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The Journal of Grey System

Volume 31 No.4, 2019

Evaluation of Chinese Industry Linkage Ability by Using an Enhanced Grey Possibility Clustering Model

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Abstract:

The input-output method can effectively quantify and analyze the industry linkage ability. The main objective of current research is to analyze the linkage ability of Chinese industry based on the interrelationship of sensitivity coefficient and the influence coefficient, which has not been reported with much accuracy so far and that is the reason leading to the monotonous results. Therefore, to address such issues and get the credible results for evaluation of the industry linkage ability, three effect indexes including the multiplier effect, absolute forward spillover effect, and the absolute backward spillover effect, are designed. Additionally, for these effect indexes, an enhanced grey possibility clustering method has also been proposed to evaluate the industry linkage based on the input-output (I-O) table. Moreover, this enhanced method can be advantageous for providing diverse weighted effects in the formulation practical advices towards industrial evaluation to the provision of indexation and characterization of industry linkage ability. The experimental results illustrate that there have been numerous similarities and differences among the enhanced grey possibility clustering method and traditional input-output research methods. Meanwhile, in an overall analysis, it is evident that the linkage ability of tertiary industry is relatively weak, whereas it is generally stronger for secondary Chinese industry for Chinese whole industry system.

Keywords: Grey Possibility Clustering Model; Industry Linkage Ability; the Multiplier Effect; the Spillover Effect

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1. Introduction

The research on the industry linkage ability among different industries plays a vital role in the economic development (Gurgul & Lach, 2016). The Input-Output tables (I-O tables), is a traditional system for observing industrial sectors from the perspective of the relationship between technology and economy (Guevara & Domingos, 2017). Furthermore, it can also quantify the roles, status and situation of various industries in the development of economy. Hence, the utility of I-O tables system is vital as it cannot only analyze different industry linkage ability among industries, but the levels of this industry linkage ability within the national economy can also be determined intuitively. Moreover, it is helpful in providing the advisory opinions towards the matters of policy formation, development planning or strategic decision-making regarding different industries in variant spatial and temporal territory (Merciai & Heijungs, 2014). Factually, the Chinese economy is going through a tough transformation phase from high speed growth to medium-high speed growth, where realizing high quality economic growth by adjusting and improving the industrial structure is a challenging endeavor (Wang et al, 2017). Industry linkage ability can strongly express and measure internal motivation of industrial restructuring. Therefore, research studies on the industrial linkage ability are great significance as they can provide structural transformation guidelines to many industries with wider business and commercial field applications (Xing et al, 2018).

2. Literature review

2.1 Current research on the industry linkage ability

Most of the scholars in their research analyzed the industry linkage ability based on the total demand coefficient matrix (as known as the Leontief inverse matrix). As for as Chinese industry linkage ability research is concerned most of the researchers used the influence coefficient and inductance coefficient as evaluation criteria, so to analyze the situation about different industries linkage ability for whole country or some selected provinces. Whereas some of the scholars only addressed one industry or a single category of the industry to establish industry linkage ability.

However, it is worth to mention that all of these referred studies were based on the Leontief inverse matrix as a measure of influence coefficient (Zheng et al, 2018). Alessia et al (2018) believed that even though the industrial linkage analysis method by the Leontief inverse matrix can completely measure the linkage effect, but total linkage effect may not be appropriate by the idea of the sum of the forward linkage effect and the backward linkage effect among the industries, based on the row and column of the Leontief inverse matrix. Whereas some researchers had also given variant opinions regarding these (Ding, 2019; Liu, 2016).

As concluded by some other researchers that the row of Leontief inverse matrix as sensitivity coefficient and the column of Ghosh model as influence coefficient could not truly reflect the scales effect among industries. In fact, the original calculation of industrial linkage coefficients had equal weights for different industries and it was observed that some small-scale industries showed large linkage coefficients, based on empirical study on Chinese industrial linkage, it did not signify that even some small scale industries owned a strong linkage ability in the entire economy, because their status had been vital within the whole society (Yang, 2014; Yang, 2005; Liu, 2002). However, the study findings actually required the validity of traditional statements, which had been mainly focused on the aspects of "output flow" (mutual supply of products) and "input flow" (mutual consumption of products) among industries, the so-called "input" or "consumption" refers only to "intermediate input" (intermediate consumption).

2.2 The research highlights

To fill such research gaps as discussed above, the present study is aiming to evaluate the comprehensive industrial linkage ability by employing an improved method i.e., grey fixed weight clustering and it will further be seeking for ranking the order of improvement measures. The following are the main research objectives:

(1) Building of some enhanced indexes to evaluate industry linkage ability by employing the technique of structural decomposition.

