models

Industries	Dependent Variable	Independent Variable	Chi-square	df	P-value	Model Selection
Primary	GDP1	agrifor, agrian	25.101	2	0.000003544	Fixed Effect
Secondary	GDP2	mine, manu, elec, constr	232.55	4	<2.2E-16	Fixed Effect
Tertiary	GDP3	trp, ei, sales, acco, fin, scie, envi, edu, welf	3880.2	9	<2.2E-16	Fixed Effect

Source: Author's Calculations

The test results in Table 4 indicate that the Hausman test statistic for the primary industry model is 25.101, with a degree of freedom of 2 and a corresponding P-value below the significance level of 0.01. Therefore, the null hypothesis of the random effects model is rejected and a fixed effects model should be used for estimation. At the same time, the test statistics of both the secondary and tertiary industry models significantly reject the random effects model. The results show that there is a strong correlation between different urban characteristics of Liaoning and fixed assets investment among agriculture, manufacturing and service industries. Therefore, subsequent analysis will use fixed effects models for estimation.

At the same time, in order to investigate the impact of time on fixed assets investment, time fixed effect is introduced to build a two-way fixed effects model. The model results indicate that the time effect F-test of the

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three industry models all passed at the 1% significance level, indicating that in addition to individual differences in cities, the year factor also has a significant impact on industry development. Therefore, it is reasonable to use a two-way fixed effects model.

Two-way Fixed Effects Model

Variance Inflation Factor and Breusch-Pagan Tests

To ensure the reliability of the estimation results of the two-way fixed effects model, this paper first uses the Variance Inflation Factor (VIF) for multicollinearity testing. Generally, a VIF greater than 5 indicates the presence of multicollinearity in the variable. And Breusch Pagan (BP) test for heteroscedasticity, a significant P-value indicates the presence of heteroscedasticity.

Table 5: Results of Variance Inflation Factor and Breusch-Pagan Test

Industry	Maximum VIF	Minimum VIF	VIF<5	BP statistic	df	P-value	Heteroscedasticity
Primary	1.2508	1.2508	*	21.826	2	1.822E-05	*
Secondary	1.2812	1.0258	*	49.269	4	5.131E-10	*
Tertiary	3.8591	1.8287	*	126.02	9	<2.2E-16	*

Source: Author's Calculations

The test results in Table 5 indicate that the VIF values of all explanatory variables in the three industries model are significantly lower than 5, indicating that there is no significant linear correlation between the explanatory variables, that is, there is no problem of multicollinearity. However, the BP statistics of the three industry models are 21.826, 49.269, and 126.020, respectively, and their corresponding P-values are significantly less than 0.01, indicating that all three models have significant heteroscedasticity issues. We need to eliminate the influence of heteroscedasticity first to prevent it from affecting the significance judgment.

The Revised Two-way Fixed Effects Model

After correcting for heteroscedasticity using the White heteroscedasticity robust standard error. Obtain the complete fixed investment in Liaoning Province and the fitting results of the two-way fixed effects model for the three industries. After correction, the regression coefficients and model goodness of fit for each variable remained unchanged, with only adjustments made for standard error, t-statistic, and variable significance level.

Table 6: Results of The Two-way Fixed Effects Model After Testing

Industries	Variable	Coefficient	Standard error	T-value	P-value	Significance
Primary	agrifor	2.2291	0.3844	5.7983	1.861E-08	***
Primary	agrian	-0.0158	0.1633	-0.0965	0.9232	
Secondary	mine	1.6894	1.1211	1.5068	0.133	
Secondary	manu	0.6708	0.0455	14.7363	<2.2E-16	***
Secondary	elec	0.6474	0.5017	1.2904	0.198	
Secondary	constr	4.8274	1.615	2.9891	0.0031	**
Tertiary	trp	-0.2181	0.2198	-0.9924	0.3219	
Tertiary	ei	3.5431	1.2351	2.8686	0.0045	**
Tertiary	sales	-2.5202	0.8055	-3.1288	0.002	**
Tertiary	acco	5.1283	3.7237	1.3772	0.1696	
Tertiary	fin	0.0011	0.0169	0.067	0.9466	

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Tertiary	scie	-6.9875	2.6233	-2.6637	0.0082	**
Tertiary	envi	1.4181	0.3597	3.9428	0.0001	***
Tertiary	edu	-1.3074	0.9757	-1.3399	0.1814	
Tertiary	welf	8.6035	2.4642	3.4914	0.0006	***
Signif. codes:'***' 0.001 '**' 0.01 '*' 0.05						

Source: Author's Calculations

In the primary industry model, the agricultural and forestry fixed assets investment is significant at the level of 1%, with a coefficient of 2.2291, indicating that every additional unit of agricultural and forestry investment will promote the growth of the primary industry by about 2.23 units. The coefficient of pure agriculture related investment (agrian) is negative and not significant, indicating that this variable has limited impact on agricultural economic growth. The low R^2 of the model indicates that the primary industry is greatly influenced by non-investment factors such as natural conditions and climate environment.

