Evaluation of the sophistication of Chinese industries using the information-geometric decomposition approach

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Abstract

Since the Open Door Policy was implemented in 1978, China economy has maintained a high economic growth. During this period, although the reform of state-owned enterprises and the introduction of foreign direct investments might cause the change of the industrial structure, the common recognition, about how those factor has changed Chinese industrial structure, has not been obtained. This paper applied information geometric decomposition to Input-Output tables of China in the period 1981 to 2010, and extracted the factors of the technological changes in the whole industry in China. This paper examines the different of evaluation of industrial structure between input coefficient index and information geometry approach. Furthermore based on the factors, two industrial sophistication indicators, which are about degree of Mechanization and degree of ICT introducing, respectively are constructed. The empirical results suggests that the degree of mechanization and included ICT has different characteristics for each other. Regarding mechanization, the mechanized manufacturing sectors showed increases in sophistication in the 1980s and 2000s; however, mechanized tertiary sectors showed increases in sophistication in the 1990s. Regarding ICT input, while manufacturing sectors showed a high level of sophistication in ICT input in the 2000s, tertiary sectors showed a high level of sophistication in ICT input in the 1990s.

Key words: Input-Output Tables, Industrial structure, RAS method, Foreign direct investment, Innovation.

JEL Classification: C02 L00 O31

1. Introduction

Since the Open Door Policy was implemented in 1978, China has achieved stable and high economic growth. According to data from the National Bureau of Statistics of China (NBSC), China’s real GDP growth has averaged 9.6% during this period. Furthermore, China’s growth rate has been comparatively stable, except during the two years after the Tiananmen Square protests. To maintain its stable and high economic growth, China must have not only sufficient total demand for goods and services but also significant productivity. Previous papers that have investigated the factors that changed China’s industrial structure have suggested that foreign direct investment (FDI) improved China’s technical level during this period; however, there is no consensus regarding how FDI contributed in improving productivity and increasing the sophistication of China’s industrial structure.

Zhou *et al.* (2011) estimated indicators of technical efficiency (TE) in China between 1985 and 2008 and suggested that inward FDI contributed in increasing China’s productivity. The authors employed a nonparametric method to estimate the production function and calculated TE based on this function. To clarify the factors that are contingent on TE, they estimated regression models of the effect of TE on FDI and other factors. The analysis showed that FDI affected TE during the examined period; however, the effects turned from positive to negative in 2000. Zhang (2014) investigated the relationship between productivity and FDI in China and suggested that the interaction between FDI and human capital (HC) raised the industrial competitiveness in China. The authors employed industrial competitiveness data from 2005 to 2010 and then conducted a panel estimation of the regression model of the effect of industrial competitiveness on FDI, HC, R&D, and their interaction variables. The results showed that a certain level of HC accumulation is necessary for FDI to raise industrial competitiveness.

On the other hand, some studies have found that FDI has had adverse effects on industrial productivity in China. Jeon *et al.* (2013) suggested that FDI crowded out less productive indigenous firms within the same industry; therefore, FDI has not raised the productivity of the firms in which it was invested. The authors classified the effects of FDI on the productivity of domestic firms into vertical effects and horizontal effects, where the latter constitute the effects of FDI on firms within the same industry in which no investment was made. The results showed that the horizontal effects reduced productivity, indicating that FDI crowded out firms within the same industry. Meanwhile, FDI caused an increase in the total demand for goods, services, and innovation in another industry; this effect constitutes a vertical effect, in contrast to the horizontal effect. Shang *et al.* (2012) studied knowledge spillovers, where knowledge was measured in terms of patents. Shang *et al.* (2012) examined the relationship between patents and covariates, such as R&D, skilled workers, and FDI. The results showed that from 2000 to 2008, the effects of FDI on patent accumulation were smaller than the effects of R&D on government research institutes and domestic firms in China.

Li (2015) and Xu (2013) investigated the transition of the leading sector and growth factor of industry in China. Li (2015) examined data from 1995 to 2005 and then found that a policy change from import substitution to export orientation has occurred with an increase in the amount of exports. Xu (2013) argued that the growth factors of the leading sector constitute an increase in not only exports but also technology innovation.

In these papers, there is a consensus that FDI has affected the productivity or competitiveness of the leading sector in China; however, they do not indicate how FDI has affected Chinese industry since the implementation of the Open Door Policy. To address this issue, this paper employs the China Industry Productivity (CIP) database and then investigates the transition of the industrial structure in China. This database includes Input-Output (IO) tables from 1981 to 2010, and it is published by the Research Institute of Economy, Trade, and Industry. The IO tables are reorganized into the IO tables published by the NBSC once in five years. For example, MPS-type IO tables are reorganized into SNA-type IO tables, and the IO tables are estimated in unpublished years by using the SUT-RAS method (Wu and Ito, 2015). The IO tables of the CIP database are constructed for 37 sectors, and the contents of the tables are shown in Table I.

This paper applies the information-geometric decomposition method (Morioka and Tsuda, 2014) to the CIP database. This method enables researchers to extract an industrial structure matrix, which is obtained to remove the effect of the change in production scale from the matrix of input coefficients. Furthermore, this paper constructs indicators of industrial sophistication, which are calculated from the industrial structure matrix, and then characterizes the Chinese industry from

1981 to 2010.

The paper is organized as follows: Section 2 outlines the information-geometric decomposition method, after which Section 3 verifies the industrial structure matrix. Section 4 shows the calculated indicators of industry sophistication, and Section 5 then concludes the paper.

2. Information-geometric decomposition

This paper employs Morioka and Tsuda's (2014) information-geometric decomposition method. This method is used to decompose a matrix of input coefficients into the space of summations of columns and rows and into the space of the industrial structure. The paper uses this method to obtain a projection for the space of the industrial structure and evaluates the transition of the degree of sophistication of Chinese industries.

Suppose an n sector IO table, where $\mathbf{A}$ denotes the matrix of input coefficients and $\mathbf{a}$ denotes the vector, which is made by vectorizing $\mathbf{A}$. Furthermore, each column of $\mathbf{b}_i$ is linearly independent of the former column. Matrix $\mathbf{B}$, which takes $\mathbf{b}_i$ as each i th column, is introduced; moreover, the first $2n-1$ rows are redefined as $\mathbf{B}_1$, and the remainder of $\mathbf{B}$ is defined as $\mathbf{B}_2$. Using this matrix as a basis, IO tables are represented by two dually spaced axes.

$\boldsymbol{\eta}$ is defined as the m-geodesic representation of the matrix of input coefficients as follows:

$$\boldsymbol{\eta} \equiv \mathbf{B}'\mathbf{a} \quad \boldsymbol{\eta}^A \equiv \mathbf{B}_1'\mathbf{a} \qquad \boldsymbol{\eta}^B \equiv \mathbf{B}_2'\mathbf{a} \qquad (1)$$

The representation of the matrix of input coefficients by an e-geodesic expression, which has the dual character of an m-geodesic expression, is as follows:

$$\mathbf{a} \equiv \exp(\mathbf{B}\boldsymbol{\theta}) \quad \theta = \mathbf{B}^{-1}\log\mathbf{a} \qquad (2)$$

2.1 RAS method

In their method, Morioka and Tsuda (2014) estimated unpublished IO tables with a method called the RAS method. With the matrix of input coefficients of the known IO tables and the summation of columns and rows of the target IO table, the matrix of input coefficients of the target IO table can then be estimated. An assumption is made that the industrial structure of the basic year and the target year are consistent; each different value in the matrix of input coefficients between the basic year and target year then only arises because of a change in the summation scale of columns and rows. From the viewpoint of information geometry, the RAS method is interpreted as a way to reproduce IO tables, whose industrial structure is represented by the basic table, while the summation scale of columns and rows is the same as that in the target table. Furthermore, the RAS method provides a projection for an e-geodesic expression that minimizes the KL divergence between two IO tables, which occurs in manifold (Morioka and Tsuda, 2014).

