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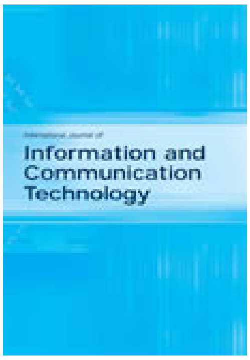

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Correlation analysis between local government debt and economic growth combined with PSTR model

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Correlation analysis between local government debt and economic growth combined with PSTR model

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Abstract: This paper innovatively combines PSTR model with federal learning data enhancement algorithm, further improves the data processing efficiency of PSTR model through computer data processing method, enriches and improves the theoretical research on industrial structure and local government debt (LGD). This paper verifies through empirical research that the correlation analysis method between LGD and economic growth combined with PSTR model has certain effects. Based on the research conclusions, we can put forward corresponding policy suggestions on how local governments should maintain scientific debt scale to give full play to the intermediary effect of industrial structure and promote economic development.

Keywords: PSTR model; local government debt; LGD; economic growth; relevance.

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1 Introduction

Faced with the changes of the world, the times and history at the current macro level, it is particularly important to prevent and resolve major domestic risks. Where the financial risk comes from and how to resolve it has become the key research issues of central and local governments and many scholars (Yusuf and Mohd, 2021). Therefore, inappropriate and unscientific division methods can easily lead to financial pressure. Heavy financial pressure leads local governments to adopt inappropriate ways to broaden their sources of income, which can easily lead to financial risks, thus making economic development face uncertain factors (Ndoricimpa, 2020).

The government is an important force to promote economic development, and the reform of the financial system is an important way to standardise the financial relations between governments, and it is also an important means to encourage the government to formulate economic policies and promote economic development (Heimberger, 2023).

In order to explore whether the internal logic between financial pressure and economic development is consistent with the above analysis, this paper brings financial pressure and economic development into the analysis framework, sorts out the performance and mechanism of local government financial pressure affecting economic development through theoretical analysis, and then investigates the impact of local government financial pressure on economic development through empirical analysis, which is helpful to provide new ideas for improving economic quality and efficiency by optimising financial pressure.

This paper innovatively combines PSTR model with federated learning data enhancement algorithm, and further improves the data processing efficiency of PSTR model through computer data processing methods.

With the standardisation and transparency of LGD, many past borrowing experiences are no longer feasible, but the importance of LGD has not decreased, and it is still an important means of development. Under the new regulatory environment and system, how should local government give full play to the intermediary effect of industrial structure through LGD to promote economic growth is a topic of high practical significance

2 Related work

Law et al. (2021) suggests that when government debt is mainly used for productive infrastructure construction, it will promote an increase in the social capital stock of the region, thereby leading to economic growth in the short term. In addition, scholars believe that LGD can alleviate government funding pressure and promote economic growth. Jacobs et al. (2020) suggests that when the driving force behind local economic growth is the government debt of each province. Empirical research has found that local debt has a crowding out effect on private capital, which is more pronounced in developing countries and can have a significant negative impact on economic growth.

Didia and Ayokunle (2020) suggests that the relationship between local debt and economic growth is a non-linear inverted U-shaped relationship, and there exists a specific threshold within this relationship. However, in the research on "nonlinear theory", scholars have come to different conclusions. The heterogeneity and temporal variability of economic development in different regions can lead to differences in LGD issues, such as natural endowments, fiscal decentralisation, industrial development, and financial differences (Sharaf, 2022).

At present, there is a problem of multiple dimensions in the statistics of government debt by government departments, academia, securities companies, and rating agencies, and the lack of distinction between narrow and broad definitions can lead to conceptual confusion. Based on the review of existing policy documents and various academic scholars' statistical calibres related to LGD (Dey and Tareque, 2020).

Swamy (2020) enriches the relevant research on the economic effects of fiscal pressure, providing theoretical guidance for regulating local government fiscal pressure and enriching the theoretical system of economics and finance.

Onifade et al. (2020) reveals the mechanism by which fiscal pressure affects economic development. Fiscal revenue is a necessary condition for ensuring that local governments fulfill their government functions. Whether it is providing public services or developing the economy, financial support is indispensable. The adequacy of financial resources largely affects the government's economic decisions. In theory, the mechanism by which fiscal pressure affects economic development is very complex. Local government fiscal pressure may have both a promoting and inhibitory effect on economic development. Currently, among the few relevant research results, the main one is based on empirical research and has not yet conducted theoretical analysis on the formation mechanism of local government fiscal pressure and its deep impact mechanism on economic development, making it difficult to accurately evaluate the economic development effects of fiscal pressure (Roth et al., 2022).

Gurdal et al. (2021) proposed a panel threshold regression model (PTR), but this model often suffers from problems such as jumps, discreteness, and abrupt changes on both sides of the threshold. However, in real life, the transformation of the possible influence mechanisms between economic variables is often not a sudden process. The STR model may effectively overcome the shortcomings of traditional research, including the possibility of characterising economic structural changes and policy shifts as a discontinuous and differentiable transformation from one linear equation to another, with unmeasurable turning points. Chandana et al. (2024) proposed a panel flat transition regression model to provide a method for studying panel data using STR models. Edo et al. (2020) studied the effect of this specific policy on economic growth. They pointed out that the model can effectively capture data interface heterogeneity and enable continuous and smooth transformation of model transformation variables. Tan et al. (2020) explored the correlation between population aging and public welfare expenditures using the basic OLG model and PSTR model, and determined the optimal form of the model through sequential testing set by the model. Hilton (2021) used the lattice method to obtain the initial parameters of the optimal algorithm for the model. It is believed that linear regression or sub sample grouping regression cannot obtain accurate results in all regional datasets, and may be affected by implicit homogeneity assumptions or loss of common information. For example, the impact of China's treasury bond burden on economic growth is analysed from the perspective of national and provincial data. Meanwhile, different economic growth effects can also be studied by transforming different transformation variables.

