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Drivers of Urban Fixed Assets Investment Efficiency across Western China

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Abstract

Many factors impact urban fixed-asset investment efficiency (FAIE) during urbanization. Significant academic attention has focused on the main factors that affect urban fixed-asset investment efficiency. However, it remains unclear what the main factors affecting urban fixed-asset investment efficiency are and how they influence it. First, we use the Group Method of Data Handling (GMDH) to automatically identify the main drivers influencing urban FAIE in western China. Then, we utilize the Nadaraya–Watson estimator of a non-parametric regression model to empirically test the nonlinear relationships between these drivers and urban FAIE. Finally, we construct a dynamic panel data model to explore the magnitude of their impact on urban FAIE. We find that the drivers influencing urban FAIE include the economic development level, urbanization investment, financial industry development, urbanization level, and education level. Urban FAIE is positively correlated with the economic development level and negatively correlated with urbanization investment. The relationship between urban FAIE and financial industry development shows a fluctuating pattern. Urban FAIE and the urbanization level have a U-shaped relationship. Urban FAIE and the education level do not appear to have a significant mutual relationship. The drivers have a significant positive impact on urban FAIE. Except for urban fixed-asset investment, economic development, financial industry development, education level, and urbanization level significantly promote urban FAIE. The education level and urbanization level interact with each other, and this interaction has a significant positive impact on urban investment efficiency.

Keywords: *Urban fixed assets, Investment efficiency, Group Method of Data Handling algorithm, non-parametric regression model*

JEL Classification: R11, C14, C33

1 INTRODUCTION

Most countries around the world face economic challenges at various times. In response to these challenges, many governments have adopted long-term investments in urban fixed assets to improve economic outcomes (Wang et al., 2019). Investment in fixed assets plays an important role in the development of cities, and high investment efficiency can promote the development of the market economy (Huang, 2021). In this study, we analyze the drivers of urban FAIE and put forward policy suggestions that are conducive to accelerating urban development and stimulating economic growth.

Urbanization refers to the concentration of rural residents into urban areas and the continuous concentration of the secondary industry (such as mining, manufacturing, production and supply of electricity, and construction) and the tertiary industry (such as transportation, warehousing and postal services, information transmission, computer services and software, wholesale and retail trade, accommodation and catering, finance, and so on) in urban areas (Li et al., 2020; Wu et al., 2022). This leads to an expansion of urban scale and an increase in the number of

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towns (Kan and Chen, 2022). The process of urbanization requires large investments in urban fixed assets.

Extant literature has extensively discussed problems related to urbanization efficiency, such as the spatial pattern of regional urbanization efficiency (Quaas and Smulders, 2018; Zhan et al., 2018), urban eco-efficiency (Bai et al., 2018), sustainability of urbanization (Cui et al., 2019), urban land-use efficiency (Koroso et al., 2020), and the distribution effects of urbanization (Dossou, 2023). However, relatively little attention has been paid to the drivers of investment efficiency in urban fixed assets, and there is a lack of analysis of the nonlinear relationships between these drivers and the investment efficiency of urban fixed assets.

To address this important knowledge gap, we analyze urban FAIE in western China (Figure 1). Western China covers a total area of 5.38 million km², accounting for 71.4% of China's territory. At present, it has about 287 million people. Western China is an underdeveloped region. Compared with eastern and central China, economic development in western China is relatively backward. Since the implementation of the urbanization development strategy in China, urbanization has become an important force driving China's economic development (Matousek and Wang, 2021; Heikkila and Xu, 2022). These conditions have led to rapid urbanization in China, with the urbanization rate increasing from 42.99% in 2005 to 63.9% in 2020. Meanwhile, the average urbanization rate in western China increased from 38.72% in 2005 to 58.62% in 2020.

In particular, urbanization in western China has many implications, including the agglomeration of rural grazing populations, ethnic minority populations, and ethnic characteristic industries into cities, the expansion of urban space, and lifestyle transformations (Wang et al., 2017; Fan and Fang, 2020). Urbanization investment in western China also covers a wide range of fields and requires large amounts of urban fixed-asset investment. In the process of urbanization investment, improving investment efficiency deserves attention. However, many factors influence this efficiency, and identifying the main factors affecting investment efficiency has become a key question in academic circles. Therefore, we focus on the main factors affecting the investment efficiency of urban fixed assets in western China. Analyzing these factors and assessing their relationships with investment efficiency can provide valuable information and useful policy references for promoting urbanization in many regions of the world, especially in less developed regions.

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Fig. 1 Western China region. Source: own research

In this study, we address the following questions: (1) What are the drivers of urban FAIE in western China? (2) How can we identify these drivers from the many factors influencing investment efficiency? (3) What is the relationship between the drivers and urban FAIE? To answer these questions, we collected panel data from 12 provinces, municipalities, and autonomous regions in western China from 2005 to 2020 and used the GMDH algorithm to identify the main influencing factors from the many variables affecting urban FAIE. Then, we applied a non-parametric regression model to test the relationship between the drivers and urban FAIE.

In contrast with the extant research, we contribute in the following three ways. First, we use the Group Method of Data Handling (GMDH) to objectively and automatically identify the drivers from the many factors affecting urban FAIE. Second, we apply a non-parametric regression model to test the nonlinear relationships between these factors and urban FAIE. Third, we construct a dynamic panel data model to assess the magnitude of the drivers' impact on urban FAIE.

The structure of the rest of this article is as follows. Section 2 provides the literature review. Section 3 summarizes the model selection, variables, and data sources. Section 4 presents the empirical study on the drivers of urban FAIE in western China. Section 5 provides the conclusions and policy recommendations.

2 LITERATURE REVIEW

Scholars around the world have conducted in-depth research on efficiency, investment efficiency, and urban FAIE, generating fruitful results. Keynes (1937) proposed the concept of the "marginal efficiency of capital," defining it as a discount rate that makes the sum of the present value of expected capital earnings in each period equal to its replacement cost. Tobin (1969) proposed the well-known Tobin's Q theory, which is used to determine excessive investment behavior by enterprises. Charnes et al. (1978) applied a nonlinear programming model to measure the efficiency of non-profit entities participating in public projects. Wurgler (2000) argued that capital should flow to where it is most needed; therefore, capital allocation should move from industries with excessive capital input to industries with relatively rapid economic growth and insufficient or unsaturated capital stock. Richardson (2006) used the residuals of an investment expectation model to measure underinvestment and overinvestment. Residuals smaller than zero indicate underinvestment; residuals larger than zero indicate overinvestment.

Urbanization efficiency depends on the spatial concentration of resources and balanced regional development. Lewis (1954) conceptualized economies consisting of a traditional agricultural sector and a modern industrial sector. Harris and Todaro (1970) examined rural–urban migration and its effects on economic development. Krugman (1991) illustrated how agglomeration economies naturally lead to regional economic specialization. Glaeser et al. (1992) evaluated how urban agglomerations contribute to regional and national economic growth.