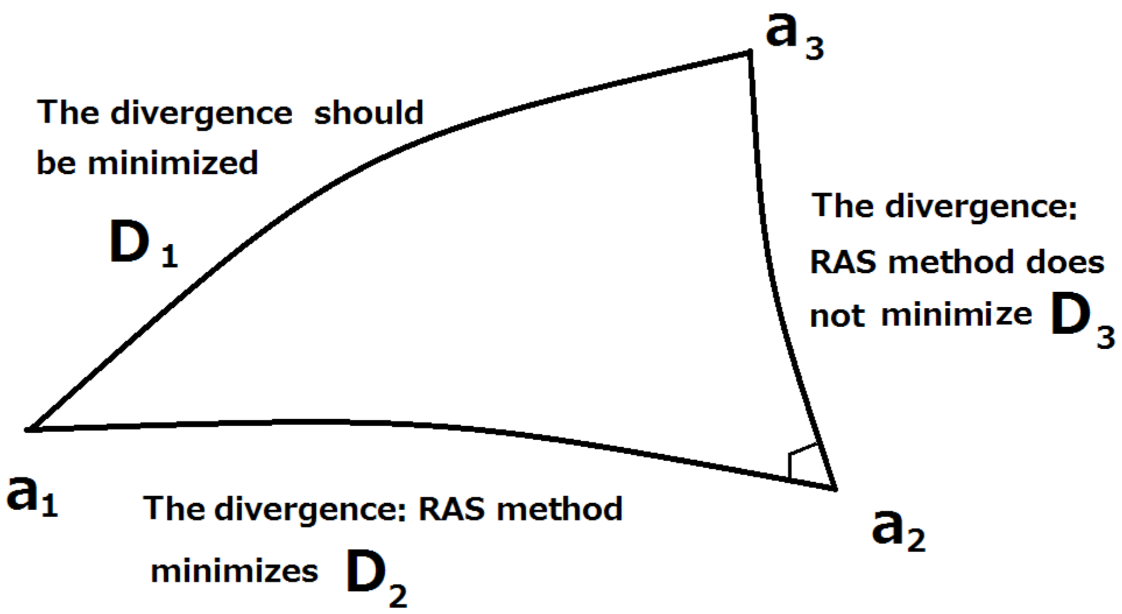

Figure 1 Generalized Pythagorean Theorem

The results show that the RAS method is a projection of the e-geodesic expression. The generalized Pythagorean theorem is satisfied; therefore, the following equation of the relationships among D_1, D_2, and D_3 in Figure 1 is valid.

$$D_1 = D_2 + D_3 \qquad (3)$$

Where $\mathbf{a}_1$ is the basic matrix of input coefficients, $\mathbf{a}_2$ is the estimated matrix of input coefficients, and $\mathbf{a}_3$ is the target matrix of input coefficients.

An IO table is represented by the e-geodesic expression as follows:

$$\begin{aligned} \log \mathbf{a} &= \mathbf{B\theta} \\ &= \mathbf{B}_1\mathbf{\theta}^A + \mathbf{B}_2\mathbf{\theta}^B \end{aligned} \qquad (4)$$

Where $\mathbf{\theta}^A$ denotes the first $2n-1$ factors of $\mathbf{\theta}$; $\mathbf{\theta}^B$ denotes the rest of $\mathbf{\theta}$. The first term on the right-hand side is the projection of the matrix of input coefficients for the space of the summation of columns and rows; the second term on the right-hand side is the projection of the coefficients matrix for the space, which is perpendicular to the space of the summation of columns and rows, where the latter is defined as the RAS invariant. The RAS invariant is equivalent to γ_{ij} , as in the following equation (Morioka and Tsuda, 2014).

$$\gamma_{ij} = \log a_{ij} - \frac{1}{n}\sum_{k=1}^{n} \log a_{ik} - \frac{1}{n}\sum_{l=1}^{n} \log a_{lj} + \frac{1}{n^2}\sum_{k=1}^{n}\sum_{l=1}^{n} \log a_{lk} \qquad (5)$$

Morioka and Tsuda (2014) recognized that a change in the matrix of input coefficients is caused by a change in the technical structure between industrial sectors and a change in economic scale. Changes in technical structure are reflected in the RAS invariant, which is specific to each of the IO tables, and such changes are considered to represent changes in industry structure. Changes in economic scale are reflected in the ratio of added value to total production or the ratio of intermediate-final demand, which is considered to be the summation of the columns and rows of the matrix of input coefficients. This paper calculates the RAS invariant from IO tables in the CIP database, which contains data on the Chinese industry from 1981 to 2010. Furthermore, it interprets the Chinese technical structure for this period.

2.2 The RAS invariant and indicators of industrial sophistication

The RAS invariant is an index related to industrial structure; it is therefore normalized, as the summation of both columns and rows is zero. Furthermore, each value of the RAS invariant represents the size of the input: when γ_{ij} is positive and when the absolute value is larger, the input of goods and services i is larger in industry j, and vice versa. As Morioka and Tsuda (2011) noted on the premise of the basic economy, which is called the maximum entropy economy, the value of the RAS invariant then indicates whether the value is larger or smaller than that of the maximum entropy economy. The maximum entropy economy has the following industrial structure: the input materials from whole sectors are the same as the input volume in the whole industry. The value of the RAS invariant is derived as follows: First, calculate the matrix of input coefficients by using the RAS method, which is the same as the maximum entropy economy for the industrial structure and the same as the target economy for the scale. Next, take the proportion between the calculated IO table and the target IO table. The logarithmic values of the proportion matrix are numerically equivalent to γ_{ij} (Morioka and Tsuda, 2014).

This paper derives two indicators of industrial sophistication, which are derived from the RAS invariant. Because the value refers to the comparison with the maximum entropy economy, its interpretation is complex. Therefore, we normalize the values of the RAS invariant for each year's CIP IO table to the values of the IO table for the initial year (1981). For this normalization process, the RAS method is applied to each RAS invariant and the summation of the rows and columns of the matrices of input coefficients in the initial year. All calculated IO tables have the same values for the summation of rows and columns, and each value is converted to the currency value for the initial year.

The indices are calculated from the normalized RAS invariant for each year and for each industry. The indices capture two factors: the degree of mechanization and the degree of included ICT. The degree of mechanization is captured by the sum of the values in the normalized RAS invariant of industries 19, 20, 21, 22, and 23 in Table 1. The values indicate the ratio of input goods produced in sectors related to mechanics to that in the target industry. Similarly, the degree of included ICT captures the sum of the values in the normalized RAS invariant of sectors 21, 29, 30, and 33 in Table 1. The values indicate the ratio of input goods produced in ICT-related industries to that in the target industry. Because the normalized RAS invariant can be considered the ratio of input goods produced in a specific industry, when the indices increase, the industry shows sophistication with respect to mechanization or included ICT.

Table. 1 Industries of CIP IO-table

ID	Sector
1	Agriculture, forestry, animal husbandry & fishery
2	Coal mining
3	Oil & gas excavation
4	Metal mining
5	Non-metallic minerals mining
6	Food and kindred products
7	Tobacco products
8	Textile mill products
9	Apparel and other textile products
10	Leather and leather products
11	Saw mill products, furniture, fixtures
12	Paper products, printing & publishing
13	Petroleum and coal products
14	Chemicals and allied products
15	Rubber and plastics products

16	Stone, clay, and glass products
17	Primary & fabricated metal industries
18	Metal products (excluding rolling products)
19	Industrial machinery and equipment
20	Electric equipment
21	Electronic and telecommunication equipment
22	Instruments and office equipment
23	Motor vehicles & other transportation equipment
24	Miscellaneous manufacturing industries
25	Power, steam, gas and tap water supply
26	Construction
27	Wholesale and retail trades
28	Hotels and restaurants
29	Transport, storage & post services
30	Information & computer services
31	Financial Intermediations
32	Real estate services
33	Leasing, technical, science & business services
34	Government, public administration, and political and social organizations, etc.
35	Education
36	Healthcare and social security services
37	Cultural, sports, entertainment services; residential and other services

3. Verification of the industrial structure matrix

To verify the normalized RAS invariant matrix (industrial structure matrix in the following), this paper compares the values of the matrix of input coefficients with the values of the industrial structure matrix for each year and each sector. Moreover, the CIP IO table has 37 sectors; therefore, interpreting the all values is complex. To address this complexity, the input sectors are aggregate to tertiary industry classifications.

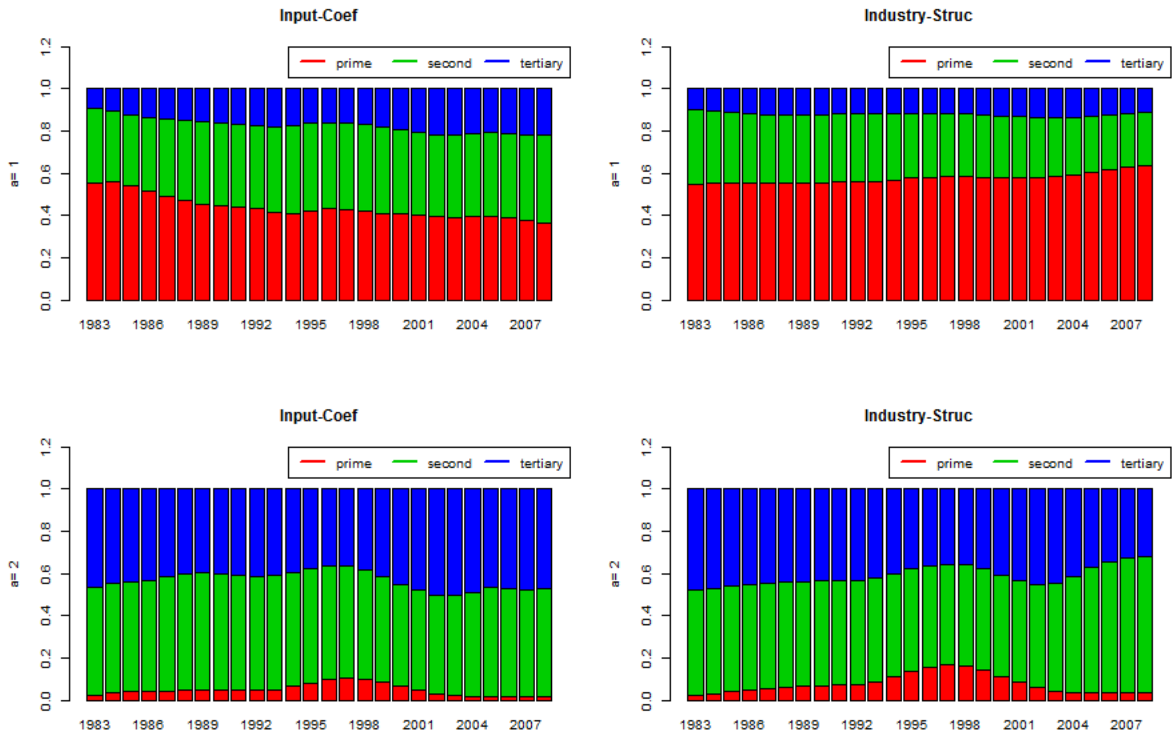

Figure. 2 Comparison of input coefficient matrix and industrial structure matrix

(sector 1 and 2)