(2) Construction of 'weighted measure' by considering the factors like industrial scale and initial investment intensity.

(3) Introduction of advanced grey fixed weight clustering method that can evaluate the industry linkage ability through comparative analysis.

As the current research is exclusively focusing on the evaluation of industry linkage ability in China, so it will be assistive to government and industrial managers for the assessment of developmental scenarios in China, and the decision-makers can be able to identify vital improvement pathways. Moreover, the government at different levels can also formulate more realistic industrial policies and take pro-active measures to improve industry linkage ability at various levels.

3. Establishment of evaluation model for industry linkage ability

3.1 Selection of new indexes

The structural decomposition technique was used to decompose the Leontief inverse matrix for the selection of new evaluation indexes. Whereas, it further explained about explaining the forward spillover effects, the backward spillover effects, the multiplier effects and the feedback effects. While considering the scale of output and input effect the forward spillover effect and the back spillover effect respectively, the absolute forward spillover effect and the absolute backward spillover effect were emphasized. Finally, these indexes have been further refined and the multiplier effect and the absolute forward spillover effect were determined in terms of the calculation indexes.

Nomenclature

Intermediate use matrix	X	*Final product for industry i*	f_i
Final use column vector	F	*Value added for industry j*	v_j
Direct consumption coefficient matrix	A	*Direct output coefficient matrix*	H
Total output value column vector	Q	*Total input value row vector*	Q'
Complete demand coefficient matrix	B	*Value added row vector*	V
Direct output coefficient matrix inverse matrix	G		

According to the structural decomposition technique, let the Leontief inverse matrix B to be decomposed to obtain eq. 3.1

$$\begin{bmatrix} B_{11} & B_{12} & \cdots & B_{1n} \\ B_{21} & B_{21} & \cdots & B_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ B_{n1} & B_{n2} & \cdots & B_{nn} \end{bmatrix} = \begin{bmatrix} B_{11} - \frac{1}{1\text{-}A_{11}} & 0 & \cdots & 0 \\ 0 & B_{22} - \frac{1}{1\text{-}A_{22}} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & B_{\mathrm{nn}} - \frac{1}{1\text{-}A_{\mathrm{nn}}} \end{bmatrix}$$

$$+ \begin{bmatrix} 0 & B_{12} & \cdots & B_{1n} \\ B_{21} & 0 & \cdots & B_{2n} \\ \cdots & \cdots & 0 & \cdots \\ B_{n1} & B_{n2} & \cdots & 0 \end{bmatrix} + \begin{bmatrix} \frac{1}{1-A_{11}} & 0 & \cdots & 0 \\ 0 & \frac{1}{1-A_{22}} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \frac{1}{1-A_{\mathrm{nn}}} \end{bmatrix} \tag{3.1}$$

In the Eq. 3.1, $\frac{1}{1\text{-}A_{ii}}(i=1,2,\cdots,n)$ it has been the multiplier effect in the industry, which represented the change in the output level of the industry caused by the final demand of the unit of any industry $i(i=1,2,\cdots n)$. $\left(B_{ij} - \frac{1}{1\text{-}A_{ii}}\right)(i=1,2,\cdots,n)$, whereas it is called as the feedback effect, $\sum_{j,j\neq i}^{n} B_{ij} = E$ is the forward spillover effect and $\sum_{i,j\neq i}^{n} B_{ij} = D$ is the backward spillover effect.

Similarly, according to directly output coefficient inverse matrix, represented as G. In the G, $\frac{1}{1\text{-}H_{11}}$, is the multiplier effect in the industry, which represents the change in the output level of the industry caused by a unit final demand in any $i(i=1,2,\cdots,n)$ industry. $\left(B_{ii} - \frac{1}{1\text{-}H_{ii}}\right)(i=1,2,\cdots,n)$, is the feedback effect. $\sum_{j,j\neq i}^{n} B_{ij} = E$, is the forward spillover effect. $\sum_{i,j\neq i}^{n} B_{ij} = D$, is the backward spillover effects.

While because of $diag(B) = diag(G)$, which means

$$\begin{bmatrix} B_{11} & 0 & \cdots & 0 \\ 0 & B_{22} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & B_{\mathrm{nn}} \end{bmatrix} = \begin{bmatrix} G_{11} & 0 & \cdots & 0 \\ 0 & G_{22} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & G_{\mathrm{nn}} \end{bmatrix},$$

so $\frac{1}{1\text{-}A_{ii}} = \frac{1}{1\text{-}H_{ii}}(i=1,2,\cdots,n)$.