Dabla-Norris et al. (2010) used the public investment efficiency index to study the efficiency of public investment. Quaas and Smulders (2012) used a dynamic model to analyze the efficiency of the urbanization model and found that if production becomes cleaner over time, a balanced urbanization path becomes efficient without a coordinating mechanism. Kim et al. (2014) applied Data Envelopment Analysis (DEA) to measure the efficiency of the Korean government's investment in renewable energy (wind, photovoltaic, and fuel cells). The study found that investment in wind energy was the most efficient. Li (2016) empirically analyzed time trends and industry differences in urban FAIE in Guizhou Province using the Incremental Capital-Output Ratio (ICOR) and DEA with the Malmquist index. Fan et al. (2019) took 38 non-ST listed forestry companies in China from 2013 to 2017 as research samples and measured their investment efficiency using a stochastic frontier production function model. Gu et al. (2020) proposed principles for measuring outbound direct investment (ODI) efficiency from an input–output perspective. Yang et al. (2021) constructed an evaluation system for green public investment efficiency and used the super-efficient SBM-DEA method to measure the efficiency of green public investment in China. These scholars have applied diverse methods to measure efficiency, investment efficiency, and urban FAIE.

Chinese scholars have extensively studied and analyzed urban FAIE, with most focusing on urban infrastructure investment efficiency. Lv (2010) constructed an evaluation system for infrastructure investment efficiency during urbanization and used DEA to analyze the efficiency of urban infrastructure investment in Hunan Province from 1991 to 2007. The results showed that after 2000, both the comprehensive and individual performance of infrastructure construction in Hunan Province exhibited a downward trend. Zeng et al. (2014) empirically analyzed the static and dynamic efficiency of agricultural infrastructure investment using a super-efficiency Slack-Based Measure (S-SBM) model and the Malmquist-Luenberger index. The results showed a downward trend in static efficiency, significant regional differences, and a convergence trend. Li (2015) used DEA to analyze the efficiency of urban infrastructure investment in China from 2004 to 2013 and found that, except for a few years, the overall efficiency was not high, with significant provincial differences. Sun et al. (2015) evaluated the economic benefits of urban public infrastructure in China using a DEA overlapping efficiency model. The results indicated that overall economic benefits were not optimistic, decreasing gradually from the southeast coast toward the western region.

Li and Zhang (2016) adopted a Stochastic Frontier Production Function (SFA) approach to construct a theoretical model of rural human capital investment (HCI) structure and empirically analyzed HCI efficiency under new urbanization. The results showed that technical training can improve rural HCI efficiency, whereas institutional changes do not. Li et al. (2016) used DEA

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to evaluate urban infrastructure investment efficiency in Beijing, Tianjin, and Hebei, finding that the overall efficiency levels in the three cities were relatively good. Zhang et al. (2016) compared transportation infrastructure investment efficiency across Belt and Road countries and found that civil aviation infrastructure investment significantly promoted economic growth, while railway investment had a negative growth effect. Wang et al. (2018) analyzed the factors influencing the professional investment efficiency of the logistics industry and found that market competition scale effects and investment scale growth promoted efficiency improvements. Gao et al. (2018) found that education capital, health capital, rural residents' income, institutional change, and informatization promoted rural HCI efficiency, while skills training and population migration restricted it. Yang et al. (2021) found that public investment efficiency is influenced by factors such as urbanization, capital investment, policy systems, and market conditions, and that improvements in new urbanization significantly promote public investment efficiency. Zhang et al. (2022) used the three-stage DEA-Malmquist index method to analyze both static and dynamic efficiency of urban infrastructure investment in China. Their results showed that environmental factors strongly affect efficiency in all provinces, with western China more affected than eastern and central regions. Urban infrastructure investment productivity (TFP) exhibited a phased upward trend, mainly driven by technological progress.

Overall, the above literature shows that existing studies have focused on measuring efficiency, investment efficiency, and infrastructure investment efficiency. However, few studies have explored the drivers that influence urban FAIE or examined the nonlinear relationships between these drivers and urban FAIE. This study focuses on identifying the factors affecting urban FAIE, screening the main factors from the many variables influencing FAIE using GMDH. The study also examines the relationships between the influencing factors and urban FAIE using a non-parametric regression model.

3 METHODS, VARIABLES AND DATA

3.1 Methods

3.1.1 GMDH algorithm

In this study, the GMDH algorithm was used to mine the factors influencing the investment efficiency of urbanization in western China. Ivakhnenko (1967) first proposed the GMDH algorithm. The principle of the GMDH algorithm embodies the processes of heredity, mutation, and survival of the fittest in biological evolution. It reflects the evolutionary characteristics of factors ranging from simple to complex. Therefore, the GMDH algorithm can automatically and objectively mine important factors impacting a research object. After 50 years of improvement and development, the GMDH algorithm has formed a family of self-organizing algorithms with many different forms. The rapid development of computers, software, and the internet has allowed the GMDH algorithm to be widely used in data mining and knowledge discovery. According to the principle of self-organization, this algorithm largely avoids the subjectivity of researchers in data mining. Many researchers have used it for complex system analysis and simulation predictions.

The general steps used to apply the GMDH algorithm are as follows:

(1) Divide the sample dataset (including N data samples) into Training Set A and Test Set B. If a prediction model is constructed, the sample data need to be further divided into a Prediction Set C.

(2) Construct the general relationship between the dependent variables (output) and the independent variables (input). Select a K–G multinomial as a reference function. Using a

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system with three inputs but only one output as an example, we adopt the following quadratic K–G polynomial as the reference function:

$$f(x_1, x_2, x_3) = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_1^2 + a_5x_2^2 + a_6x_3^2 + a_7x_1x_2 + a_8x_1x_3 + a_9x_2x_3 \quad (1)$$

The sub-items are set as m initial models for the modeling network structure:

$$v_1 = a_0, v_2 = a_1x_1, v_3 = a_2x_2, \ldots, v_{10} = a_9x_2x_3 \quad (2)$$

Where, m=10.

(3) Select one or several selection criteria from criteria having an external complementary nature as objective functions (or systems), or external standards (or systems). External standards mainly include an accuracy standard, compatibility criteria, correlativity criteria, portfolio guidelines, cross-validation criteria, or variable balance criteria. As the criteria and rules for model selection, external standards directly affect the selection and quality of the optimal model. Modelers select external standards according to concrete conditions.

(4) Obtain the first layer intermediate models. The transfer functions $y_k = f_k(v_i, v_j)$, (i, j=1, 2, 3, …, 10) are the first layer of intermediate models. They are generated adaptively by the self-organization process. The number of variables and functional structure differ from each other. At the same time, the parameters of y_k are estimated in Training Set A.

(5) Filter the first layer of intermediate models according to the external standards in Test Set B and obtain the intermediate models w_k. Apply w_k as the input variables of the second layer of the network.