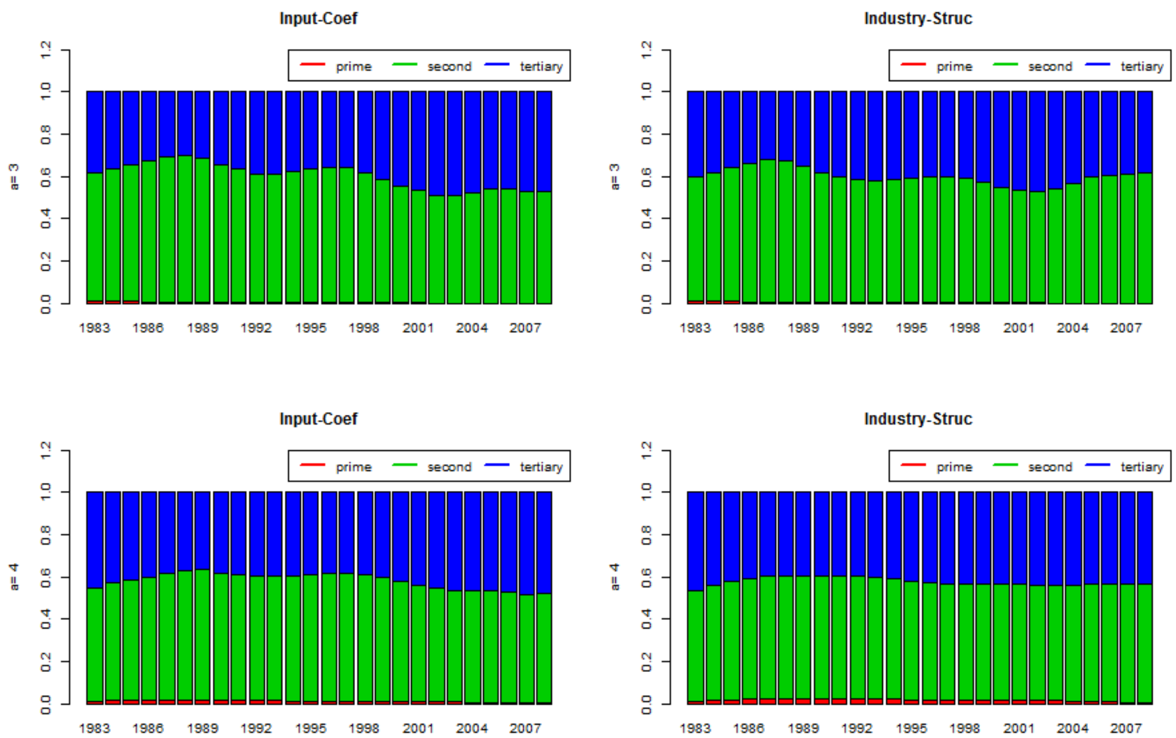

Figure. 3 Comparison of input coefficient matrix and industrial structure matrix

(sector 3 and 4)

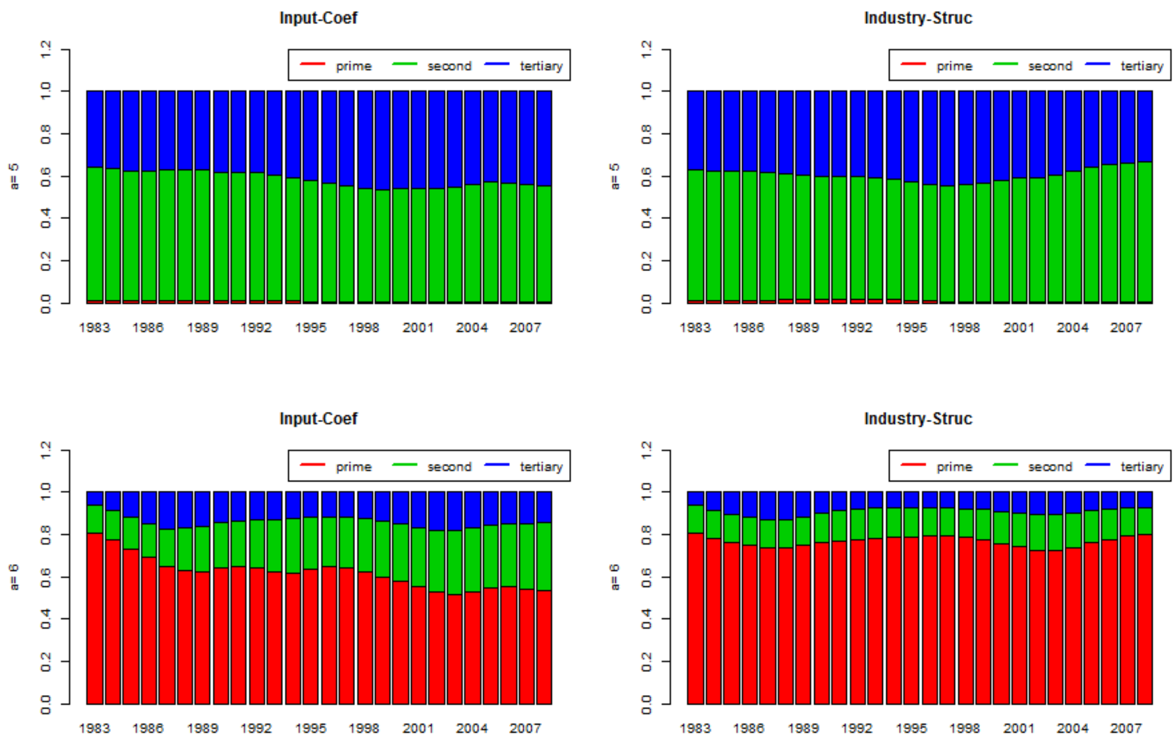

Figure. 4 Comparison of input coefficient matrix and industrial structure matrix

(sector 5 and 6)

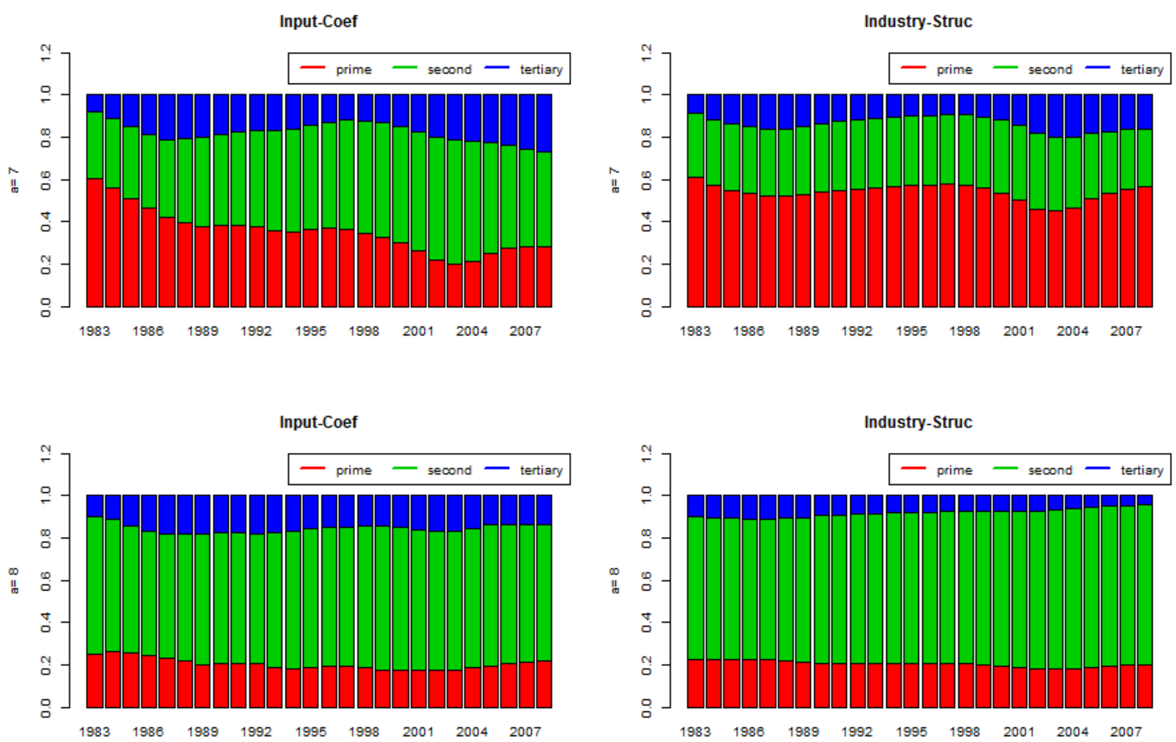

Figure. 5 Comparison of input coefficient matrix and industrial structure matrix

(sector 7 and 8)