In the secondary industry model, both manufacturing investment (manu) and construction investment (const r) have a significant positive impact, with the construction investment coefficient reaching 4.8274, indicating that it has the strongest driving effect on industrial economic growth. However, mining investment and electricity investment lost their significance after correction, indicating that their original significance was partially affected by heteroscedasticity. The industrial growth in Liaoning is still supported by infrastructure construction.

The model R^2 is increased to 0.3324, indicating that fixed assets investment has significantly enhanced its ability to explain industrial economy.

The tertiary industry model exhibits the strongest explanatory power, with an R^2 of 0.6792. Investment in the information transmission industry (EI), environmental governance investment (ENVI), and social welfare investment (Welf) with a coefficient of 8.6035 all have a significant promoting effect on the development of the tertiary industry. At the same time, wholesale and retail investment (sales) and technology service investment (scie) show a significant negative impact, indicating that some service industry investments may have structural imbalances or insufficient resource allocation efficiency. Financial investment (finance) and education investment (edu) did not show significant impact.

A comprehensive comparison of the three industries shows that fixed assets investment plays the strongest role in promoting the tertiary industry, followed by the secondary industry, and has a relatively weak ability to explain the primary industry. This indicates that Liaoning's economy is gradually shifting from being dominated by traditional agriculture and industry to being dominated by the service industry. The revised results can more truly reflect the actual impact of fixed assets investment on the industrial development of Liaoning.

Cluster Analysis

Determining the Number of Clusters

The determination of the number of clusters is mainly based on the comprehensive judgment of three effective indicators: partition coefficient (PC), partition entropy (PE), and Xie Beni (XB) index.

Table 7: Fuzzy C-Means Cluster Validity Indices of The Optimal Number in Liaoning

K	PC1	PE1	XB1	PC2	PE2	XB2	PC3	PE3	XB3
2	0.625	0.551*	0.748	0.631	0.550*	0.846	0.812*	0.319*	0.151
3	0.656*	0.590	0.252*	0.659*	0.629	0.192*	0.771	0.446	0.1360*
4	0.588	0.764	0.318	0.562	0.823	0.728	0.645	0.668	0.649
5	0.563	0.874	0.277	0.569	0.865	0.461	0.555	0.868	1.433

Source: Author's Calculations

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From the clustering results of the primary industry, when the number of clusters K=3, PC reaches the maximum value of 0.6558, while XB reaches the minimum value of 0.2521, indicating that the clustering scheme has good intra class compactness and inter class separability. Therefore, it is most reasonable to divide the primary industry into three categories. When K=3, the maximum PC and minimum XB in the secondary industry are significantly better than other clustering numbers, and a 3-class scheme is also chosen. The clustering results of the tertiary industry are slightly different. When K=2, PC and PE reach their optimal values respectively. Although XB is the smallest when K=3, there is not much difference from K=2. It should be said that K=2 is more in line with the urban division of Liaoning's tertiary industry.

On the whole, the utility of fixed assets investment in Liaoning shows an obvious three-layer structure in both the primary and secondary industries, while the tertiary industry shows strong two types of agglomeration characteristics.

Analysis of Fuzzy C-Means Clustering Results

After determining the optimal number of clusters for each industry, 14 cities in Liaoning can be clustered by using the Fuzzy C-Means method in combination with the difference of fixed assets investment to industrial development, the sensitivity of urban fixed effect and time effect, and the variation coefficient, trend slope, dominant frequency amplitude and other indicators.