From the above analysis, it can be seen that in the research on the correlation between local government debt (LGD) and economic growth, most non-linear relationship processing is carried out through data processing models. However, there are certain issues in data collection that may not lead to problems with the data source, and the data processing process is not perfect enough, making it difficult to combine intelligent learning technology to improve data output results. The efficiency of data processing needs to be improved This article innovatively combines the PSTR model with federated learning data augmentation algorithms, and further improves the data processing efficiency of the PSTR model through computer data processing methods.

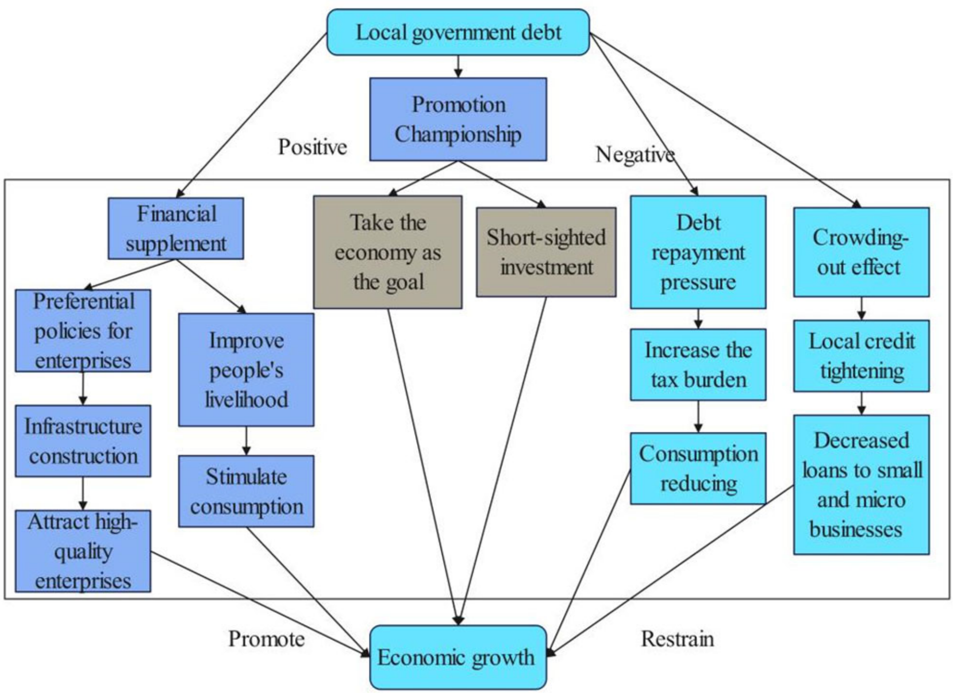
3 Economic data collection and processing models

3.1 PSTR model analysis

The PSTR model, also known as the panel Smooth Transmission model, uses a continuous transformation function to effectively solve the problem of abrupt changes before and after the threshold value, making the transformation function more closely related to economic reality. This model effectively solves the problem of abrupt changes before and after the threshold value, and uses a continuous transformation function to make the transformation function more in line with economic reality. This model can also effectively capture the heterogeneity of different cross-sections, making it suitable for the study of multiple cross-sections.

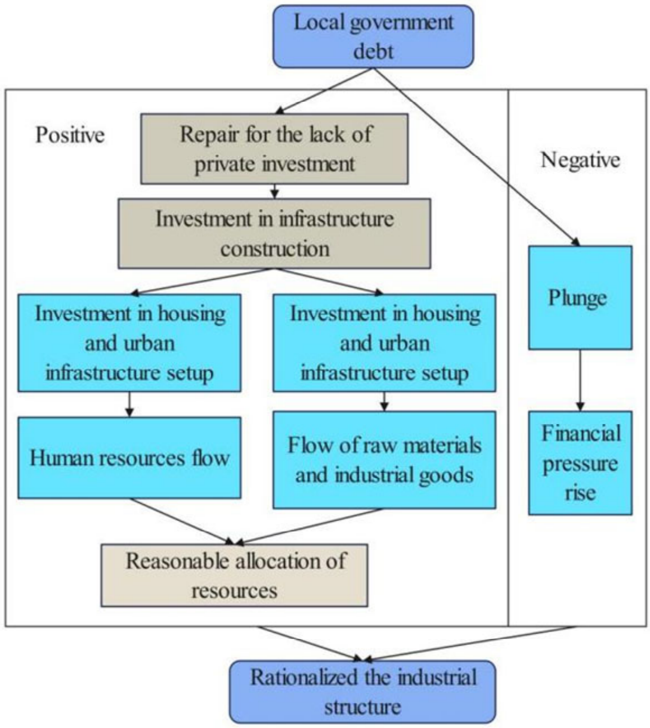
This paper believes that LGD expansion can affect local economic growth through four channels. Figure 1 shows the direct impact of LGD.

Figure 1 Direct impact of LGD (see online version for colours)



Hypothesis 1 The influence of LGD on economic growth is non-linear, local debt under a certain threshold can promote local economic growth, but local debt beyond the threshold will inhibit economic growth.