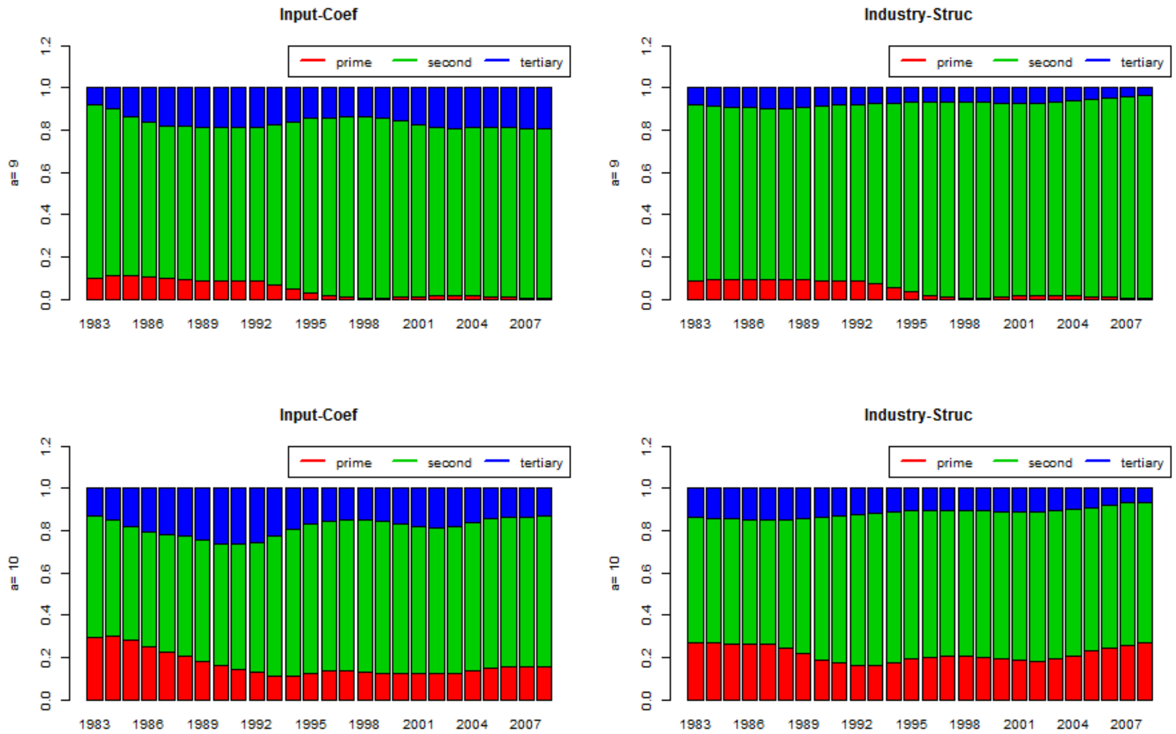

Figure. 6 Comparison of input coefficient matrix and industrial structure matrix

(sector 9 and 10)

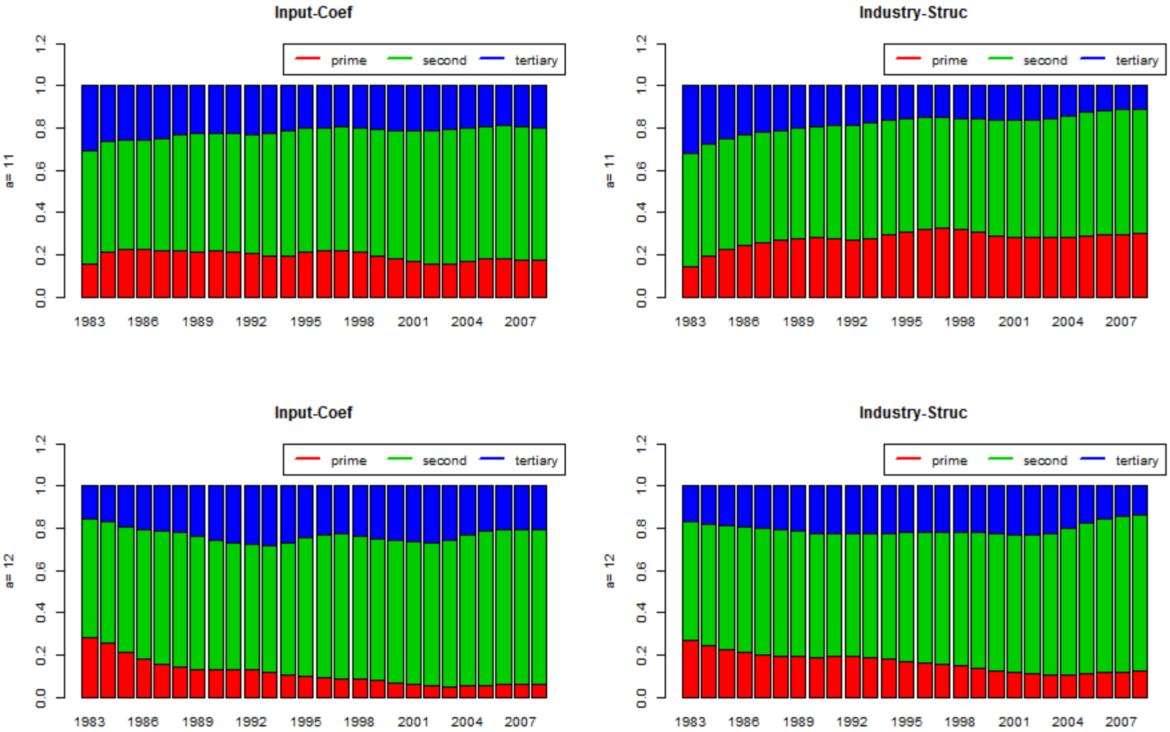

Figure. 7 Comparison of input coefficient matrix and industrial structure matrix

(sector 11 and 12)

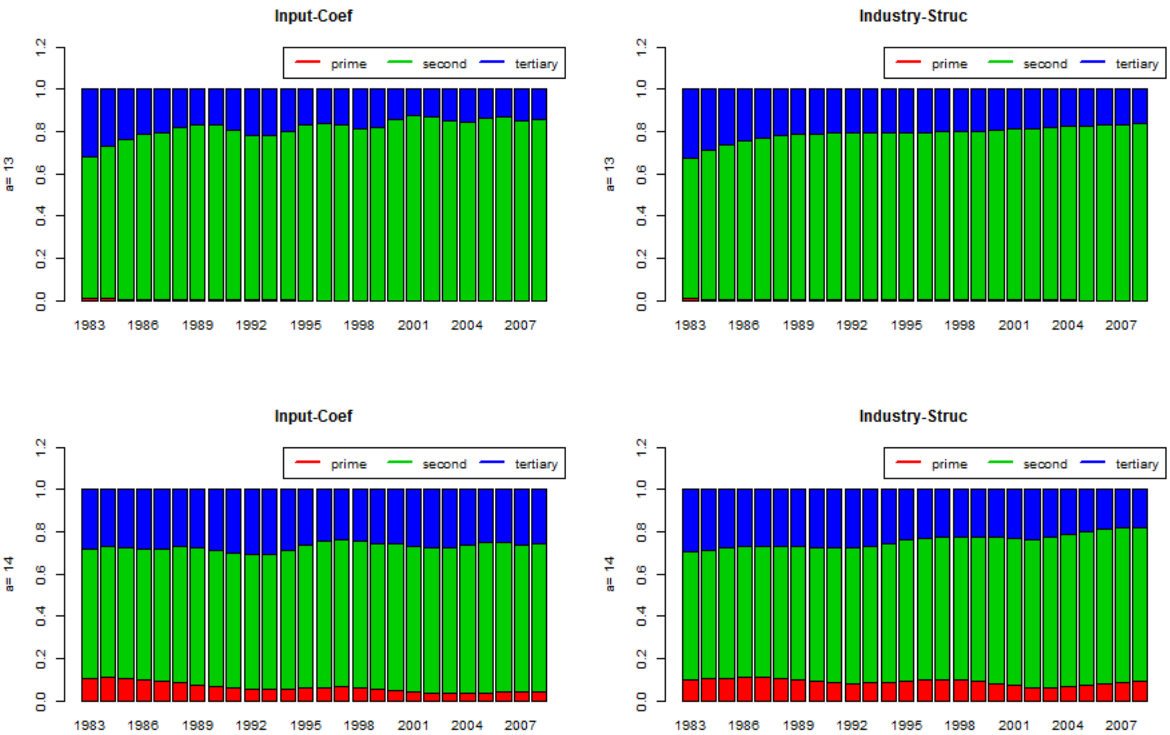

Figure. 8 Comparison of input coefficient matrix and industrial structure matrix

(sector 13 and 14)