The multiplier effect $\frac{1}{1\text{-}A_{ii}} = \frac{1}{1\text{-}H_{ii}}(i=1,2,\cdots,n)$ reflected the industrial self-regulation and sustainable development capabilities or it can be termed as the industrial viability. The feedback effect, it has been meant to determine the impact and demand of one industry in-relation to the other industries. In addition, the forward spillover effect is the total sum of the indirect and indirect effect from total industries except $i(i=1,2,\cdots,n)$ impact on $i(i=1,2,\cdots,n)$ industry, reflects the influence ability of $i(i=1,2,\cdots,n)$ industry. Whereas the backward spillover effect is the sum of indirect and indirect effect from $i(i=1,2,\cdots,n)$ industry in terms of impact on others industries.

However, while considering that some small-scale industries show a large linkage ability at same time, it does not mean that such industries have a pivotal position within the economy system. Therefore, the scale of industries (final product column vector f_i or value added row vector v_j) and initial investment has been taken into account, and the methods of weighted measures as represented in eq.3.2:

Whereas the forward absolute linkage coefficient of the industry is termed as γ, and its calculation formula can be made as per eq.3.2:

$$\gamma=\frac{\sum_{i=1}^{n}B_{ij}f_i}{\frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{n}B_{ij}f_i} \tag{3.2}$$

The backward absolute linkage coefficient is denoted as β, and its calculations can be done via eq. 3.3:

$$\beta=\frac{\sum_{j=1}^{n}H_{ij}v_j}{\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}H_{ij}v_j} \tag{3.3}$$

Furthermore, as the backward absolute linkage coefficient and the forward absolute linkage coefficient could not cover and account the whole industries, by employing the multiplier effect and feedback effect, have been required and drawn to. Therefore to resolve the issue the backward absolute spillover effect and forward absolute spillover effect have been obtained. Whereas, the calculations of these are as represented in eq. 3.4 and 3.5 respectively:

$$\gamma^*=\frac{\sum_{i,i\neq 1}^{n}B_{ij}f_i}{\frac{1}{n-1}\sum_{j,j\neq 1}^{n}\sum_{i,i\neq 1}^{n}B_{ij}f_i} \tag{3.4}$$

$$\beta^*=\frac{\sum_{j,j\neq 1}^{n}H_{ij}v_j}{\frac{1}{n-1}\sum_{i,i\neq 1}^{n}\sum_{j,j\neq 1}^{n}H_{ij}v_j} \tag{3.5}$$

These forward absolute spillover effect and the backward absolute spillover effect are like the effects of induction capability and influence capability respectively, and these are reflecting the linkage effect of an industry to the forward sector and the backward sector. These effects have proven to be are more rational than the traditional sensitivity coefficient and influence coefficient. As these are able to reflect the connection among industries. And the spillover effect does not only consider the individual impact of an industry but as well as the scale of industries have also been determined.

This study has addressed the construction of new indexes of industries in China by employing structural decomposition techniques, and the forward absolute spillover effect, backward absolute spillover effects and multiplier effect are represented as final indexes used for further analysis. The designed indexes and data will affect the future analysis of traditional industries profoundly.

3.2 Construction and elaboration of grey possibility clustering model

3.2.1 Mechanism of the model

The grey possibility clustering is an intelligent and multi-dimensional evaluation method based on the grey system theory (Liu et al, 2013). The comprehensive effect of whole system or a sub-system can be determined and categorized as high, medium and low and so on within a given period under this analysis method. Whereas the system of the indexes has been established based on the different industrial linkage effects to delineate the situation of macroeconomic operation. Therefore, this method of evaluation is also called multi-dimensional grey evaluation (Liu et al, 2018). The core thought of the grey evaluation method has established the grey possible function, which is used to quantify certain evaluation objects belonged to a certain grey class (Zhang et al, 2019; Wang & Zuo, 2018). Moreover, the comprehensive clustering coefficient of the evaluation object can also be calculated through the weight and membership degree. Finally, the comprehensive evaluation index is representable according to size of the comprehensive clustering coefficient along-with the triangular coordinate system and the golden proportional coefficient (Guo & Wang, 2014). As such the results show that the ranking problem of the evaluation object has been resolved.