(6) Form the optimal complexity network structure. Repeating Steps (3) and (4), successively generate the second-layer intermediate models, the third-layer intermediate models, etc. Ultimately, this generates the optimal model used to analyze the problem.

Before applying the GMDH algorithm, dimensionless processing of the original data was needed. The dimensionless processing of the original data was conducted using Formula (3):

$$\overline{x_i} = \frac{x_i}{max(x_i)} \quad (3)$$

The variable data after dimensionless processing were placed into the GMDH algorithm for learning and training. The GMDH algorithm deleted variables with little or no correlation in the training process. In this study, the GMDH algorithm was used to eliminate the factors having little relationship with the urban FAIE or little impact on the urban FAIE. The algorithm retained the factors with significant impact.

3.1.2 non-parametric regression model

There may be a nonlinear relationship between the drivers and the urban FAIE. Therefore, we used a non-parametric regression model to test the nonlinear relationship between urban FAIE and its influencing factors. The non-parametric regression model was developed in the mid- and late-1930s (Siegel, 1956). Its main advantage is that it can be independent of the population distribution and its parameters. Therefore, it is not restricted by the form of the variable distribution. The form of the non-parametric regression function can be arbitrary, and there are few restrictions on the distribution of explanatory variables. Therefore, the non-parametric regression model is appropriate for the analysis here. The non-parametric regression model is defined as follows (Ye, 2008).

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Let Y be the explained variable, which is a random variable. The variable X is the explanatory variable, which is the factor influencing Y. It can be either a deterministic variable or a random variable. The sample observations $(Y_1, X_1), (Y_2, X_2), \cdots, (Y_n, X_n)$ are provided. Assume that $\{Y_i\}$ is independent and identically distributed. As such, non-parametric regression model is:

$$Y_i = m(X_i) + \mu_i, i = 1,2,\dots,n \tag{4}$$

In the formula, $m(\cdot)$ is the unknown function, and u_i represents the random error term. This term reflects the influence of other observable or unobservable factors on the explained variable.

There are many estimation methods for non-parametric regression models, including Nadaraya-Watson (N-W) estimation, Priestley-Chao (P-C) estimation, and Gasser-Miiller (G-M) estimation. The Nadaraya-Watson estimation method was selected in this study. It is a non-parametric regression model estimation method proposed by Nadaraya and Watson in 1964. First, the probability density function $K(\bullet)$ of the origin symmetry is selected. Let $\int K(u)du = 1$ be the kernel function, and width be $h_n > 0$. The kernel weight function is:

$$W_{ni}(x) = \frac{K_{h_n}(X_i - x)}{\sum_{i=1}^{n} K_{h_n}(X_i - x)} \tag{5}$$

In this expression, $K_{h_n}(u) = h_n^{-1} K_{h_n}(u h_n^{-1})$ is a probability density function. Therefore, the kernel estimation of Nadaraya-Watson is defined as:

$$\widehat{m}_n(x) = \sum_{i=1}^{n} W_{ni}(x)\, Y_i \tag{6}$$

3.1.3 Dynamic panel data model

Since the non-parametric regression model cannot conduct structural analysis, that is, it cannot analyze the impact degree of these drivers on urban FAIE and their impact significance, this article constructs a dynamic panel data model to empirically analyze the impact degree of the drivers and their impact significance. The dynamic panel data model constructed in this research is shown in equation (7).

$$lnY_{it} = \alpha_0 + \beta_0 lnY_{it-1} + \beta_1 ln(X_{1it}) + \beta_2 ln(X_{2it}) + \cdots + \beta_n ln(X_{nit})X_n + v_i + \varepsilon_{it} \tag{7}$$

Where, Y denotes the urban FAIE. $X_1, X_2, \cdots, X_n$ denote the drivers mined by the GDMH algorithm, respectively. α_0 and β_i denote the coefficients of the constant term and impact of the independent variable, respectively. v_i denotes the individual trait effect. ε_{it} denotes the random error term. The endogeneity of dynamic panel data models may cause bias in traditional estimation methods. Traditional estimation methods such as Generalized Least Squares (GLS) estimation of dynamic panel data models may produce biased and inconsistent estimation results. Therefore, the following two estimation methods are usually used to estimate dynamic panel data models: First-Differenced GMM estimation and System GMM estimation. In this study, we use these two methods to estimate dynamic panel data models.

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3.2 Variables

There are many factors that could impact urban FAIE. Based on previous studies and data limitations in underdeveloped western China, we selected the following variables as the influencing factors of investment efficiency of urban fixed assets: economic development, urbanization level, urbanization investment, per capita income, education level, financial industry development, communication development, and construction industry development (Gao et al., 2018; Ma et al., 2020; Abban et al., 2020; Yang et al., 2021; Kapuria et al., 2021). Some important macroeconomic and institutional factors may be omitted, which we will study in depth in the future.

(1) Investment efficiency of urbanization ($ICOR$)

Scholars use DEA, TEP, and the incremental capital-output ratio (ICOR) to measure investment efficiency (Kim et al., 2014; Sun et al., 2015; Li, 2016). However, DEA is a non-parametric method suitable for multiple inputs and outputs scenarios. TEP measures the contribution of factors other than capital and labor to output growth, but it is complex to calculate and requires extensive data. Due to limited data, as well as ICOR being simple to calculate, easy to understand, and able to depict our problem completely, this study adopted ICOR to measure the investment efficiency of urbanization (Li, 2016; Li and Zhang, 2016). The incremental capital-output ratio represents the capital increment needed to increase total output by one unit; this better describes the effective use of capital in urbanization construction. In this study, the incremental capital-output ratio was calculated using the following formula:

$$ICOR = \frac{\Delta K}{\Delta Y} \tag{8}$$

In the formula, ΔK is the incremental change in capital, and ΔY is the incremental change in total output. In general, the gross output is often expressed as gross domestic product (GDP). If there is no depreciation of fixed assets, the change of capital stock is equal to the total investment (I). Therefore, the incremental capital-output ratio can be calculated using the following formula:

$$ICOR = \frac{I}{\Delta GDP} \tag{9}$$

Formula (2) shows that ICOR indicates the number of incremental investment units required to increase GDP by one unit. Therefore, the larger the ICOR, the lower the investment efficiency.

(2) Economic development (ED)

Economic development can influence urbanization construction and, in turn, affect the investment demand and investment intensity of urbanization construction. Rapid economic development increases investment demand and intensity, improving urban FAIE. In contrast, lower economic development reduces investment demand and intensity, reducing urban FAIE. This study used the GDP growth rate to represent economic development in the western region.

(3) Urbanization level (UL)

Urbanization construction and urbanization level are factors impacting investment efficiency. Within a certain range, urbanization level positively relates to the investment efficiency of urbanization. However, during urbanization, ineffective allocation of resources may lead to inefficient urbanization investment. In this study, the commonly used population proportion index, defined as the proportion of the urban population in the total population, was used to describe the level of urbanization.