Figure 2 Intermediary effect of industrial structure rationalisation (see online version for colours)



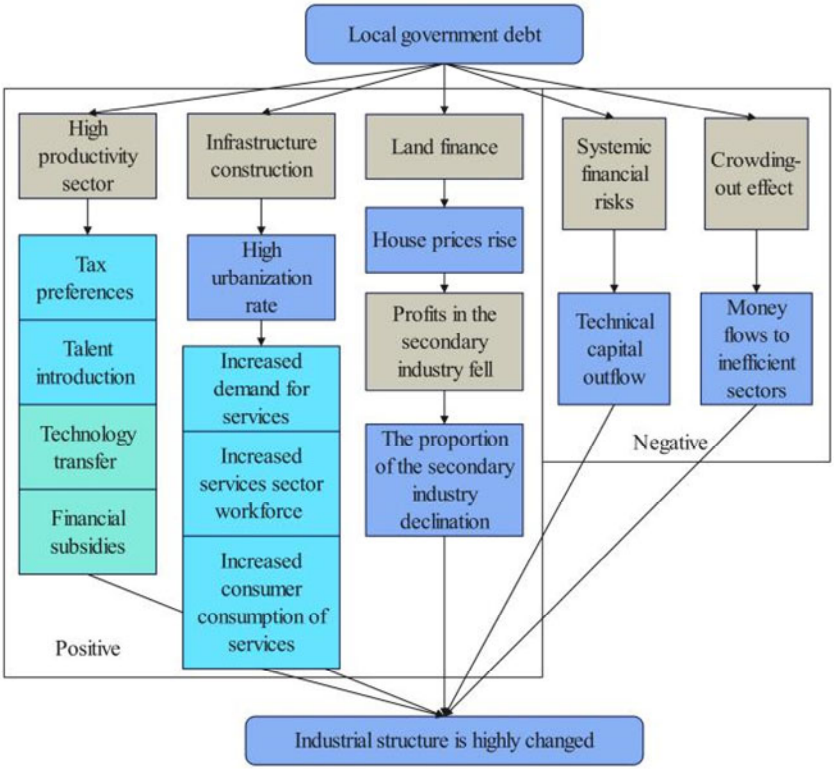
As shown in Figure 2. LGD funds are invested in this area where private and private investment are difficult to fully invest, thus making up for the lack of infrastructure investment. The improvement of infrastructure promotes the flow of resources, is conducive to reducing the irrational industrial structure (Annisa and Taher, 2022).

Hypothesis 2 The scale of LGD has a nonlinear impact on the rationalisation of industrial structure. There is a negative correlation between LGD and industrial structure.

Hypothesis 3 The impact of industrial structure rationalisation on economic growth in different debt ratio ranges is always positive, but the impact in different ranges may be different.

As shown in Figure 3. In line with the dynamic factor endowment and comparative advantage of the economy, the combination of effective market and promising government can promote industrial upgrading. The reason why local governments can borrow debts to support industrial progress is that they need complete infrastructure and perfect institutional support to protect them. At the same time, there are obvious uncertainty, information asymmetry and capital threshold in technological upgrading (Ahuja and Pandit, 2020).

Figure 3 Intermediary effect of high industrial structure (see online version for colours)



Hypothesis 4 The scale of LGD is highly negatively correlated with industrial structure.

The variables selected in this paper are as follows.

3.1.1 Explained variables

- Economic growth (y): this variable is the explained variable selected in this paper, which is expressed by the growth rate of regional GDP. Before calculating the growth rate, the consumer price index CPI is used to revise the data, and the impact of price changes is eliminated.

3.1.2 Explanatory variables

- LGD scale (debt): this variable is the core explanatory variable selected, which is expressed by LGD ratio, that is, the percentage of LGD balance to local government comprehensive financial resources. The reason why local financing platform debt is not used to represent implicit debt is that the supervision of local implicit debt has been greatly strengthened in the period adopted in this paper, and using local financing platform to represent implicit debt may overestimate the scale of implicit debt. The government comprehensive financial resources are used as the denominator because it can better reflect the ability of local governments to repay debts than regional GDP.

3.1.3 Mediation variables

Industrial structure rationalisation (RIS): this variable is one of the mediator variables selected in this paper, which is constructed by Theil index (Alinaghi and Reed, 2021):

$$TL = -\sum_{i=1}^{3} y_i \, ln \frac{y_i}{l_i} \tag{1}$$

Among them, y_i represents the percentage of the i^{th} industry in the regional GDP, and l_i represents the percentage of the number of employees in the i^{th} industry in the total number of employees. The economy is in equilibrium when $TL = 0$. However, generally speaking, the Theil index of an economy is less than 0 after adding a negative sign. The larger it is, the closer it is to 0, the more reasonable the industrial structure is. At the same time, this paper also constructs the following variable RIS2:

$$\sum_{m=1}^{3} y_{i,m,t} \left| \left(y_{i,m,t} / l_{i,m,t} \right) - 1 \right| \tag{2}$$

Among them, l is the proportion of labour force engaged in the i^{th} industry in this region, and the meaning of y is the same as above. This variable can also reflect the rationalisation of industrial structure and be used for subsequent robustness test.

Industrial structure height (UIS): this variable is one of the intermediary variables selected in this paper. This paper uses the following industrial structure hierarchy coefficient UIS to measure the industrial structure height level.

$$\sum_{m=1}^{3} y_{i,m,t} \times m \tag{3}$$

Among them, represents the industrial output value, and m is 1, 2, and 3.