3.2.2 Establishment of the grey possibility clustering model

Step 1. Determination of evaluation index and evaluation matrix

The required data has been collected and sorted on the assumption that there are n subjects, which has been structured into a subject set called as; P, $P=(P_1,P_2,\dots P_n)$,and m indexes structured into an index set termed as T, $T=(T_1,T_2,\dots T_m)^{\mathrm{T}}$. Then the observed values $y_{ij}\,(i = 1,2,\cdots, n, j = 1, 2,\cdots, m)$ have been composed by the subjects; $P_i\,(i=1,2\cdots n)$, indexes; $T_j\,(j=1,2\cdots m)$, and the observation matrix has been designed as represnted in eq. 3.6

$$Y=\begin{bmatrix} y_1(1) & y_1(2) & \cdots & y_1(m) \\ y_2(1) & y_2(2) & \cdots & y_2(m) \\ \cdots & \cdots & \cdots & \cdots \\ y_n(1) & y_n(2) & \cdots & y_n(m) \end{bmatrix} \tag{3.6}$$

Step 2. Formulations of possibility function

Firstly, it has been assumed that there is; $t\,(t=1,2\cdots,s)$ for a certain grey category, so the each value range $[a_{j,}b_j]$ in index j is subdivided into s categories. Later, two respective possibility functions have been formulated i.e. an upper measure possibility function $f_j^s(x)=[\lambda_j^{s\text{-}1},\lambda_j^s,\text{-},\text{-}]$ for category s and a lower measure possibility function $f_j^1=[\text{-},\text{-},\lambda_j^1,\lambda_j^2]$ for grey class 1. The further grey categories are formulated as; $k\,(k{=}2,3,\cdots s-1)$, at connection point $(\lambda_j^k,1)$

with the center-point $\left(\lambda_j^{k-1},0\right)$ of grey class k-1 (may be termed as the turning point for $\left(\lambda_j^1,0\right)$ under grey class 1) Moreover, the connection $\left(\lambda_j^k,1\right)$ with the center-point $\left(\lambda_j^{k+1},0\right)$ of grey class $k+1$ (termed as the turning point $\left(\lambda_j^s,0\right)$ under grey class s), whereas the possibility function can be marked as $f_j^k\left(x\right)=[\lambda_j^{k-1},\lambda_j^k,$ -, $\lambda_j^{k+1}]$. For each of the observation value x_{ij} in terms of the grey categories s , the possibility function can be divided into λ_j^1 , λ_j^s and $\lambda_j^k\left(k=2,3,\cdots s-1\right)$

Step 3. Determination of weight of indexes

The relevant weights, $w_j\left(j=1,2,\cdots m\right)$ for each of the index have been determined by various different methods like f objective methods subjective method and other mixed methods.

Step 4. Calculations of the weighting coefficient

These calculations are done regarding a specific grey category so to evaluate the clustering value for each industry. Whereas the required object has been computed as $i(i = 1,2,\cdots, n)$ in terms of a grey category $t(t = 1, 2,3)$, so to determine a clustering coefficient as per eq.3.7.

$$\delta_i^t=\sum_{j=1}^{m} f_j^t\left(x\right)\cdot w_j \tag{3.7}$$

Step 5: Determining the ranking of evaluation objects

According to relationship of $\max\limits_{1\le t\le 3}\left\langle \delta_i^t \right\rangle$, it has been found that for a typical grey category $t(t = 1, 2,3)$ to be chosen by the maximal value the grey category $t(t = 1, 2,3)$ of observation objects $i(i = 1,2,\cdots, n)$ are belong to. Then, a new connection can be formulated in the form of a triangle coordinate system as illustrated in Fig. 1. Where the golden ratio had been introduced into grey evaluation system for more clear and accurate analysis and respective results. The triangle coordinates (Fig. 1) has been divide into 10 sections, and as such there are a more specific and unambiguous sub-classes. Moreover, for each observational value regarding observation objects, there is a grey point for each of the grey category as it has been represented on the grey evaluation triangle (Fig. 1). Whereas for each of the grey point will represent a position for a certain grey category.

The evaluation samples can be sorted in a single order below:

$$F_i=\left(f_{i1}+0.618f_{i2}+0.382f_{i3}\right)\times 100\% \tag{3.8}$$

Whereas in the eq. 3.20, F_i is the grey evaluation value of the $i(i = 1,2,\cdots, n)$ samples, f_{i1}, f_{i2}, f_{i3} represents s the category of high, medium and low comprehensive weight coefficients in samples $i(i = 1,2,\cdots, n)$ respectively and the evaluation range of the grey evaluation value is denoted by $\left[38.2,100\right]$.