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(4) Urbanization investment (UI)

In the process of urbanization construction, fixed asset investments support infrastructure, urban housing, and commercial service facilities. Fixed asset investments also play a significant role in promoting urbanization construction and urbanization level. This study selected total fixed asset investment to measure the investment situation associated with urbanization in western provinces, municipalities, and autonomous regions.

(5) Per capita income (PI)

Most studies have found a positive correlation between per capita income and efficiency (Ma et al., 2020; Abban et al., 2020). This is because residents in wealthier towns have higher expectations for their living environment and urbanization construction, increasing pressure on the local government and raising requirements for urban FAIE. However, some scholars have hypothesized that higher income areas may lead to idle government workers and low office efficiency. This may result in lower incentives to further improve urban FAIE, decreasing investment efficiency. In this study, the per capita disposable income of urban residents is used to represent per capita income.

(6) Education level (EL)

Improved educational levels, especially higher education development, can actively promote the construction of cities and towns in a region. Cities and towns with more developed higher education have higher requirements for urbanization development and higher investment efficiency. Therefore, the study projected that education level would affect urban FAIE. This study used the number of students in colleges and universities in the western region to represent education level.

(7) Financial development (FD)

Urbanization construction investment requires significant funds. The ability to raise funds quickly affects urban FAIE. While raising funds for urbanization construction, the financial industry can provide financial support and help the government and enterprises rapidly raise funds. Therefore, financial industry development has an important impact on urban FAIE. This study used the added value of the financial industry in the western region to represent financial industry development.

(8) Communication development (CD)

During urbanization construction, investment situation and investment efficiency require timely communication between construction staff and investment staff. Staff communication facilitates progress in urbanization construction and investment efficiency. This timely staff-to-staff communication requires a more developed communication industry. Therefore, communication development may affect urban FAIE. In this study, the number of mobile phone users is used to represent communication development.

(9) Development of the construction industry (AD)

Rapid development of the construction industry signals a faster pace of urbanization construction; the investment intensity of urbanization construction is greater, and investment efficiency may be higher. It is possible that investment in urbanization construction significantly increases, while the unit output of the investment does not increase. In other words, investment efficiency may not improve. However, development of the construction industry reflects the urbanization construction situation, which may affect the investment intensity and

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efficiency of urbanization construction. In this study, the gross output value of the construction industry was used to describe construction industry development.

The variables were defined as shown in Table 1.

Tab. 1 Variables definition table. Source: own research

Variables	Symbols	Explanations
Urbanization investment efficiency	*ICOR*	Calculated by incremental capital-output ratio
Economy development	*ED*	Measured by Gross Domestic Product Growth Rate
Urbanization level	*UL*	Describe by the proportion of urban population to the total population
Urbanization investment	*UI*	Measured by the Total Investment of Fixed Assets
Per capita income	*PI*	Reflected by disposable income per capita of urban residents
Education level	*EL*	Characterize by the Number of Students in Colleges and Universities
Financial development	*FD*	Measured the added value of financial industry
Communication development	*CD*	Characterized by the number of mobile phone users
Development of Construction Industry	*AD*	Reflected by the Gross Output Value of Construction Industry to

3.3 Data

Some statistics for certain provinces and autonomous regions in the western region before 2005 were incomplete. As such, provincial panel data were selected for 12 provinces, municipalities, and autonomous regions in western China over 2005–2020. The data for the above variables were derived from the statistical yearbooks of the 12 provinces, municipalities, and autonomous regions in western China over 2006–2021, the National Bureau of Statistics website (http://www.stats.gov.cn/), and the statistical bureau websites of the respective provinces, municipalities, and autonomous regions.

4 RESULTS

4.1 Drivers influencing urban FAIE

GMDH modeling software—Knowledgeminer 5.0 was used for the modeling. In this study, we divided the sample dataset into three parts: 70% for the Training Set A, 20% for the Testing Set B, and 10% for the Prediction Set C. The default parameter settings of the software are as follows: Polynomial degree = 2, layers = 5, and the selection threshold (RMSE) = 0.15. Additionally, the stopping criteria in our study are based on the Akaike Information Criterion (AIC) to control complexity and prevent overfitting. Finally, the models generated the following results:

$$ICOR = 3.08e^{-1}z_{11} + 2.10z_{12} + 2.35 \tag{10}$$

$$z_{11} = 6.18ED - 1.17UI(t-2) + 2.54 \quad (11)$$

$$z_{12} = 3.82FD + 2.36EL * UL(t-1) + 2.63 \quad (12)$$

Within these expressions, for the western region, $ICOR$ is the investment efficiency of urbanization; ED is the economic development; UI is the urbanization investment; FD is the financial development; UL is the urbanization level; and the EL is the education level. The variables z_{11} and z_{12} are two intermediate variables of the model, automatically set by the computer.

Formulas (11) and (12) are placed into Formula (10), leading to the following results:

$$ICOR = 3.08e^{-1}(6.18ED - 1.17UI(t-2) + 2.54) + 2.10(3.82FD + 2.36EL * UL(t-1) + 2.63) + 2.35 \quad (13)$$

Formula (15) shows the optimal complexity model of the drivers that influence urban FAIE in the western region. Sorting out Formula (13), we get the following formula.

$$ICOR = 7.0024ED - 1.3257UI(t-2) + 8.0220FD + 4.9560EL * UL(t-1) + 10.7510 \quad (14)$$

Formula (14) shows that the optimal complexity model is a nonlinear model. This reflects a nonlinear relationship between the investment efficiency of urbanization in the western region and its influencing factors. There are both linear and nonlinear factors influencing the efficiency of this urbanization investment.

The optimal complexity model shows that the drivers affecting the urban FAIE in the western region selected by the GDMH algorithm include: the level of economic development, urbanization investment, financial industry development, urbanization level, and education level. Analyzing the impact of these factors on the investment efficiency of urbanization leads to the following conclusions.

First, the coefficient of the economic development level in the western region is positive, indicating that the economic development level in the western region has a positive impact on the urban FAIE, and the impact is large. Raising the level of economic development in the western region can significantly enhance the investment efficiency of urbanization.

Second, the coefficient of financial development is positive, indicating that financial industry development has a positive impact on the urban FAIE. Promoting financial industry development in the western region can significantly increase the investment efficiency of urbanization.

Third, in the optimal complexity model, there are $UI(t-2)$ and $EL * UL(t-1)$ items. The coefficients are positive, indicating that the urbanization investment and urbanization level have a hysteretic nature on the urban FAIE in the western region, and the impact is positive. At the same time, the coefficient of $EL * UL(t-1)$ item is 4.9560. The symbol is positive, indicating there is an interaction between the education level and urbanization level. This interaction has a greater positive impact on the urban FAIE.

4.2 Nonlinear Relationship between the Investment Efficiency and Its drivers

In this study, the Nadaraya-Watson estimation method with a unary non-parametric regression model was used to test the nonlinear relationship between urban FAIE and the drivers in western China. A Gaussian kernel and optimal theoretical window width were selected, and the window width was estimated as $H = 0.5$. The nonlinear relationships between the investment efficiency and each driver assessed are shown in Figures 2–6.