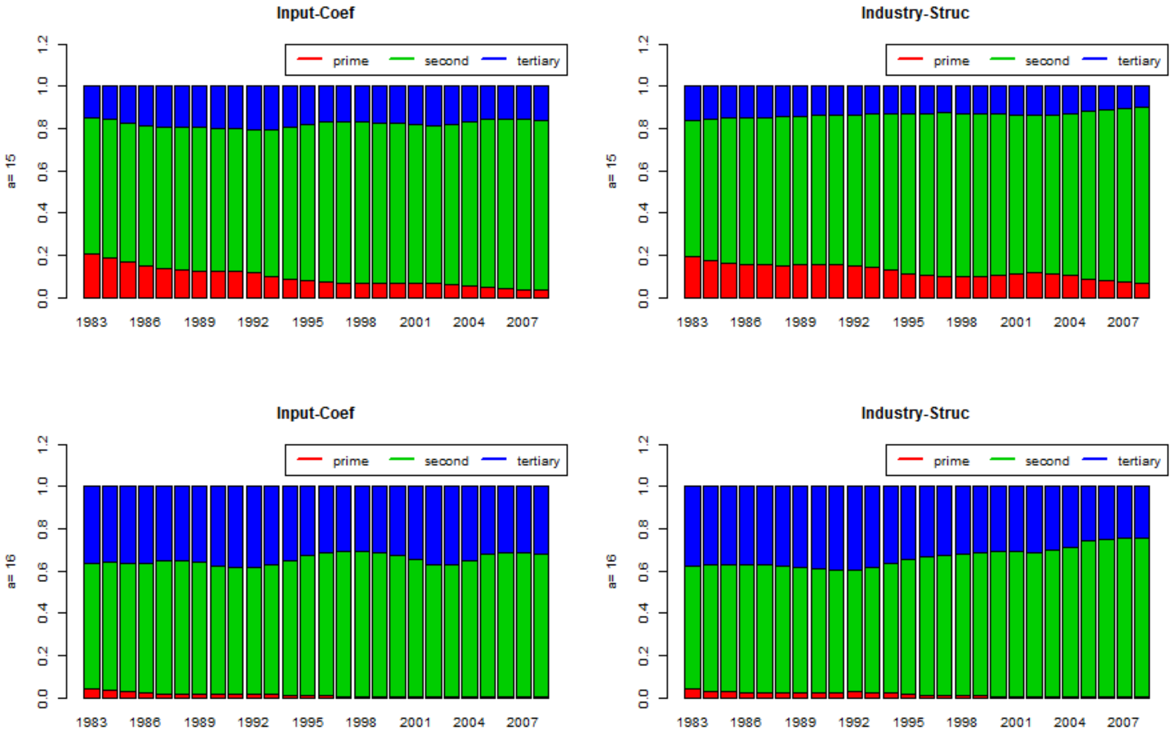

Figure. 9 Comparison of input coefficient matrix and industrial structure matrix

(sector 15 and 16)

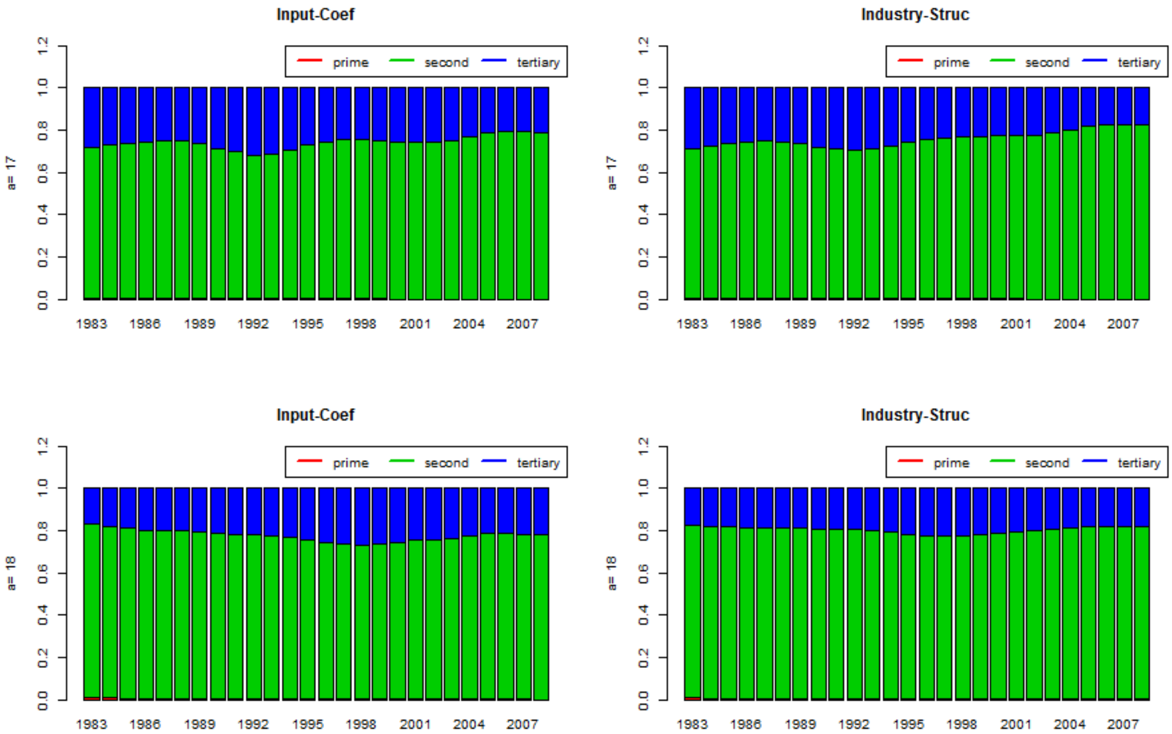

Figure. 10 Comparison of input coefficient matrix and industrial structure matrix

(sector 17 and 18)

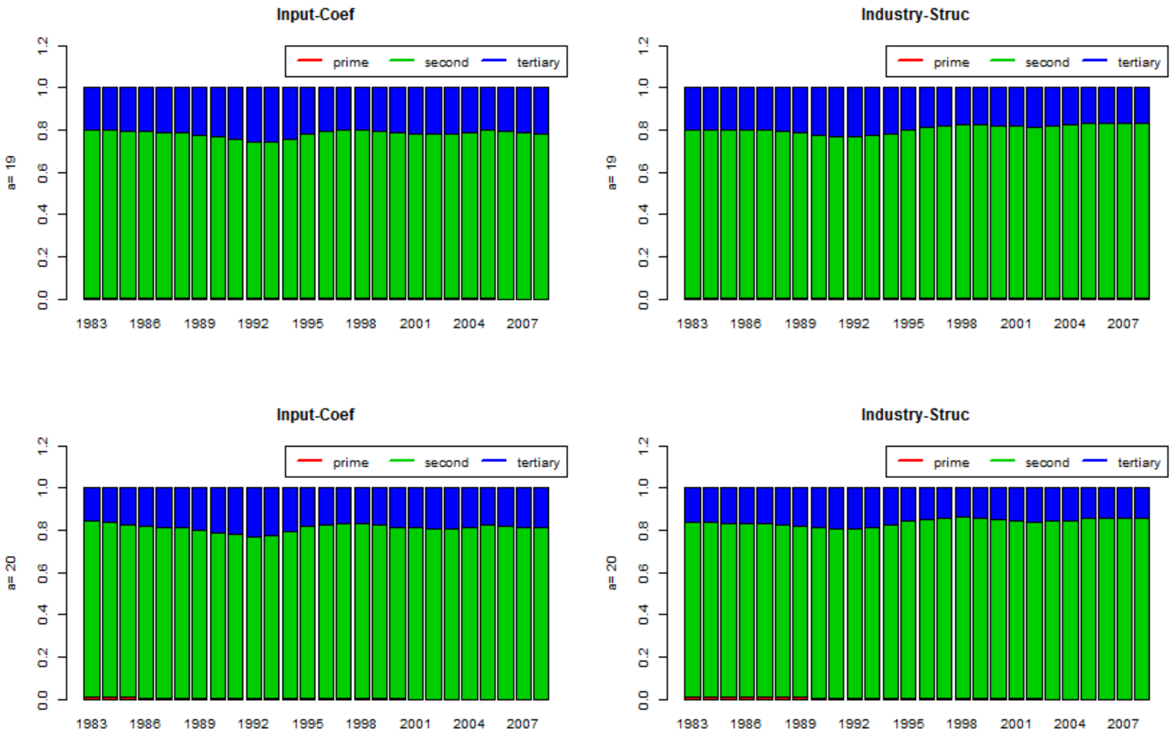

Figure. 11 Comparison of input coefficient matrix and industrial structure matrix

(sector 19 and 20)