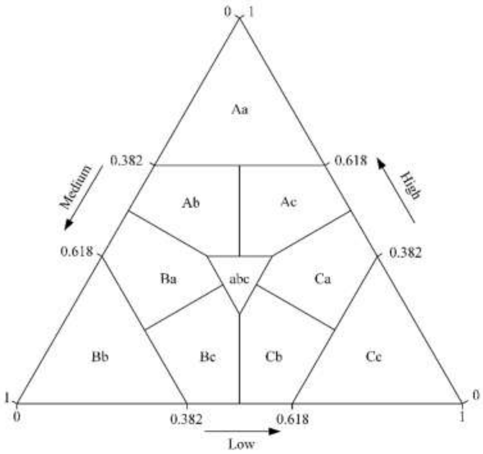

Figure 1 The triangle coordinates to determine the standard of certain grey category

4. Evaluation and application of the proposed model

4.1 Data selection

The Chinese National input-output (I-O table) has been compiled after every five years. Therefore, the latest I-O table has been available and employed is the tale of the year of 2012, which included 144 industries as an original sample. As there has been large number of industries in the original input-output table, so it is not viable to account all for data observations and analysis. However, these 144 industries have been clustered into 19 larger industrial sectors, and accordingly the analysis of industry linkage ability is represented in terms of larger general industrial classification.

Table 1 Specification chart for triangle coordinate standard

Type code		Criteria	Category description
High	Aa	$f_1 \geq 0.618$	Overall indexes are high
	Ab	$f_1 \geq 0.382 and f_2 > f_3$	Most of the indexes are higher than the individual
	Ac	$f_1 \geq 0.382 and f_3 > f_2$	Most of the indexes are higher than the lower levels.
Medium	Ba	$f_2 \geq 0.382 and f_1 > f_3$	Most of the indexes are medium to high
	Bb	$f_2 \geq 0.618$	The overall index is medium level
	Bc	$f_2 \geq 0.382 and f_3 > f_1$	Most of the indexes are medium-level and low
Low	Ca	$f_3 \geq 0.382 and f_1 > f_2$	Most of the indexes are low and individual high
	Cb	$f_3 \geq 0.382 and f_2 > f_1$	Most of the indexes are low-level individual biases
	Cc	$f_3 \geq 0.618$	Overall indexes are low
Mixing	abc	$f_1 and f_2 and f_3 \leq 0.382$	There is no significant difference between the indexes

Furthermore, the multiplier effect has been obtained by Eq. 3.1 in Table 2, the forward absolute spillover effect is obtained by Eq. 3.4, and the backward absolute spillover effect is obtained by Eq. 3.5.

4.2 Calculations and results

Step1: Determination of evaluation matrix

There have been three types of observation indexes employed as $j(j=1,2,3)$ the industrial observation objects representing 19 industrial sectors as $i(i=1,2,\cdots,19)$, which are further sub-divided into three grey categories as $t(t=1,2,3)$. The derived observation value matrix Y has been depicted in eq. 4.1.

$$Y=\begin{vmatrix} y_{11} & y_{21} & \cdots & y_{19,1} \\ y_{12} & y_{22} & \cdots & y_{19,2} \\ y_{13} & y_{23} & \cdots & y_{19,3} \end{vmatrix}$$

$$=\begin{vmatrix} 1.15 & 1.65 & 0.64 & 0.36 & 0.57 & 2.51 & 1.35 & 2.73 & 0.45 & 0.27 & 1.13 & 0.18 & 0.88 & 0.71 & 0.90 & 0.41 & 0.93 & 0.24 & 0.94 \\ 0.48 & 0.38 & 0.22 & 0.86 & 0.63 & 1.80 & 1.04 & 1.99 & 0.93 & 0.90 & 1.66 & 0.07 & 0.61 & 2.29 & 0.63 & 0.50 & 0.44 & 0.15 & 1.42 \\ 1.16 & 1.19 & 1.26 & 1.80 & 1.44 & 1.52 & 1.27 & 1.63 & 1.23 & 1.46 & 1.68 & 1.04 & 1.46 & 1.04 & 1.17 & 1.08 & 1.07 & 1.03 & 1.08 \end{vmatrix} \quad (4.1)$$