This paper also constructs the following coefficient UIS2:

$$UIS = \frac{Y_3}{Y_2} \tag{4}$$

It represents the proportion of tertiary industry and secondary industry in the city in the t^{th} year.

3.1.4 Control variables

- Government intervention level (Gov): it represents the level of local government intervention in the local economy
- Local innovation level (Innov): the improvement of innovation level is beneficial to local economic development.

- Resource endowment (res): the economic development of some resource-based cities relies heavily on mineral resources, and the economic development is greatly affected after mineral depletion.
- Informatisation level (Info): informatisation level is an important driving force for economic growth.
- Freight construction level (tran): generally speaking, the improvement of freight construction level is conducive to local economic growth. This paper measures it by the highway freight volume in this area in that year.

The level of informatisation and freight construction actually reflect the level of local infrastructure construction.

Using PSTR model and mediation effect model, the benchmark regression model in this paper is as follows (Broner et al., 2022):

$$y_{i,t} = \alpha_i + \lambda_0 debt_{i,t} + \sum_{j=1}^{r} \lambda_j debt_{i,t} G_j \left(debt_{i,t}^{j}, \gamma_j, c_j \right) + \beta X_{i,t} + \varepsilon_{i,t} \tag{5}$$

α_i is the individual effect, λ_0 is the regression coefficient explaining the linear part of the main explanatory variable debt, λ_j is the regression coefficient of its nonlinear part, $X_{i,t}$ represents other control variables, β is the coefficient of other control variables, and $\varepsilon_{i,t}$ is the random error term.

$G_j\left(debt_{i,t}^{j}, \gamma_j, c_j \right)$ is a conversion function, which satisfies the form of logistic function, that is:

$$G_j\left(debt_{i,t}^{j}, \gamma_j, c_j \right) = \left(1 + \exp\left[-\gamma j \prod_{j=1}^{m} \left(debt_{i,t}^{j} - c_j \right) \right] \right) - 1, \gamma > 0 \tag{6}$$

r and m need to be obtained through hypothesis testing. Generally, r is 1 or 2 and m is 1 or 2. By further investigating the mediating effect

$$RIS_{i,t} = a_i^t + \lambda_0 debt_{i,t} + \sum_{j=1}^{r} \lambda_j debt_{i,t} G_j \left(debt_i^t, \gamma_j, c_j \right) + \beta_1 X_{i,t} + \varepsilon_{i,t} \tag{7}$$

$$UIS_{i,t} = a_i^t + \lambda_0 debt_{i,t} + \sum_{j=1}^{r} \lambda_j debt_{i,t} G_j \left(debt_i^t, \gamma_j, c_j \right) + \beta_0 UIS_{i,t} + \beta_1 X_{i,t} + \varepsilon_{i,t} \tag{8}$$

We can see that both equaitons (7) and (8) clearly show that there are intermediary effects of industrial structure rationalisation (RIS) and industrial structure heightening (UIS).

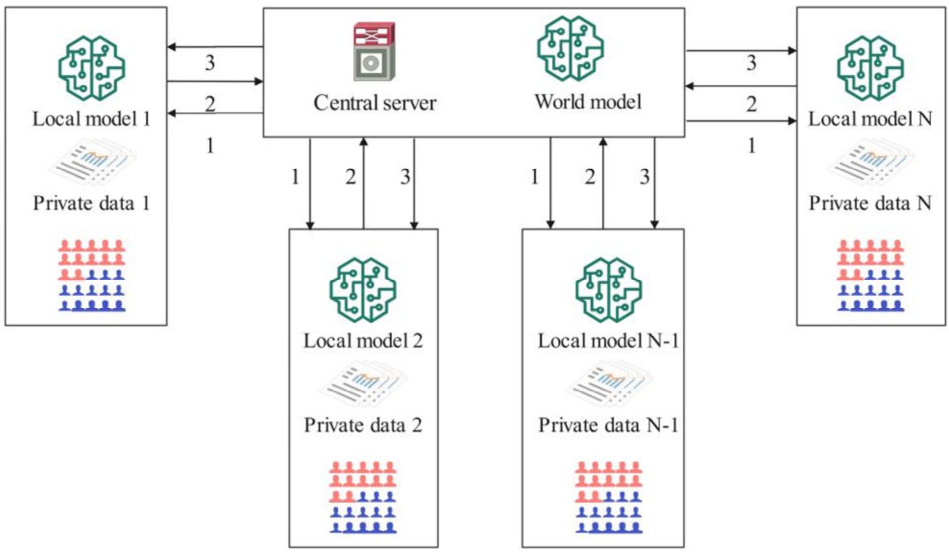
3.2 Federated learning data enhancement algorithm

The federated learning algorithm uses data distributed across various mobile devices for local training, and updates the global model through the aggregation process performed by the central server. This centralised architecture has problems such as unstable network topology, high communication load on central nodes, and susceptibility to malicious attacks. Since federated learning essentially belongs to the category of distributed machine learning, effective solutions can be found in the field of distributed machine learning.

Compared with traditional machine learning, federated learning solves the dependence on the computing power and training data of centralised servers.

In the process of federated learning, since the training of the model does not need to transmit the original data on the front-end device and is completed directly on the front-end device, the privacy and security of users are well protected. The workflow of the federated learning algorithm is shown in Figure 4.