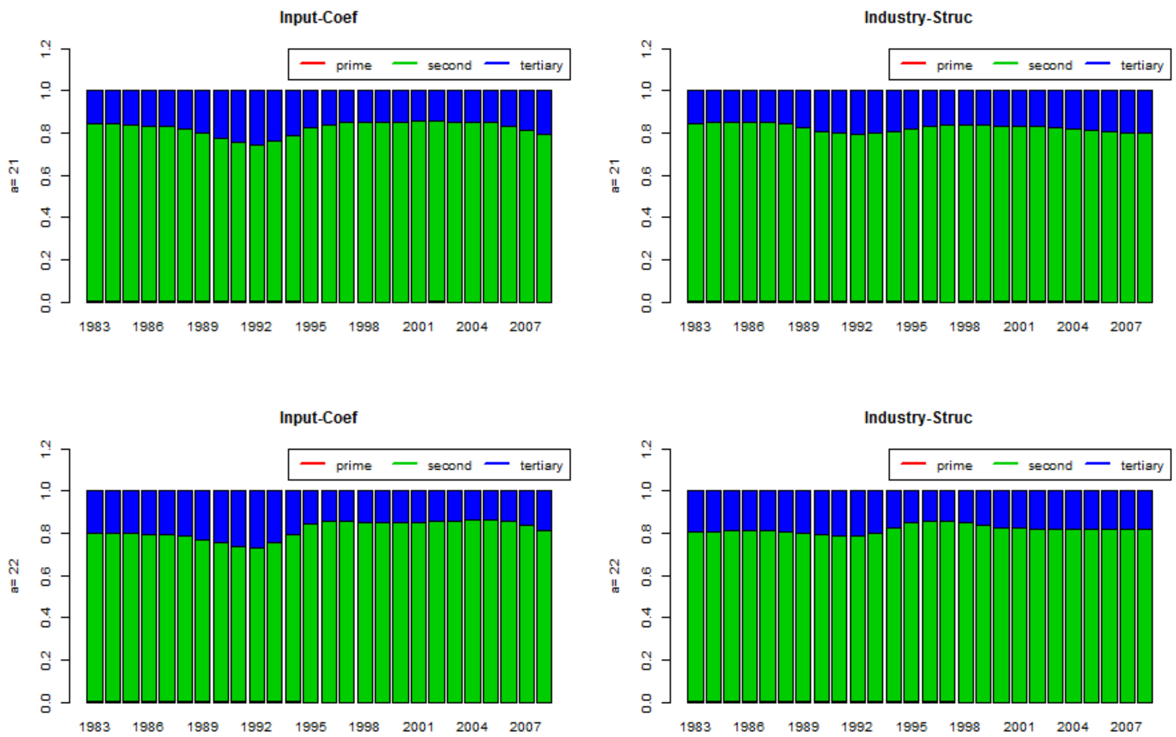

Figure. 12 Comparison of input coefficient matrix and industrial structure matrix

(sector 21 and 22)

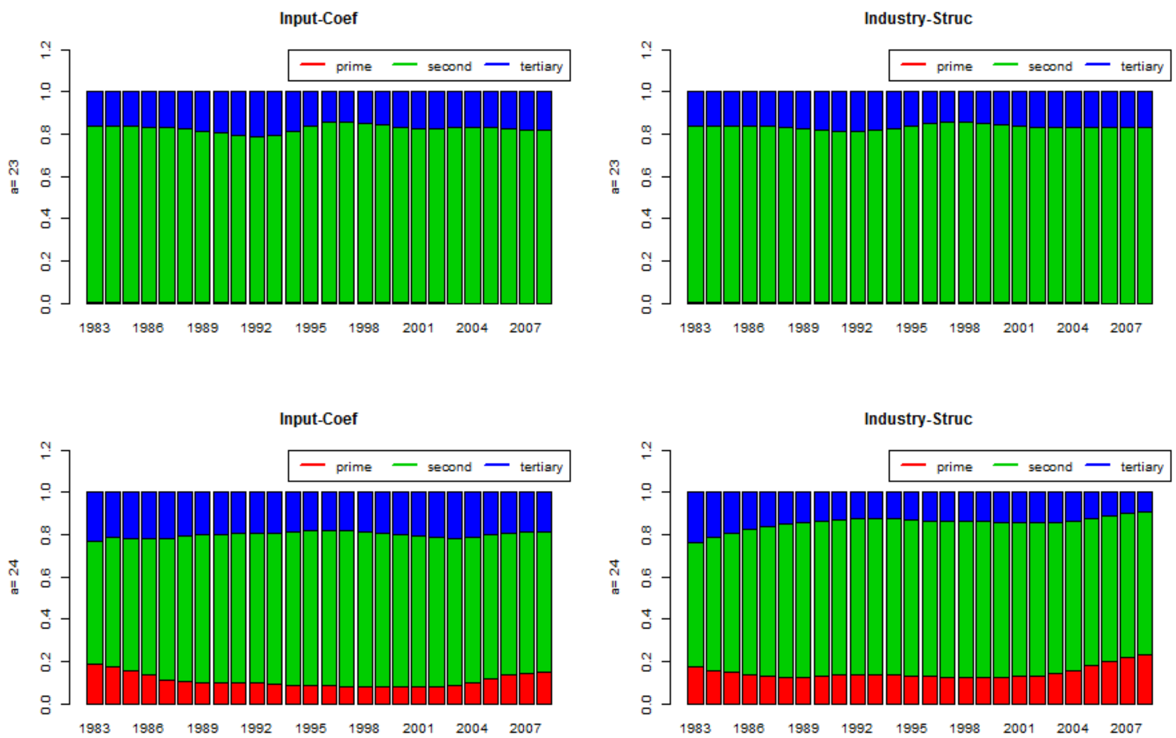

Figure. 13 Comparison of input coefficient matrix and industrial structure matrix

(sector 23 and 24)

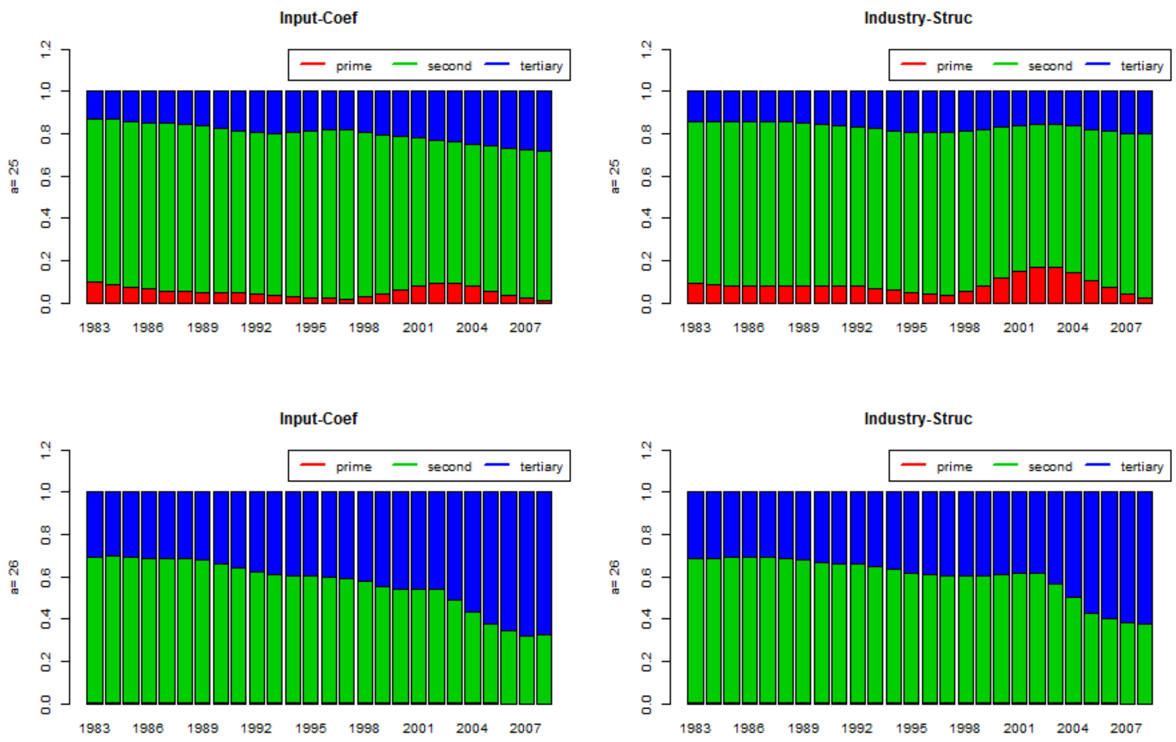

Figure. 14 Comparison of input coefficient matrix and industrial structure matrix

(sector 25 and 26)