Table 2 Value of indexes and ranking for 19 industries

Industry	**Multiplier effect**		**Absolute forward spillover effect**		**Absolute backward spillover effect**	
	Coefficient	Ranking	Coefficient	Ranking	Coefficient	Ranking
1 Agriculture, forestry, animal husbandry	1.1598	12	0.4758	15	1.1462	5
2 Extractive industry	1.1542	13	0.3778	17	1.6469	3
3 Food and beverage industry	1.2947	8	1.2197	6	0.6360	12
4 Textile and garment industry	1.8043	1	0.8561	10	0.3645	16
5 Wood processing paper industry	1.4435	7	0.6345	11	0.5715	13
6 Petroleum and Chemical Industry	1.5159	4	1.8002	3	2.5145	2
7 Non-metallic mineral products industry	1.2686	9	1.0413	7	1.3475	4
8 Metal smelting processing industry	1.6324	3	1.9902	2	2.7292	1
9 Electrical machinery and equipment manufacturing	1.2347	10	0.9285	8	0.4518	14
10 Transportation equipment manufacturing	1.4588	5	0.8971	9	0.2729	17
11 Electronic information industry	1.6796	2	1.6648	4	1.1313	6
12 Other manufacturing industries	1.0364	18	0.0700	19	0.1784	19
13 Electricity, gas and water production and supply	1.4561	6	0.6123	13	0.8792	10
14 Construction industry	1.0429	17	2.2894	1	0.7110	11
15 Transport warehousing industry	1.1656	11	0.6277	12	0.8992	9
16 Commercial catering industry	1.0757	15	0.5013	14	0.4079	15
17 Financial industry	1.0659	16	0.4379	16	0.9282	8
18 Real estate industry	1.0341	19	0.1524	18	0.2389	18
19 Other service industries	1.0789	14	1.4232	5	0.9449	7

Step 2: Formulation of possibility function for 19 industrial sectors

To formulate this possibility function $f_j^t\left(x_{ij}\right)$ for each the calculations have employed the mean values as $\bar{x}_j$, $\bar{x}_j=\sum_{i=1}^{19} x_{ij} / 19$, and standard deviation as $\sigma_j, \sigma_j=\left\{\sum_{i=1}^{19}\left(x_{ij}-\bar{x}\right)^2 / 19\right\}^{1/2}$ for the three representative grey categories (high, medium and low) and the three selected observational indexes (multiplier effect，front spillover effect and back spillover effect). This is termed as the turning point of grey possibility function that has been computed as $f_j^1\left(x\right)=[\sigma_j, \sigma_j+\bar{x}, \text{-}, \text{-}]$, $f_j^2\left(x\right)=[\bar{x}\text{-}\sigma_j, \bar{x}, \text{-}, \sigma_j+\bar{x}]$，$f_j^3\left(x\right)=[\text{-}, \text{-}, \bar{x}\text{-}\sigma_j, \bar{x}]$.

$f_1^1\left(x\right)=[0.9474, 1.6387, -, -,]$, $f_1^2\left(x\right)=[0.2561, 0.9474, -, 1.6387,]$, $f_1^3=[-, -, 0.2561, 0.9474,]$;

$f_2^1\left(x\right)=[0.9474, 1.5617, -, -,]$, $f_2^2\left(x\right)=[0.3330, 0.9474, -, 1.5617,]$, $f_2^3=[-, -, 0.333, 0.9474,]$;

$f_3^1\left(x\right)=[1.2948, 1.5299, -, -,]$, $f_3^2\left(x\right)=[1.0598, 1.2948, -, 1.5299,]$, $f_3^3=[-, -, 1.0598, 1.2948,]$;

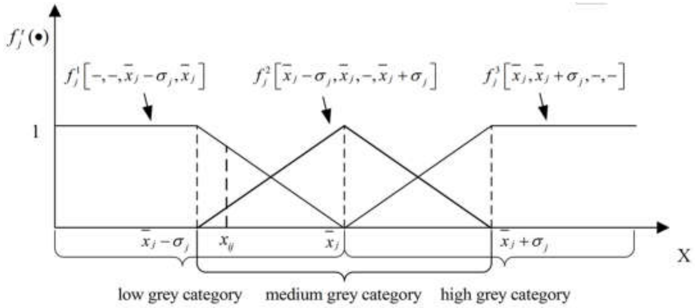

Figure 2 Grey possibility weight function $f_j^t\left(x_{ij}\right)$ of evaluation index j for grey categories $t\left(t=1,2,3\right)$

Step 3: Weighting of the evaluation index

It has been decided according to the assessment criteria, the system pf evaluation indexes are designed and set by the relevant experts in the fields, so the weighting methodology of the relevant evaluation indexes has been quite pre-determined and applied accordingly.