Fig. 2 shows that the economic development level is positively related to urban FAIE in western China. The increase in the level of economic development in western China can promote the increase of urban FAIE. The positive correlation between economic development and investment efficiency reflects how economic growth enables better resource allocation and technological adoption.

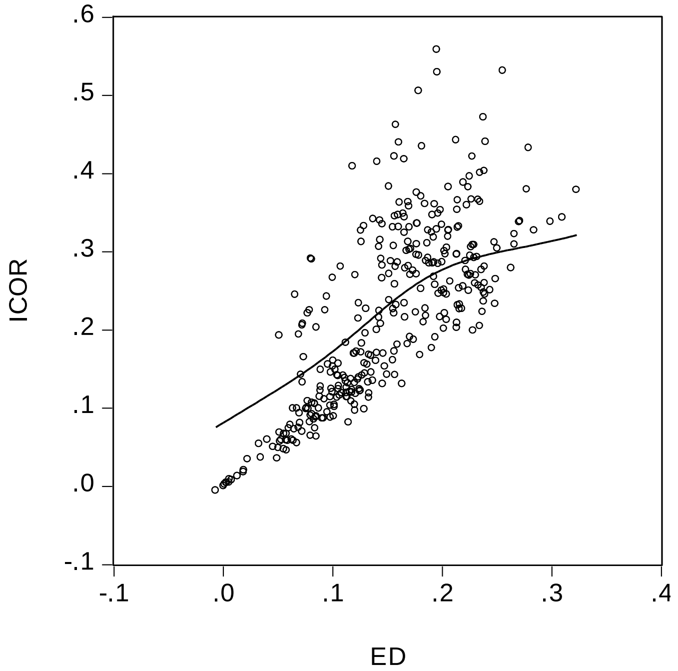

Fig. 2 The relationship between economic development level and urban FAIE. Source: own research

Fig. 3 shows a negative correlation between urbanization investment and urban FAIE. Urban FAIE is equal to the incremental growth in total investment and GDP. This indicates the number of incremental investment units required to increase GDP by one unit. Furthermore, the negative correlation may indicate diminishing returns in infrastructure spending.

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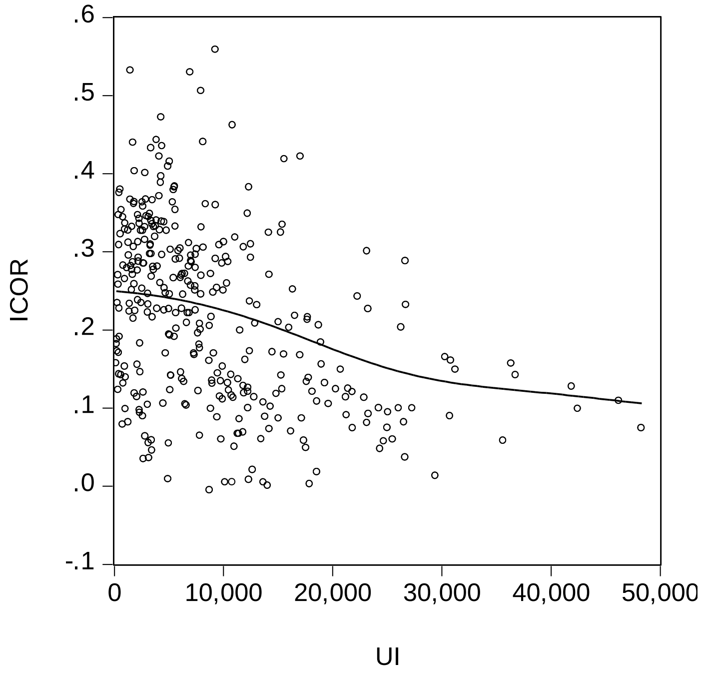

Fig. 3 The relationship between urbanization investment and urban FAIE. Source: own research

Fig. 4 shows a curved and fluctuating relationship between financial industry development and the investment efficiency of urbanization. The investment efficiency of urbanization in the western region fluctuated between 0.15 and 0.25. When financial industry development was approximately 350 billion RMB, the overall urban FAIE reached its maximum.

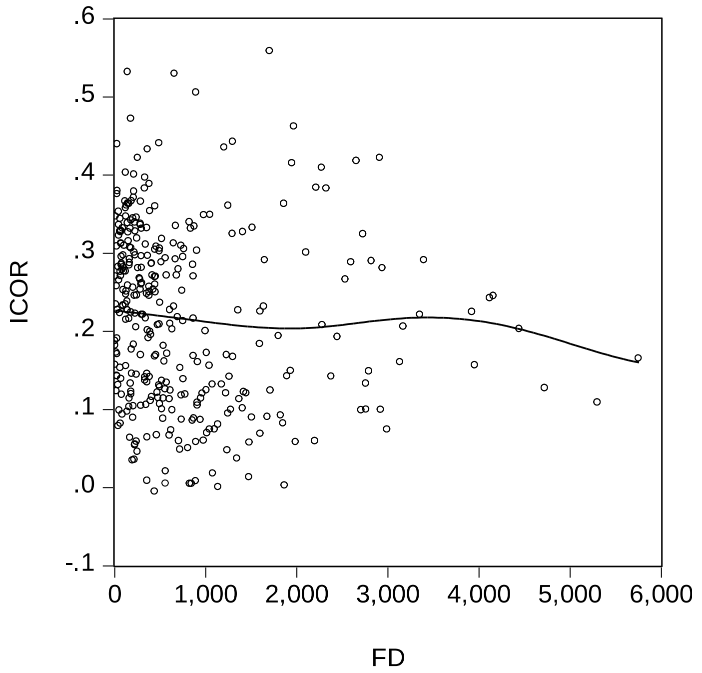

Fig. 4 The relationship between financial industry development and urban FAIE. Source: own research

Fig. 5 shows that the urban FAIE and urbanization level have a U-shaped relationship. When the urbanization level exceeds 60%, the urbanization level and the urban FAIE are positively correlated. When the urbanization level is less than 60%, the urbanization level and the investment efficiency of urbanization are negatively correlated. When the urbanization rate exceeds 0.5, with an increase in urbanization level, the efficiency of urbanization improves. The U-shaped relationship suggests an initial efficiency penalty during rapid urban expansion, which later reverses as agglomeration benefits emerge.