Figure 4 FedAvg workflow (see online version for colours)



As shown in Figure 1, federated learning is a process in which multiple front-end devices participate in training. If it is assumed that there are N front-end devices in a certain federated learning training process, and the whole composition of these front-end devices is represented by $\mathbb{P}$, then there is $N = |\mathbb{P}|$. For each front-end device S_i, there is a private dataset D_i, and the corresponding data amount is y, then there is $D_i = |S_i|$. Then, in the sum of the data amounts of all front-end devices is $D = \sum_{i=1}^{N} D_i$. If it is assumed that the weight parameter of the whole model is W, and each front-end device corresponds to a plurality of users, then sampling the z^{th} user in the i^{th} front-end device will obtain a plurality of data points. The j^{th} data point (x_i, y_i) is fitted, and the obtained loss function is shown in equation (9).

$$f_i(W) = \ell\left(x_j, y_i, W\right) \tag{9}$$

In the front-end device i, the loss functions of all data points inside the front-end device are averaged and calculated to obtain the loss function of the i^{th} front-end device, and the calculated loss function is shown in equation (10).

$$F_i(W) = \frac{1}{D_i}\sum_{j \in S_i} f_j(W) \tag{10}$$

After the front-end device calculates the loss function of this round, it will upload the calculated result $F_i(W)$ to the central server to realise the calculation of the next round of parameters W. Because federated learning is distributed, whether each front-end device in $\mathbb{P}$ obeys independent and identical distribution has an important influence on the whole training process.

In order to ensure the smooth progress of federated learning and avoid the greater impact of data distribution on the learning process, nowadays, most of the research results of deep learning rely on stochastic gradient descent algorithm (SGD). The core idea of SGD is to select some samples from all front-end devices, iterate continuously in the opposite direction of the function gradient, and finally find the local minimum value. In the process of federated learning, the weight W is updated by the SGD algorithm, and the update is shown in equation (11).

$$W < -W - \eta \nabla F(W) \tag{11}$$

Then, in the entire process of federated learning, the federated learning model is trained through continuous iteration, and the ultimate purpose is to minimise the loss function. The final optimisation goal can be defined as shown in equation (12):

$$\min_{W \in \mathbb{R}^m} = \sum_{i=1}^{N} \frac{D_i}{D} F_i(W) \tag{12}$$

In the federated learning process, in each round of iteration, because the SGD algorithm is used, the central server will randomly select some front-end devices to participate in the new round of calculation according to the actual situation. C is used to represent the selection of equipment. If $C = 1$, it indicates that the front-end equipment participates in this round of training. If $C = 0$, it indicates that the front-end equipment does not participate in this round of training. In the training process of the t^{th} round, the new W_t is calculated from the previous round's W_{t-1}, the learning rate η and the gradient $\nabla f(W_{t-1})$, and the result is shown in equation (13):

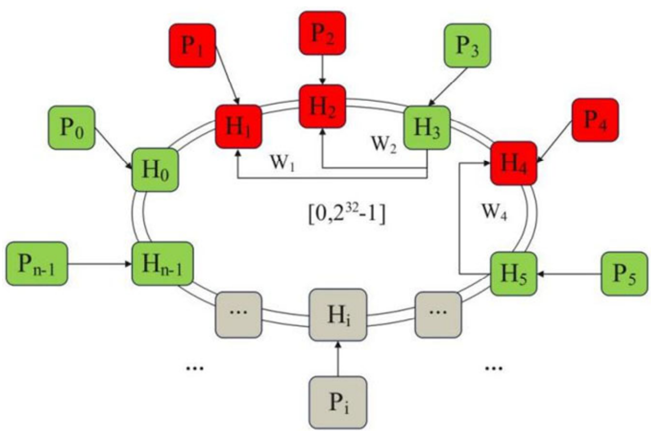
$$W_t = W_{t-1} - \eta \sum_{i=1}^{N} \frac{D_n}{D} \nabla f\left(W_{t-1}\right) \tag{13}$$

HRA-based decentralised federated learning (HRA-DFL) algorithm is proposed. Consistency hash algorithm and HRA algorithm are used to build a hierarchical ring network topology, so as to realise a decentralised federated learning algorithm. We assume that the number of nodes of federated learning participants is n and the number of trusted nodes is m, then there are n–m untrusted nodes, and the set of nodes of all participants is $p = \{P_0, P_1, \ldots, P_i, \ldots, P_{n-1}\}$. First, the HRA-DFL algorithm generates a circular structure containing 232 virtual nodes using a consistent hash algorithm and does not include any physical nodes at the beginning. Then, the HRA-DFL algorithm uses the Ketama hash function to calculate the hash value of the real IP address *IPi* of node *Pi*, and at the same time, the hash address H_i of P_i on the ring can be obtained by taking the modulo of 2^{32}, as shown in equation (14).

$$H_i = KetamaHash(IP_i) mod 2^{32} \tag{14}$$

Among them, *KetamaHash* is an *Ketama* hash function and *mod* represents a modulo operation. In this way, each participant node P_i has a corresponding hash address H_i on this ring. The ring structure constructed by the consistent hash algorithm is shown in Figure 5, in which trusted nodes are represented in green, untrusted nodes are represented in red, and other possible nodes are represented in gray. Because untrusted nodes may poison or tamper with the model, the aggregation process cannot be performed on untrusted nodes. The untrusted node looks for the next trusted node clockwise along the ring structure, and passes the model parameters to the found trusted node. In Figure 5, the model parameters W_1 and W_2 of the untrusted nodes P_1 and P_2 will be forwarded to the trusted node P_3i, and the model parameter W_4 of the untrusted node P_4 will be forwarded to the trusted node P_5.