Step 4: Determination of weighting coefficient

To determine weight coefficient of observation objective $i\left(i=1,2,\cdots,19\right)$ in terms of grey categories $t\left(t=1,2,3\right)$ has been calculated by full relationship for δ_i^t has been represented in details by eq. 4.2

$$\delta_i^t=\sum_{j=1}^{3} f_j^t\left(x_{ij}\right)\cdot w_j\left(i=1,2,\cdots,19; t=1,2,3\right) \tag{4.2}$$

Step 5: Formulation of a ranking system

It can be based on the supposition that grey category of observation objective by grey coefficient $\max_{1\le s\le 3}\left\langle\delta_i^t\right\rangle=\max\left\langle\delta_i^1, \delta_i^2, \delta_i^3\right\rangle\left(i=1,2,\cdots 19; t=1,2,3\right)$, and it is representing an observation industry i that may belong to a typical categories t as depicted in eq. 4.3.

$$\begin{aligned}
&\delta_1=\left(\delta_1^1,\delta_1^2,\delta_1^3\right)=\left(0.1237,0.4678,0.4086\right)\delta_2=\left(\delta_2^1,\delta_2^2,\delta_2^3\right)=\left(0.4300,0.0909,0.4791\right)\\
&\delta_3=\left(\delta_3^1,\delta_3^2,\delta_3^3\right)=\left(0.1862,0.6201,0.1937\right)\delta_4=\left(\delta_4^1,\delta_4^2,\delta_4^3\right)=\left(0.1500,0.4250,0.4250\right)\\
&\delta_5=\left(\delta_5^1,\delta_5^2,\delta_5^3\right)=\left(0.0949,0.4574,0.4478\right)\delta_6=\left(\delta_6^1,\delta_6^2,\delta_6^3\right)=\left(0.9911,0.0089,0.0000\right)\\
&\delta_7=\left(\delta_7^1,\delta_7^2,\delta_7^3\right)=\left(0.3131,0.6702,0.0167\right)\delta_8=\left(\delta_8^1,\delta_8^2,\delta_8^3\right)=\left(1.0000,0.0000,0.0000\right)\\
&\delta_9=\left(\delta_9^1,\delta_9^2,\delta_9^3\right)=\left(0.0000,0.6404,0.3596\right)\delta_{10}=\left(\delta_{10}^1,\delta_{10}^2,\delta_{10}^3\right)=\left(0.1046,0.4414,0.4539\right)\\
&\delta_{11}=\left(\delta_{11}^1,\delta_{11}^2,\delta_{11}^3\right)=\left(0.6844,0.3156,0.0000\right)\delta_{12}=\left(\delta_{12}^1,\delta_{12}^2,\delta_{12}^3\right)=\left(0.0000,0.0000,1.0000\right)\\
&\delta_{13}=\left(\delta_{13}^1,\delta_{13}^2,\delta_{13}^3\right)=\left(0.1029.0.6256.0.2715\right)\delta_{14}=\left(\delta_{14}^1,\delta_{14}^2,\delta_{14}^3\right)=\left(0.4200,0.2830,0.2970\right)\\
&\delta_{15}=\left(\delta_{15}^1,\delta_{15}^2,\delta_{15}^3\right)=\left(0.0000,0.6690,0.3310\right)\delta_{16}=\left(\delta_{16}^1,\delta_{16}^2,\delta_{16}^3\right)=\left(0.0000,0.2196,0.7804\right)\\
&\delta_{17}=\left(\delta_{17}^1,\delta_{17}^2,\delta_{17}^3\right)=\left(0.0000,0.4937,0.5063\right)\delta_{18}=\left(\delta_{18}^1,\delta_{18}^2,\delta_{18}^3\right)=\left(0.0000,0.0000,1.0000\right)\\
&\delta_{19}=\left(\delta_{19}^1,\delta_{19}^2,\delta_{19}^3\right)=\left(0.3253,0.5353,0.1394\right)
\end{aligned}\tag{4.3}$$

The observation objectives belong to grey category [1]: 6, 8, 11, 14,
The observation objectives belong to grey category [2]: 1, 3, 4, 5, 7, 9, 13, 15, 19,
The observation objectives belong to grey category [3]: 2, 10, 12, 16, 17, 18,

1) As it has already been indicated in described Table 1, the results of grey categories classification are summarized into 10 specified general categories.

2) The golden ratio depicts the sum of three weighted possibility functions i.e. multiple of each weight, which is then termed as grey evaluation index. Likewise, the Table 3 has illustrated the specific categories and grey evaluation index for each observation objective $i\left(i=1,2,\cdots 19\right)$.