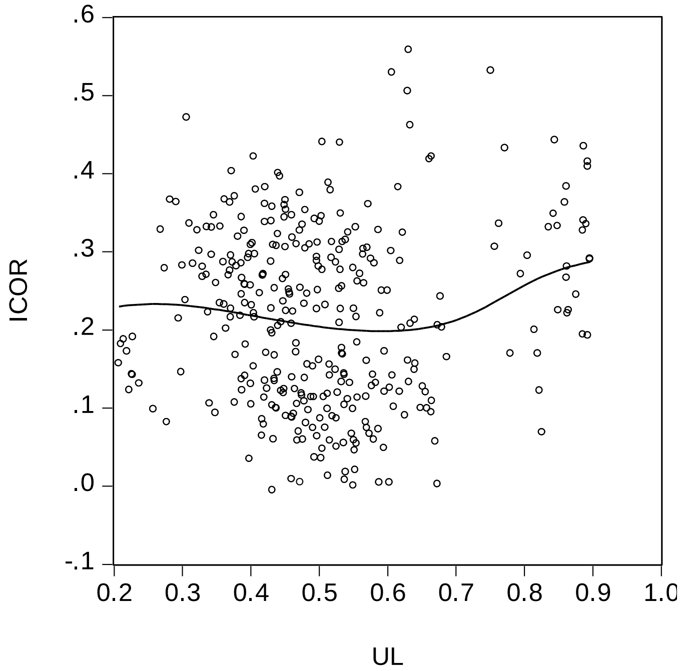

Fig. 5 The relationship between urbanization level and urban FAIE. Source: own research

Fig. 6 shows that there is a steady interaction between the urban FAIE and the education level in western China. The interaction ranges between 0.2 and 0.3. However, the interaction is gradually decreasing.

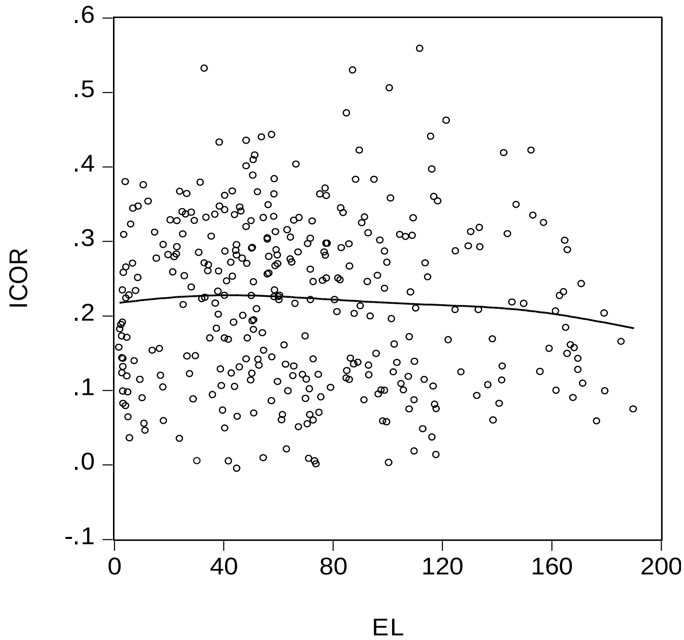

Fig. 6 The relationship between education level and urban FAIE

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4.3 Impact of the drivers on the investment efficiency

In order to avoid the phenomenon of "pseudo-regression", we used the Fisher-ADF Test and Fisher-PP Test to perform a panel unit root test. The test results are shown in Table 3. The results indicate that the original time series is non-stationary, while the first-order differenced time series is stationary. It can also be determined that the variables are first-order integrated sequences.

Tab. 2 Panel unit root test results. Source: own research

Test Method	*LNICOR*	*LNED*	*LNUI*	*LNFD*	*LNEL*	*LNUL*
Fisher-ADF Test	2.7828 (0.1310)	3.8280 (0.3921)	3.2224 (0.2234)	3.2982 (0.5503)	3.8233 (0.6928)	4.2202 (0.4029)
Fisher-PP Test	2.7852 (0.1452)	3.2828 (0.3820)	3.3650 (0.2617)	3.1094 (0.5683)	3.6620 (0.6105)	4.1027 (0.4182)
Test Method	*DLNICOR*	*DLNED*	*DLNUI*	*DLNFD*	*DLNEL*	*DLNUL*
Fisher-ADF Test	4.1030 (0.0000)	7.9013 (0.0000)	6.6286 (0.0004)	4.2982 (0.0002)	4.4730 (0.0018)	8.8256 (0.0000)
Fisher-PP Test	4.2166 (0.0000)	8.0920 (0.0005)	6.5839 (0.0003)	4.3552 (0.0000)	4.5829 (0.0000)	8.7740 (0.0001)

Note: The values in () are the probability values.

In this study, we use the first-order difference GMM and system GMM methods to estimate the dynamic panel data model. The estimation results are shown in Table 4. The P-values of the joint significance Wald tests in Table 4 are all 0.000, indicating that the model estimation results are significant. The Sargan over-identification test and AR test are both greater than 0.05, indicating that the data series constructed in this study meet the GMM estimation requirements and that the instrumental variables selected are valid. Due to the higher estimation efficiency of the system GMM, we use the estimation results of the system GMM to analyze the impact of the influencing factors on urban FAIE in China. From the system GMM estimation results in Table 4, we obtain the following results:

(1) The lagged term of urban FAIE. The coefficient of urban FAIE lagged by one period is 0.7025, which is significant at the 1% level, indicating that the urban FAIE lagged by one period has a significant positive impact on the urban FAIE in the current period. The urban FAIE in the previous period significantly promotes the improvement of urban FAIE in the future.

(2) Economic development. The coefficient of the level of economic development is 0.6610, which is significant at the 1% level. For every 5% increase in GDP, the urban FAIE will increase by 0.6610%. This indicates that economic development plays a significant role in promoting urban FAIE. Vigorous economic development will improve urban FAIE.

(3) Urban fixed asset investment. The coefficient of urban fixed asset investment is -0.6692, which is significant at the 1% level, indicating that for every 1% increase in urban fixed asset investment, urban FAIE decreases by 0.6692%. This indicates that urban fixed asset investment has a negative contribution to the improvement of urban FAIE. However, this outcome may initially seem to contradict traditional capital accumulation theories. The potential reasons, particularly in the context of developing western China, include over-investment in low-return infrastructure (e.g., "ghost cities") and resource misallocation.

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In addition, financial industry development, education level, and urbanization level are significant at the 5% level, with coefficients of 0.7138, 0.8273, and 0.7702, respectively, all positively related to urban FAIE. Therefore, promoting financial industry development, raising the education level, and increasing urbanization can improve urban FAIE.

Tab. 3 Estimation results of dynamic panel data model

Variables	Dif-GMM	Sys-GMM
α	0.8290 (0.3020)	0.9922 (0.4981)
$\ln ICOR(t-1)$	0.6692*** (0.2794)	0.7025*** (0.3883)
$\ln ED$	0.4922** (0.4995)	0.6610** (0.4930)
$\ln UI$	-0.7382*** (0.2357)	-0.6692*** (0.3805)
$\ln FD$	0.9462** (0.2434)	0.7138** (0.2484)
$\ln EL$	0.8933* (0.2905)	0.8273** (0.2198)
$\ln UL$	0.8024** (0.5832)	0.7702** (0.7529)
Joint Significant Wald Test	0.0000	0.0000
Sargan Over-identification Test	0.6882	0.6462
AR Test	0.8029	0.7981

Note:(1)***, ** and *indicate that they are significant at the 1%, 5%, and 10% levels, respectively. (2)The value within ( ) is the standard error.