Table 8: Fuzzy C-Means Clustering Membership Matrix of The Three Industries in Liaoning

	Primary Industry			Secondary Industry			Tertiary Industry	
City	C1	C2	C3	C1	C2	C3	C1	C2
shenyang	0.375	0.168	0.457	0.107	0.749	0.144	0.751	0.249
dalian	0.001	0.997	0.002	0.1	0.775	0.125	0.774	0.226
anshan	0.878	0.024	0.098	0.866	0.048	0.086	0.131	0.869
fushun	0.343	0.029	0.628	0.069	0.053	0.877	0.932	0.068
benxi	0.731	0.056	0.213	0.773	0.079	0.148	0.138	0.862
dandong	0.063	0.022	0.915	0.057	0.036	0.907	0.952	0.048
jinzhou	0.398	0.064	0.538	0.074	0.05	0.876	0.983	0.017
yingkou	0.192	0.033	0.775	0.126	0.098	0.776	0.978	0.022
fuxin	0.321	0.032	0.647	0.089	0.053	0.859	0.811	0.189
liaoyang	0.128	0.041	0.831	0.078	0.055	0.867	0.967	0.033
panjin	0.384	0.045	0.571	0.253	0.201	0.546	0.924	0.076
tieling	0.934	0.008	0.058	0.169	0.095	0.737	0.7	0.3
chaoyang	0.238	0.083	0.679	0.107	0.053	0.839	0.933	0.067
huludao	0.044	0.012	0.944	0.428	0.123	0.449	0.954	0.046

Source: Author's Calculations

Analysed the membership matrix of clustering results. The first industry of agriculture can be divided into three categories in Liaoning cities. Among them, Dalian forms the second category separately, with a membership degree of 0.997 in C2, indicating significant differences in its agricultural development characteristics compared to other cities. Anshan and Tieling mainly belong to the first category, with membership degrees of 0.878 and 0.934 respectively, indicating that their agricultural development models are relatively similar. Most of the other cities belong to the third category. The membership degree of Shenyang is relatively close between the first and third categories, showing a certain transitional characteristic.

The manufacturing industry in the secondary sector can also be divided into three categories in Liaoning cities. Shenyang and Dalian mainly belong to the second category, with membership degrees of 0.749 and 0.775 respectively, indicating that the two cities are significantly ahead of other cities in terms of industrial investment scale, growth trend, and fixed effects. Anshan and Benxi mainly belong to the first category, reflecting the common characteristics of traditional industrial cities. The membership distribution of Huludao and Panjin is relatively scattered, while most other cities belong to the third category.

The tertiary service industry is clustered into two types of structures. Anshan and Benxi mainly belong to the second category, with membership degrees exceeding 0.86, indicating that their service industry development characteristics are significantly different from other cities. The remaining 12 cities mainly belong to the first category, among which cities such as Jinzhou, Yingkou, and Liaoyang have membership degrees exceeding 0.95, and their classification characteristics are very clear. The relative dispersion of membership degrees between Shenyang and Tieling indicates that they have both the first type of characteristics and a tendency to develop towards the second type.

CONCLUSION

Based on the panel data of 14 cities in Liaoning Province from 2003 to 2024, this research studies the impact of fixed assets investment on the development of three industries, and further analyses the heterogeneity of industrial development among cities. Firstly, the Hausman test was conducted to determine the use of a fixed effects model, and the time effect test was used to verify that the two-way fixed effects model was superior to the unidirectional fixed effects model. The model diagnosis results indicate that there is no serious multicollinearity problem in each model, but heteroscedasticity exists in all models. Therefore, White robust standard error is used for correction to ensure the reliability of the estimation results.

The empirical results show that the impact of fixed assets investment on the development of the three industries in Liaoning Province is significantly different. In the primary industry, investment in agriculture and forestry has a significant promoting effect on agricultural added value; In the secondary industry, investment in manufacturing and construction is an important driving force for industrial growth; In the tertiary industry, information services, environmental governance, and social welfare investment have a significant positive impact on the development of the service industry, and the explanatory power of the tertiary industry model is the strongest, indicating that Liaoning's economic growth has gradually shifted towards being dominated by the service industry.

Furthermore, based on indicators such as fixed effects, time sensitivity, coefficient of variation, trend slope, and dominant frequency amplitude, the Fuzzy C-Means clustering method was used to classify 14 cities. The results show that both the primary and secondary industries exhibit three types of structures, while the tertiary industry presents two types of structures.

Overall, Anshan and Benxi cities in Liaoning Province have a strong foundation in steel and resource-based industries, and their service industry development path is different from other cities; Most cities in Liaoxi and Liaodong exhibit strong homogeneity in agriculture and industry, and are therefore classified under the same category. Shenyang and Dalian have a clear core position in the industrial sector, while the development pattern of the service industry is relatively concentrated, with weaker regional differences than agriculture and industry. Differentiated investment and industrial policies should be implemented based on the development stage and industrial characteristics of different cities.

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