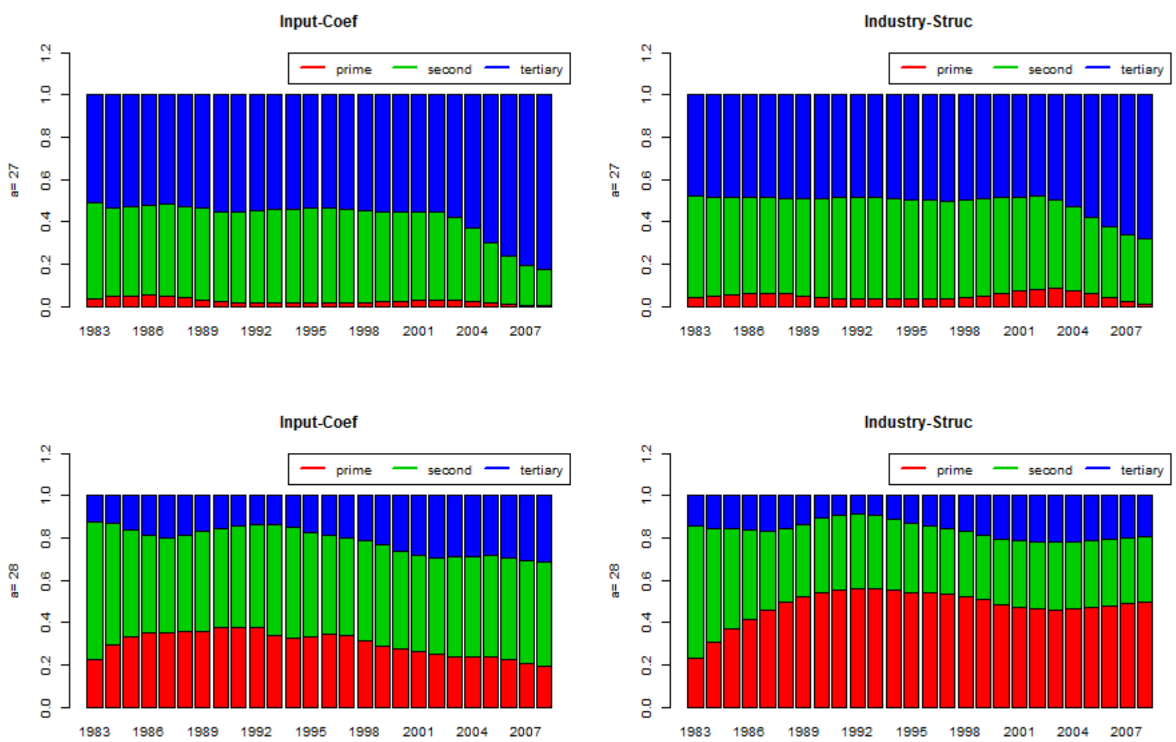

Figure. 15 Comparison of input coefficient matrix and industrial structure matrix

(sector 27 and 28)

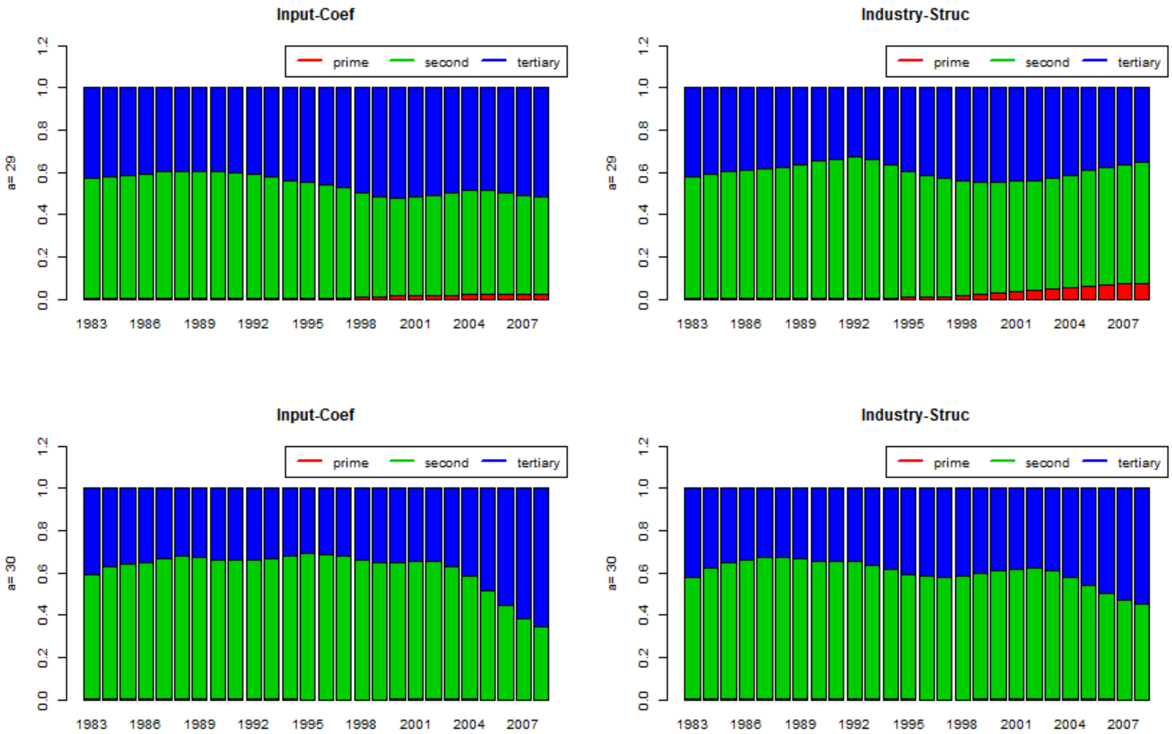

Figure. 16 Comparison of input coefficient matrix and industrial structure matrix

(sector 29 and 30)

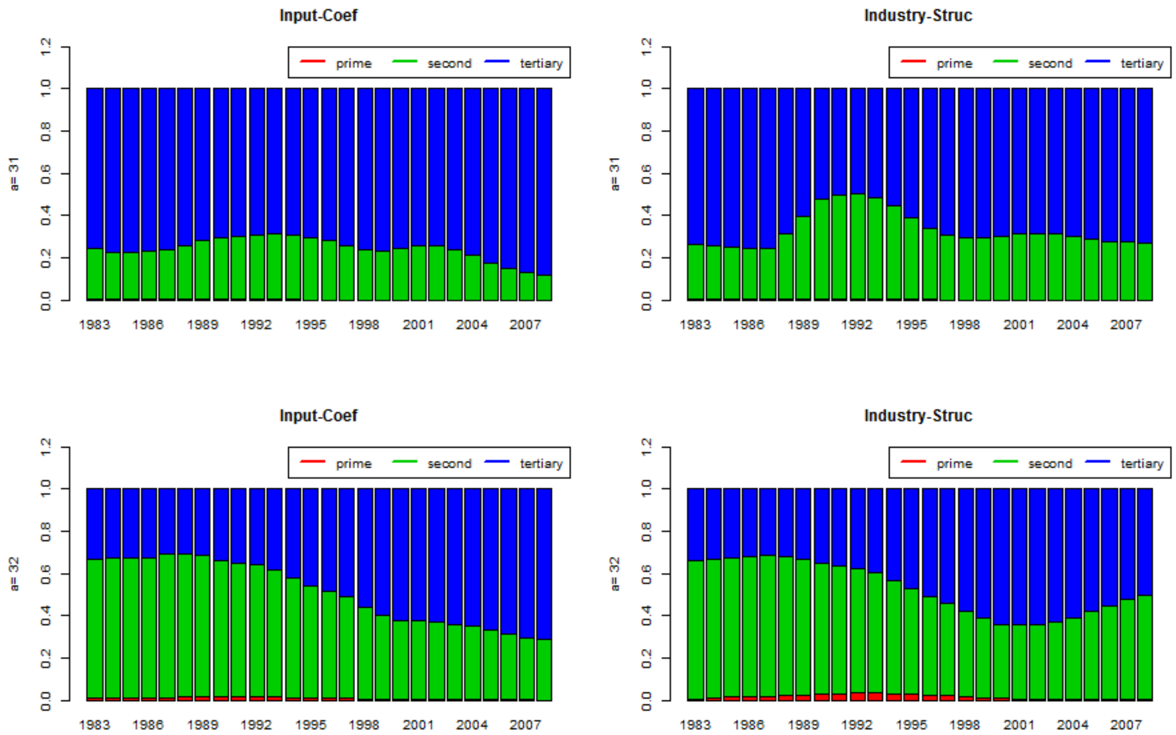

Figure. 17 Comparison of input coefficient matrix and industrial structure matrix

(sector 31 and 32)

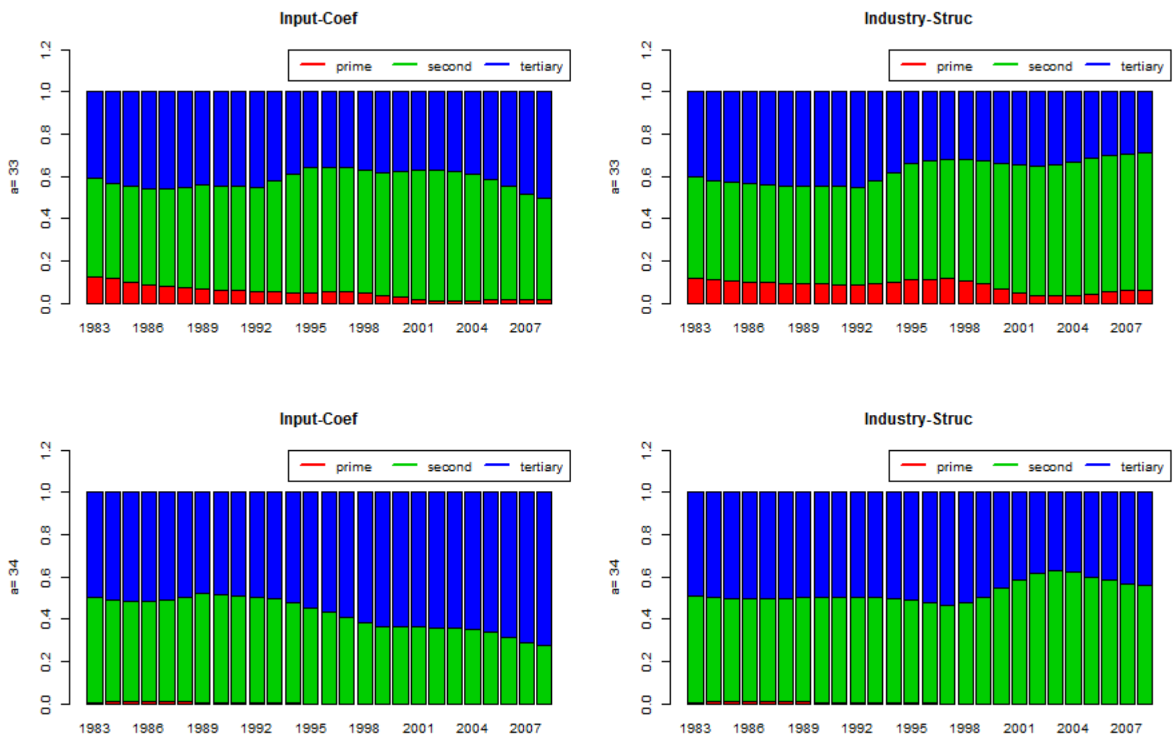

Figure. 18 Comparison of input coefficient matrix and industrial structure matrix