Table 3 The result of the enhanced grey evaluation and traditional method for 19 industries

Industry	Enhanced Grey evaluation	Specific grey category	Rank -ing	Traditional industry measure	Rank -ing
1 Agriculture, forestry, animal husbandry	56.89%	Bc	11	1.7401	11
2 Extractive industry	66.92%	Ac	7	2.2568	6
3 Food and beverage industry	64.34%	Bb	8	1.7915	10
4 Textile and garment industry	57.50%	Bc	10	1.8159	9
5 Wood processing paper industry	54.86%	Bc	13	1.6052	15
6 Petroleum and Chemical Industry	99.66%	Aa	2	3.6365	2
7 Non-metallic mineral products industry	73.37%	Ba	4	2.0383	7
8 Metal smelting processing industry	100.00%	Aa	1	3.9982	1
9 Electrical machinery and equipment manufacturing	53.31%	Bb	15	1.7393	12
10 Transportation equipment manufacturing	55.08%	Bc	12	1.6647	14
11 Electronic information industry	87.94%	Aa	3	2.7872	3
12 Other manufacturing industries	38.20%	Cc	18	0.8105	19
13 Electricity, gas and water production and supply	59.32%	Bb	9	1.9467	8
14 Construction industry	70.83%	Ac	6	2.7074	4
15 Transport warehousing industry	53.99%	Bb	14	1.6665	13
16 Commercial catering industry	43.39%	Cc	17	1.1697	17
17 Financial industry	49.85%	Cb	16	1.4647	16
18 Real estate industry	38.20%	Cc	18	0.8810	18
19 Other service industries	70.94%	Ba	5	2.2798	5

5. Comparative analysis and discussion

The overall analysis revealed that the higher grey category of comprehensive linkage ability has meant that the industrial chain is long with greater degree of impact effect towards other industries as well for the overall industrial development. In other words, it has larger degree of impact not only on the industry itself but also on forward and backward industries. It has been evident that four industrial sectors fall in the high grey category of comprehensive linkage ability, which are petroleum and chemical, metal smelting and processing, electronic information and construction sectors. All of these four industrial sectors belong to the secondary industry, that depicts the comprehensive linkage ability of China has been dominated by secondary industry. Moreover, as the construction industry has also been in high grey category, which predicts that Chinese current urban construction and related infrastructure systems are developing faster than past, that is in line with the urban developmental goals of China. The industries in medium category encompasses nine industrial sectors that has been distributed in all of three industries. The industrial sectors in primary or secondary classification are ranked in the medium grey category, and the sectors in tertiary industry classification have been relatively ranked later. It reveals that the development of tertiary industry has not been strong enough to link with other industries in the aspect of industry linkage ability, therefore in this specific sector more industrial reform are needed. Furthermore, within the weaker grey industrial sectors, the traditional heavy industry and the tertiary industries like commercial catering, financial and real estate are included. It is evident that most of the tertiary industry has been lacking industry linkage ability, which reflects the deficiencies in Chinese economic policy. It is fact that in the developing economies financial and the real estate sectors play a key role in the whole economic system, as the real estate industry has to reflect wider bonding and impact over other business sectors. This indicates a certain gap among Chinese developmental structure with other emerging economies of the world. The lack of a comprehensive linkage ability for Chinese real estate and the financial sectors depicts the weaker strategies of these sectors under development of marketing systems, which warns about the criticality and reforms agendas mainly at macro-level, such as proper operating mechanism during the economic transitions.

Moreover, the analyses revealed that the ranking by the grey evaluation and traditional measurement methods are mostly comparable although there are slight variations for ranking of few industries. The specific findings of grey evaluation deliberated three highest ranked industrial sectors as petroleum and chemical, metal smelting processing and electronic information. Whereas the lowest four sectors as per ranking are commercial catering, real estate business, financial industry and other manufacturing sectors. These patterns are similar to the rankings under traditional measuring method, it means of industries have shown solid characteristics in terms of industry linkage ability. However, for other sector of industries, such ranking have been no connection or impact in terms of their performance, and categorization remains static.

6. Conclusion

The current study has addressed the development of industry linkage ability, by establishing a grey evaluation system, where new measurement indexes were designed and combined with enhanced grey possibility clustering method to evaluate industry linkage ability by multi-dimension analysis. The three new indexes were designed. The backward absolute spillover effect which considered the factor of scale of industry scale in the system based on Leontief model, the forward absolute spillover effect which considered the factor of industry scale based on Gosh model and characters of each industry, and the multiplier effect reflected the viability of industry without considering the other industries for determination of linkage ability. Whereas the backward absolute spillover effect and the forward absolute spillover effect considered the industry scale in terms of final product and primary input, which had affected industry linkage ability. The study further concluded that the overall industry linkage ability of Chinese tertiary industry was weaker and Chinese secondary industry was stronger. It would provide a way forward for policy reforms focusing on the industrial sectors as indicated with weaker linkage ability.

Acknowledgements

National Natural Science Foundation of China (71771119, 71901191，71971194). Jiangsu Provincial Social Science Fund Key Project (NP2017301). Short-term visiting program of NUAA (180906DF09). The Ministry of education of Humanities and Social Science project (19YJC630167).

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