5 DISCUSSION

In this study, we automatically and objectively mined the drivers of urban FAIE in western China, which is affected by human subjective factors. The Group Method of Data Handling (GMDH) algorithm is used to objectively and automatically excavate the main influencing factors from the many influencing factors of urban FAIE, and we find that the drivers of urban FAIE include economic development, financial industry development, and urbanization investment and urbanization level. However, using the optimal complexity model results obtained from the GMDH algorithm, we cannot analyze the impact degree of the drivers on the urban FAIE. Therefore, we construct the dynamic panel data model to assess the impact degree of the drivers on the urban FAIE. Furthermore, in order to explore the nonlinear relationship between the drivers and urban FAIE in western China, we adopt the non-parametric regression model to test their relationship. The advantages of this method are that non-parametric

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regression is highly adaptive and robust, the regression model is completely data-driven, the regression function is free in form and less constrained, and the accuracy of the model is high (Siegel, 1956).

In terms of linear impact, the drivers significantly positively impact urban FAIE in western China. For economic development, on the one hand, economic development promotes the transformation and upgrading of industrial structure, promotes spatial urbanization, population urbanization, and industrial urbanization, and brings huge investment opportunities for urbanization construction (Zhao et al., 2022). On the other hand, because economic development and urbanization development need to be coordinated, the faster the economic development, objectively it requires an increase in urban fixed asset investment, improvement in the efficiency of urban resource allocation, and improvement in the efficiency of urban fixed asset investment. For urban fixed asset investment, urban fixed investment not only needs to increase urbanization investment, industrial structure transformation, financial development, and people's livelihood fiscal expenditure, but also needs to improve the allocation efficiency and utilization efficiency of various production factors such as labor, capital, land, and resources, pay attention to the improvement of current investment efficiency, and lay the foundation for the improvement of urbanization investment efficiency in the later stage (Ma et al., 2020). However, due to the underdeveloped economy and industry in western China, backward financial development, lack of investment talents, and urban fixed asset investment only paying attention to the investment scale while not paying attention to the investment quality and efficiency, the investment efficiency declines with the increase of urban fixed asset investment. For financial development, the faster the development of the financial industry, the more financing can be provided for urbanization construction, the faster the flow of funds, the higher the financial support efficiency for urban fixed asset investment. Financial institutions have professional knowledge and experience to provide financing, listing, or investment services, provide richer financing channels, improve the efficiency of capital allocation, and help improve urban FAIE (Abban et al., 2020). For education level, due to the low level of education and lack of talents in western China, the improvement of education level can provide many professional and technical personnel, management talents, and financial talents for urban fixed asset investment. For urbanization level, the level of urbanization in western China has entered a virtuous circle, which requires continuous investment in urban infrastructure, public utilities, urban housing, and supporting commercial service facilities. The increase in these investments has further promoted urban FAIE (Kapuria et al., 2021).

There are nonlinear relationships between the drivers and urban FAIE, and the nonlinear relationships are different in western China. First, when economic development is fast, an increase in the investment demand and investment intensity of urbanization will promote urban FAIE (Abban et al., 2020). In contrast, when the level of economic development is relatively low, the investment efficiency of urbanization will not be high. Second, the economic development foundation of the western region is relatively poor, the economic growth effect brought by incremental urbanization investment is not significant, and urban FAIE is low (Wesemann et al., 2022). This leads to a negative correlation between urban FAIE and urbanization investment. Third, in the process of urbanization construction, the financial industry provides financial support for urbanization construction. The initial stage requires a large amount of construction funds. At this time, increasing investment speeds up the development of urbanization and improves urban FAIE. Once the overall city investment scale is optimized, increasing funds will lead to wasted resources and reduce urban FAIE. Therefore, reasonable development in the financial industry supports improvements in urban FAIE. Fourth, at a low urbanization level, poor urban infrastructure and lack of human resources lead to a

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negative correlation between urbanization level and urban FAIE. When urbanization reaches a reasonable level, the cities and towns attract a large number of talents and funds and can increase urban FAIE (Rivera-Padilla, 2021). Fifth, urbanization construction in western China reflects extensive investment. This relies on large-scale labor input. Education provides labor resources and intellectual support. The labor resources and intellectual support are steady and have a less direct and visible effect on urban fixed asset investment than financial development and urban investment, resulting in the non-significant impact of education level on urban FAIE.

Urbanization investment efficiency should consider sustainability factors such as green finance, climate adaptation, and renewable energy integration. Our study's findings on urbanization investment efficiency must be contextualized within the growing imperative of sustainable urban development. While we initially focused on traditional economic drivers, recent scholarship and policy priorities increasingly emphasize the integration of sustainability factors—a perspective rightly highlighted by reviewers. The potential incorporation of green finance mechanisms would significantly alter our efficiency calculus. Current models show western China's financial sector development (coefficient: 0.9462 and 0.7138) already contributes substantially to investment efficiency. Introducing green bonds and ESG-focused lending could amplify these effects while addressing environmental externalities. Climate adaptation considerations would substantially impact our U-shaped urbanization efficiency relationship (Figure 4). The inflection point at 60% urbanization may shift when accounting for climate-resilient infrastructure costs. Cities surpassing this threshold might achieve higher sustainable efficiency by retrofitting existing assets rather than pursuing expansion. Renewable energy integration presents complex trade-offs with our observed negative urbanization investment-efficiency relationship. While additional clean energy infrastructure might initially depress ICOR measures, long-term operational savings and co-benefits could reverse this trend. Our dynamic panel model's one-period lag structure (coefficient: 0.6692 and 0.7025) may need adjustment to capture these delayed returns.

Given China’s dual-carbon goals, urban investment policies should align with long-term sustainability objectives. First, the positive relationship between financial development and investment efficiency (coefficient: 0.9462 and 0.7138) suggests that green financial instruments such as carbon trading mechanisms and green bonds could amplify efficiency gains while supporting decarbonization. Western China's emerging financial sector presents a unique opportunity to “leapfrog” traditional carbon-intensive investment patterns by directly incorporating climate-aligned lending criteria. Our finding of fluctuating returns from financial development further underscores the need for policy stability mechanisms, such as long-term green credit guarantees, to sustain both efficiency and sustainability outcomes. Second, the U-shaped relationship between urbanization level and investment efficiency (Figure 4) implies distinct phase-specific strategies for low-carbon urban development. Below the 60% urbanization threshold, efficiency could be improved by prioritizing compact, transit-oriented urban forms that reduce per capita emissions. Beyond this threshold, our results suggest that retrofitting existing infrastructure particularly through energy-efficient building upgrades and district renewable energy systems may yield greater efficiency and carbon reduction co-benefits than continued spatial expansion. Third, the negative correlation between urbanization investment scale and efficiency presents a paradox for sustainability transition. While massive investments in renewable energy and electrification are needed to meet dual-carbon goals, our results caution against blanket increases in capital expenditure without rigorous efficiency safeguards.