Figure 5 Schematic diagram of consistent hash ring structure (see online version for colours)



However, when the next trusted node in the clockwise direction of multiple untrusted nodes along the ring structure is the same node (for example, the next trusted node of untrusted nodes P_1 and P_2 is both P_3), the trusted node may encounter network bandwidth bottlenecks. The virtual node mechanism in consistent hash algorithm can effectively solve this kind of problem. The hash address of the virtual node is not the same as that of the real node. It uses the virtual IP address of the real node to calculate the hash address, as shown in equation (15).

$$H_i^* = KetamaHash(IP_i) mod 2^{32} \tag{15}$$

Among them, IP_i is a virtual IP address of the real node P_i, and H_i^* is the hash address of a virtual node mapped by P_i on the ring structure. Virtual nodes are introduced into the ring structure constructed by using consistent hash algorithm. As shown in Figure 6, the real node corresponding to the trusted node P_0 on the ring structure is H_0, and node H_0^* is a virtual node mapped by P_0 on the ring structure. When the untrusted node P_1 looks for the next trusted node clockwise along the ring structure, a virtual node H_0^* mapped by the trusted node P_0 on the ring structure is found. Then, the untrusted node P_1 sends the model parameter W_1 to the trusted node P_0 mapped by the virtual node H_0. Then, the trusted node P_2 only needs to receive the model parameter W_2 sent by the untrusted node P_2. Compared with when no virtual node is introduced, the trusted node P_2 no longer needs to receive the model parameters W_1 and W_2 sent by the untrusted nodes P_1 and P_2.

Figure 6 Schematic diagram of consistent hash ring structure introducing virtual nodes

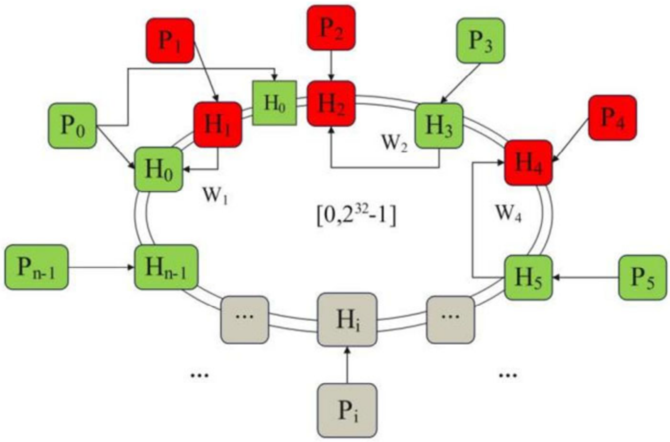
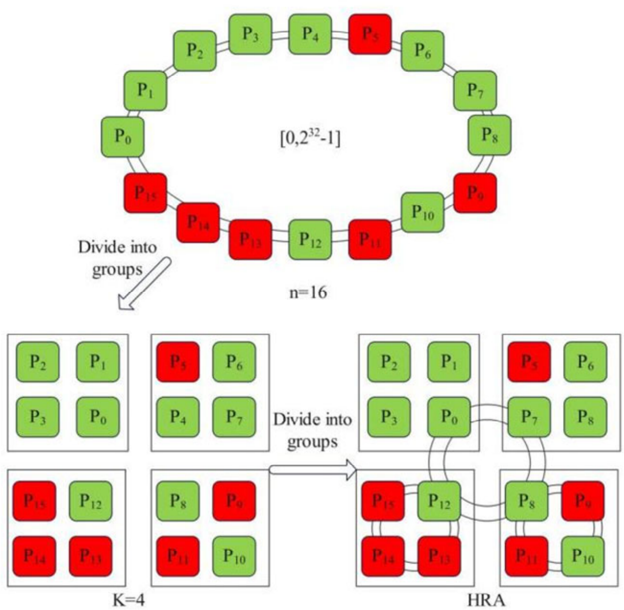


Figure 7 Schematic diagram of topology construction of hierarchical ring network (see online version for colours)



Next, HRA-DFL algorithm applies HRA algorithm to group all nodes on the ring structure according to the position distance on the ring, and divide them into k groups. For the convenience of discussion, it is assumed that $n = 16$ and $k = 4$, that is, there are 16 participant nodes, which are divided into 4 groups. At the same time, it is assumed that there is at least one trusted node in each group and there is no virtual node. As shown in Figure 7, there are a total of 16 nodes in the ring structure constructed by using the consistent hash algorithm, which are divided into 4 groups according to the location distance. The first group is $\{P_0, P_1, P_2, P_3\}$, the second group is $\{P_4, P_5, P_6, P_7\}$, the third group is $\{P_8, P_9, P_{10}, P_{11}\}$, and the fourth group is $\{P_{12}, P_{13}, P_{14}, P_{15}\}$. Except for nodes, P_5, P_9, P_{11}, P_{13}, P_{13} and P_{15} are untrusted nodes, the rest of the nodes are trusted nodes, and there is at least one trusted node and no virtual node in each group.

4 Empirical analysis

4.1 Data sources

All LGD related data used in this article were compiled by Big Wisdom Caihui based on local governments and local financing platforms. In addition, there are missing data on economic growth, labour supply, foreign direct investment, etc. in the "China Urban Statistical Yearbook", such as patent numbers. After deleting samples with excessive missing data, the missing values are filled in by city. For a few cities with overall missing data, the average of all data is filled in.

All LGD-related data used in this paper are compiled by great wisdom finance exchange according to local governments and local financing platforms. The missing values are filled according to the city, and the missing data of a few cities as a whole are filled according to the average value of all data. Finally, the data needed for empirical analysis are obtained through standardisation processing. Descriptive statistics before variables are not normalised are shown in Table 1.