In this study, we mined the drivers of urban FAIE and explored the linear and nonlinear relationships between them. For future research, we have the following suggestions. First, we

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can automatically and objectively mine the drivers from more factors influencing urban FAIE, incorporating additional macroeconomic, institutional, or environmental variables (e.g., government policies, technological innovation, environmental regulations, or foreign direct investment) to further validate and enrich our findings. Second, to explore the applicability of different regions and countries, we can conduct comparative analyses across other regions (e.g., Eastern/Central China) or countries (e.g., other developing economies) to enhance external validity. Third, we could divide western China into different sub-regions according to indicators such as geographic factors, and compare the differences in the impact of the drivers of urban FAIE across different regions. Fourth, further analysis (e.g., moderation/mediation models) could deepen this understanding and provide a future research direction to explore synergistic effects using structural equation modeling (SEM) or machine learning.

6 CONCLUSION AND POLICY RECOMMENDATIONS

This study applies the GMDH to automatically and objectively determine the drivers affecting the urban FAIE in China’s western region. The Nadaraya–Watson estimation method of the non-parametric regression model is used to empirically analyze the nonlinear relationship between the urban FAIE and the determined influencing factors. The dynamic panel data model is utilized to explore the impact degree of the drivers on the urban FAIE. We find the following three key results.

First, the factors influencing the urban FAIE include economic development level, urbanization investment, financial industry development, urbanization level, and education level in the western region. The economic development level in the western region positively impacted the investment efficiency of urbanization, and the impact was large. Financial industry development in the western region also positively impacted the investment efficiency of urbanization. Urbanization investment and urbanization level had a hysteretic nature on the urban FAIE in the western region. The education level and urbanization level positively interacted, with a positive impact on the investment efficiency of urbanization.

Second, the test results of the non-parametric regression model found a positive correlation between the investment efficiency of urbanization in the western region and the economic development level. The investment efficiency of urbanization was negatively correlated with urbanization investment, showed a curving and fluctuating relationship with financial industry development, and showed a U-shaped relationship with the urbanization level. However, there was no significant interaction between the efficiency of investment in urbanization and the educational level.

Third, the urban FAIE in the previous period significantly upgraded the improvement of the urban FAIE in the future. Economic development, financial industry development, education level, and urbanization level significantly and positively promoted the urban FAIE. However, urban fixed asset investment significantly negatively impacted the urban FAIE.

Based on the above research results, we propose the following policy recommendations:

First, the government should promote the economic development level in western China. The government should take appropriate policies and measures according to the actual situation in western China to provide impetus for economic development, so that each industry in each region can fully develop and drive comprehensive and sustainable economic development through industry development. The government should prioritize policies that stimulate sustainable economic growth, such as supporting high-value industries and technological innovation. This can enhance the efficiency of urban fixed asset investments by ensuring that capital flows to sectors with the highest productivity gains. The government should provide

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incentives for green industries and digital infrastructure to align economic growth with long-term urbanization goals. Governments at different levels need to adopt different policies to promote the efficiency of urban fixed asset investment. At the national level, macroeconomic coordination and framework-setting policies are emphasized. This includes establishing standardized investment efficiency evaluation metrics, implementing cross-regional fiscal transfer mechanisms to reduce disparities, and creating national guidelines for sustainable urbanization investment. Regional governments should focus on adaptation and implementation: developing region-specific investment portfolios based on comparative advantages; coordinating infrastructure planning across municipal boundaries; and establishing regional financial intermediaries to improve capital allocation. Local governments should highlight operational and community-focused measures: implementing participatory budgeting for public investment projects; streamlining approval processes for high-efficiency developments; and adopting smart city technologies for real-time investment monitoring.

Second, the government and local enterprises should increase investment in urbanization and improve the level of urbanization. The government can encourage local enterprises to invest in urbanization and also invest more funds to participate in urbanization construction in the western region. At the same time, the government should improve investment allocation strategies and adopt a more strategic approach to infrastructure spending. This includes conducting cost-benefit analyses for large projects, avoiding over-investment in low-return areas (e.g., "ghost cities"), and focusing on projects that maximize social and economic returns, such as public transportation and affordable housing. The government should utilize policy instruments such as subsidies, tax incentives, and land-use regulations to improve urbanization investment efficiency. The government should establish tiered subsidy schemes: 30–50% for green infrastructure, 20–30% for smart city technologies, and 10–15% for general urban renewal projects, and develop sunset clauses requiring periodic efficiency evaluations to maintain subsidy eligibility. The government can implement differentiated tax incentives: creating tax credit systems scaled to investment efficiency metrics (e.g., 5–15% reductions for projects exceeding baseline ICOR thresholds); implementing location-based tax holidays (3–5 years for emerging urban clusters and 1–2 years for mature urban areas); and introducing capital gains tax exemptions for efficiency-improving retrofits of existing infrastructure. For land-use regulations, the government can develop smart land-use regulations, including adopting dynamic zoning that adjusts density bonuses based on real-time efficiency monitoring; implementing "efficiency exchange" programs allowing developers to transfer development rights from low-efficiency to high-efficiency zones; and requiring integrated land-use efficiency assessments in environmental impact statements.

Third, the government should vigorously develop the financial industry and provide funds for urban fixed asset investment. The government should provide incentives for financial institutions and encourage them to establish branches to carry out business in western China. The government should promote the development of the financial industry to provide a stable flow of funds for urban fixed asset investment. At the same time, the government and financial institutions should improve financial risk control capabilities and upgrade corporate governance regulations as well as resource allocation efficiency. Furthermore, the government should strengthen financial institutions' capacity and leverage the positive impact of financial development to support urbanization. This involves improving regulatory frameworks to encourage responsible lending, expanding access to credit for small and medium-sized enterprises (SMEs), and promoting fintech solutions to enhance capital allocation efficiency.

Fourth, the government should promote educational development. The government should modestly increase investment in education, talent introduction, and policy support, especially

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in the context of the underdeveloped educational level in western China. The government should increase education and training for professionals in urbanization, investment, finance, and related fields to improve the efficiency of urban fixed asset investment.

Fifth, the government should differentiate between short-term and long-term investment strategies. For short-term strategies (3–5 year horizon), priority should be given to energy efficiency upgrades for existing buildings (potential 20–30% energy savings); implementing smart grid technologies in urban cores to reduce transmission losses; and establishing municipal green investment platforms with tiered interest rates (4–6% range) based on project efficiency. For long-term strategies (5–15 year horizon), the government should promote spatial planning transformation, implement "15-minute city" principles in new urban districts, develop integrated renewable energy microgrids (solar/wind + storage), enhance industrial ecosystem development, establish regional circular economy industrial parks, and create innovation hubs focused on green construction materials.

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