Table 1 Descriptive statistics of variables

	Average	*Standard deviation*	*Minimum value*	*Maximum value*
y	0.0609	0.0876	–0.4639	0.4233
Debt	1.5998	1.1581	0.1453	9.1843
Gov	0.5126	1.3030	–1.0265	12.0971
FDI	0.1395	1.6308	–0.5598	10.3239
Innov	–0.2669	0.4780	–0.4341	3.1518
Res	0.1488	0.5419	0.0001	10.0045
Info	0.1413	1.1963	–0.8698	8.6761
Tran	0.0225	1.5088	–0.7553	17.3705
RIS	–0.3184	1.1101	–3.5719	1.3697
RIS2	0.0413	0.7608	–7.5416	0.5119
UIS	–0.2867	0.9605	–2.0954	2.9002
UIS2	–0.0457	0.9637	–1.3413	4.9888

4.2 Results

The results of the overall empirical analysis of the sample are shown in Table 2.

The sample population robustness test results are shown in Table 3.

Table 2 Results of overall empirical analysis of samples

Position slope	*Benchmark formula*		*RIS intermediary*		*UIS intermediary*		*RIS total formula*		*UIS general formula*	
	270.80%		*91.34%*		*132.33%*		*259.51%*		*261.46%*	
	1.1646		*4.5664*		*1.5168*		*1.1336*		*1.2024*	
Debt	0.7562***	–0.41112**	0.4365*	–0.4395*	0.8254***	0.8102***	0.6685***	–0.4399***	0.6497***	–0.3679**
	3.558654	–2.479158	1.818927	–1.939608	2.960397	3.704085	3.133548	–2.629341	3.090978	–2.242845
GOV	0.035739	–0.501633	–0.3111***	0.6498***	0.7113***	1.8601***	0.097911	0.207702	0.113157	–0.3698**
	0.439065	–0.954756	–4.179384	3.672999	3.881394	4.44114	0.776853	0.269577	1.524996	2.275614
FDI	0.084744	–0.194238	2.292543	–12.1002**	0.51112***	0.8294***	26.2413***	32.3395**	0.039798	0.029106
	0.729432	–0.665973	0.484209	–1.954359	3.364911	3.114837	3.031677	2.143449	0.34848	0.11088
Innov.	0.2689**	–3.3786***	–0.02871	–0.5603***	0.080685	2.2887***	0.2486**	2.5303**	0.2196*	2.3132*
	2.241063	–2.630727	–0.561231	–3.642408	0.404811	3.723489	1.989405	2.163546	1.888128	1.82853
Res	0.088407	0.085635	–0.054945	0.036036	0.2096**	0.2864*	0.195426	0.336006	0.119889	0.01089
	0.557865	0.178794	–0.623403	0.382833	2.005344	1.657359	1.256112	0.769428	0.793287	0.025146
Info	–0.032967	0.429957	0.110781	0.3635*	0.4654**	0.071379	0.2365*	0.824868	0.068013	0.32769
	–0.384813	0.852192	1.269576	1.62063	2.377881	0.180279	1.778238	1.15137	0.80487	0.714384
Tran	–0.071874	–0.013068	0.121869	0.157509	0.023364	0.268785	0.108504	0.04356	0.074052	0.135234
	–0.487476	–0.041481	0.844965	1.039203	0.099198	0.790317	0.709929	0.139788	0.510444	0.44748
RIS	.	.	.	.	.	.	0.1113**	0.004158	.	.
	.	.	.	.	.	.	2.267001	0.030789	.	.
UIS	.	.	.	.	.	.	.	.	0.047916	0.3967**
	.	.	.	.	.	.	.	.	1.14939	2.495889

Note: The values in the second row are t values. *, * *, * * * represent significance levels of 10%, 5%, 1%, respectively.

Table 3 Overall robustness test of samples

	RIS intermediary		*UIS intermediary*		*RIS total formula*		*UIS general formula*	
Position	*116.52%*		*265.09%*		*297.09%*		*343.64%*	
slope	*45.046485*		*1.163745*		*1.216215*		*1.571031*	
Debt	0.155529	−0.173745	0.5096***	0.4012***	0.6203***	−0.211959	0.554202	−0.453321
	1.179387	−1.282941	3.285018	3.512124	3.352833	−1.391544	2.784573	−2.633994
RIS2	.	.	.	.	0.1301**	−0.328284	.	.
	.	.	.	.	2.150775	−1.256904	.	.
UIS2	.	.	.	.	.	.	−0.0404	0.5113***
	.	.	.	.	.	.	−0.6208	3.309768

Table 4 Robustness test in eastern region

	RIS intermediary		*UIS intermediary*		*RIS total formula*		*UIS general formula*	
Position parameters	*122.23%*		*111.63%*		*80.25%*		*584.16%*	
slope coefficient	8.64854		29.6578		3811.5		1.1650	
Debt	0	−0.0001	0	−0.0001	−0.0001*	0	0	−0.0889 **
	0.6633	−0.3865	0.3421	−0.0125	−1.8531	1.2121	−0.0966	−2.0121
RIS2	.	.	.	.	0.0001 ***	−0.0001 ***	.	.
	.	.	.	.	4.7985	−4.4652	.	.
UIS2	.	.	.	.	.	.	0.0000 ***	−0.0799 ***
	.	.	.	.	.	.	3.4652	−5.5632

Table 5 Robustness test in central region

Position parameters slope coefficient	*RIS intermediary*		*UIS intermediary*		*RIS total formula*		*UIS general formula*	
	116.52%		*122.23%*		*428.03%*		*227.87%*	
	48.945402		*0.152064*		*0.062865*		*2.792295*	
Debt	0	0	–0.0013***	–0.0019***	0.0021***	0.0029***	0.0028**	0
	0.0123	–0.1325	–3.0995	8954	4.4012	4.3965	2.3965	0.1235
RIS2	.	.	.	.	0.0000***	0.0001	.	.
	.	.	.	.	4.365	1.1625	.	.
UIS2	.	.	.	.	.	.	–0.0018**	–0.0039**
	.	.	.	.	.	.	–2.0098	–2.0957

Table 6 Robustness test in western region

	RIS intermediary		*UIS intermediary*		*RIS total formula*		*UIS general formula*	
Position parameters	*331.96%*		*105.82%*		*204.70%*		*203.73%*	
slope coefficient	*155.43*		*7.0191*		*90.0712*		*66.0904*	
Debt	0.1236 **	–0.0398	–0.8795 ***	0.7598 ***	–0.1235	–0.1921	–0.1865	0.0125
	2.2965	–0.3564	–3.3654	2.684	–0.8465	–0.3965	–1.3595	0.0789
RIS2	.	.	.	.	–0.0798	0.0597	.	.
	.	.	.	.	–1.0684	0.4565	.	.
UIS2	.	.	.	.	.	.	–0.0894 *	–0.1532
	.	.	.	.	.	.	–1.869	–1.4965

The results of the robustness test in the eastern region are shown in Table 4.

The results of the robustness test in the central region are shown in Table 5.

The results of the robustness test in the western region are shown in Table 6.

4.3 Analysis and discussion

On the whole, the differences in empirical results among different regions are mainly due to the differences in government governance level, marketisation level and development stage. Because of the higher level of government finance, market capital flow and marketisation, the demand for government debt funds for economic development in cities in the eastern region is obviously smaller than that in the central and western regions. Therefore, LGD funds in eastern cities are no longer the main driving force for economic growth, and social funds are enough to fully and efficiently promote economic growth. At the same time, the economic development in the eastern region is more sufficient and the industrial structure is more reasonable. Therefore, more debt funds are invested in the high industrial structure, and the tertiary industry in the eastern cities is more advanced. Compared with the central and western regions, the productivity is higher, and the higher governance level is also conducive to the government's accurate selection of enterprises and industries conducive to economic growth for support. Therefore, its high industrial structure can promote economic growth rather than the other way around.

In contrast, the central region's government finances and market funds are not as abundant as those in the eastern region. Therefore, the government debt funds in the central region have a significant driving effect on economic development. The rationalisation of industrial structure is also more important for the central region, which has a lower level of development and an insufficiently rational industrial structure, and can effectively promote economic growth. In terms of industrial structure upgrading, the tertiary industry relies more on capital investment compared to the secondary industry. Only sufficient capital investment can drive the upgrading of industrial structure. However, even so, the poor attractiveness of high-tech tertiary industry in the central region and the gap in government governance level make capital investment not accurate and reasonable enough. The increased production efficiency of the tertiary industry is not as good as that of the original secondary industry, which in turn hinders economic growth. The situation in the western region is similar to that in the central region, but the poorer financial situation, governance level, and lack of funds have made the impact of local debt funds and the rationalisation and upgrading of industrial structure more apparent. In terms of industrial structure rationalisation, the threshold for government debt funds to promote industrial structure rationalisation is higher. This is because the level of industrial rationalisation in the western region is much lower than that in the eastern and central regions, and there is greater room for improvement. The lower attractiveness of high-tech talents and enterprises in the western region has also raised the threshold for LGD funds to promote industrial structure rationalisation. The government in the western region needs to invest much more land resources than in the central region to promote the development of the tertiary industry. However, the industrial structure rationalisation brought about by the growth of the underdeveloped tertiary industry has dragged down economic growth, and blind detachment from reality and neglect of industrial structure rationalisation have led to the failure of industrial structure rationalisation to play its due role in promoting the economy.

In the original empirical analysis, there are 31 coefficients with significant empirical results for the key variables: LGD level, industrial structure height and industrial structure rationalisation. In the robustness test, there are 18 corresponding coefficients that are equally significant and completely consistent in positive and negative, 9 coefficients are not significant enough, but positive and negative are consistent, and only 4 coefficients are inconsistent in positive and negative.

Specifically, most of the coefficients of significance and even positive and negative inconsistency appear in the overall robustness test. The possible reason lies in the fact that the empirical analysis in this paper is highly regional, and the LGD in some areas has little impact on economic growth, and the empirical results are more susceptible to the influence of variable substitution.

5 Conclusions

Through theoretical analysis and industrial structure intermediary effect model combined with PSTR model, this paper studies how the scale of LGD affects local economic growth and what role the industrial structure heightening and rationalisation as intermediary variables play in this. It provides a decision-making basis for how local government should deal with LGD to achieve the purpose of promoting economic development under the new economic situation. Through empirical research, it is verified that the correlation analysis method of LGD and economic growth combined with PSTR model has certain effect and can play a certain reference role in economic development. Based on the research conclusions, we can put forward corresponding policy suggestions on how local governments should maintain scientific debt scale to give full play to the intermediary effect of industrial structure and promote economic development.

In practical application scenarios, the algorithm model in this article also has vertical federated learning scenarios where data features and sample space distributions are inconsistent. Therefore, exploring the decentralisation of vertical federated learning is also a valuable research direction.

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