(sector 33 and 34)

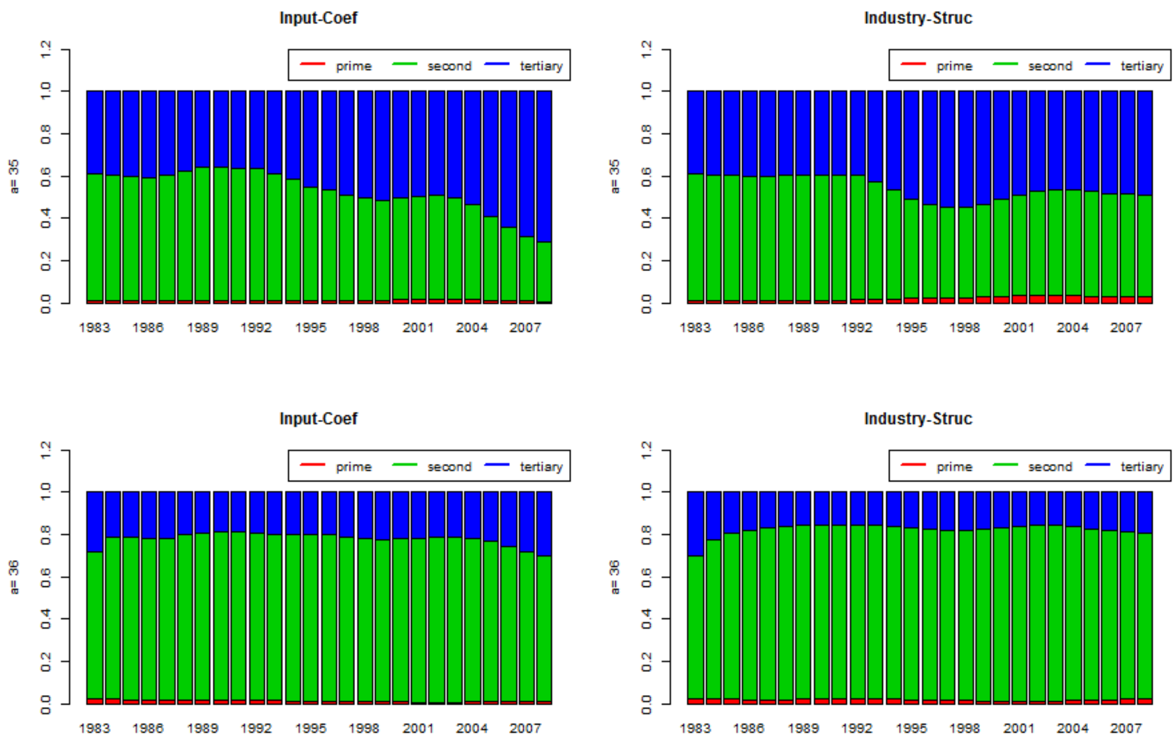

Figure. 19 Comparison of input coefficient matrix and industrial structure matrix

(sector 35 and 36)

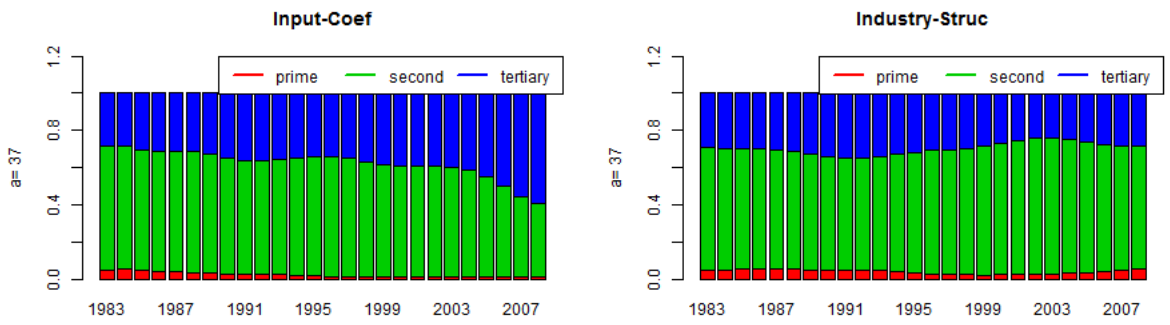

Figure. 20 Comparison of input coefficient matrix and industrial structure matrix

(sector 37)

Figure 2 to Figure 20 show the comparisons of the two indicators. Each bar shows the input share of each tertiary classification of input goods to all input goods in each period. Left-hand side of the graphs in each figure show input coefficient matrices and another side of the graphs in each figure show industrial structure matrices. As an overall trend, the share of tertiary goods in the matrices of input coefficients is larger than the same share in the industrial structure matrices. The differences in the two indicators are noted as follows. The industrial structure matrix is only reflected by changes to the technical structure, while the matrix of input coefficients is reflected changes to not only the technical structure but also the input-added value ratio or the intermediate-final demand ratio. Therefore, the industrial structure matrix can be reasonably used to evaluate the technical structure; however, the input share of tertiary goods might be overevaluated by using the matrix of input coefficients. As a trend, the final demand in secondary sectors increases faster than the intermediate demand. Moreover, this effect is greater for secondary sectors than for tertiary sectors, which means that the total input of the share of secondary sectors is underevaluated. In the next section, indices for the degree of mechanization and the degree of the included ICT are constructed from the industrial structure matrix and examined.

4. Indicators of industry sophistication

This section presents the characteristics of China's industrial sophistication from 1981 to 2010 by using the industrial structure matrix. The evaluation criteria are the degree of mechanization and the degree of included ICT in each sectors. The indicators in each sector are the input share of sectors related to mechanics and the input share of sectors related to ICT, which are calculated from the industrial structure matrix. Sectors related to mechanics are the industrial machinery and equipment sector (ID=19), electrical equipment sector (ID=20), electronics and telecommunication equipment sector (ID=21), instruments and office equipment sector (ID=22), and motor vehicles & other transportation equipment sector (ID=23). Sectors related to ICT are the electronics and telecommunication equipment sector (ID=21), transport, storage, & post services sector (ID=29), information & computer services sector (ID=30), and Leasing, technical, science, & business services sector (ID=33).

Table. 2 Average values and growth of Mechanization indicator

ID	Average value (1981-2010)	Average value (1981-1990)	Average value (1991-2000)	Average value (2001-2010)	Growth rate (1982-1990)	Growth rate (1991-2000)	Growth rate (2001-2010)
1	1.9%	2.0%	2.1%	1.5%	-3.9%	-0.1%	-3.8%
2	13.0%	14.6%	11.2%	13.2%	-1.3%	-1.9%	1.9%
3	20.7%	25.0%	18.5%	18.6%	4.7%	-4.5%	2.6%
4	10.5%	9.9%	8.9%	12.8%	-3.9%	1.7%	4.5%
5	11.5%	11.4%	11.4%	11.9%	-2.1%	0.5%	0.2%
6	0.5%	0.5%	0.7%	0.5%	6.7%	-3.8%	-4.5%
7	1.3%	0.7%	1.7%	1.5%	7.3%	3.1%	-2.5%
8	1.0%	0.9%	1.2%	0.9%	6.0%	0.7%	-4.6%
9	0.5%	0.4%	0.5%	0.5%	-3.1%	6.8%	-1.8%
10	0.8%	0.7%	0.9%	0.9%	4.0%	-2.3%	1.8%
11	2.9%	5.1%	1.7%	1.9%	-13.2%	-4.7%	2.3%
12	2.7%	1.9%	3.0%	3.3%	8.9%	2.2%	1.2%
13	2.8%	2.5%	3.1%	2.8%	2.5%	0.2%	-0.2%
14	2.6%	2.6%	2.7%	2.5%	10.5%	-2.2%	0.0%
15	1.8%	1.3%	1.8%	2.2%	6.5%	3.0%	1.1%
16	5.3%	6.1%	5.1%	4.8%	-3.5%	-0.4%	-1.1%
17	5.0%	5.9%	4.5%	4.7%	-3.7%	-1.3%	2.1%
18	5.1%	4.6%	4.3%	6.3%	1.6%	-1.8%	8.0%
19	31.1%	30.9%	28.6%	33.8%	2.2%	-0.7%	2.3%
20	19.6%	19.9%	18.0%	20.7%	3.8%	-2.3%	2.6%
21	51.5%	58.7%	49.4%	46.4%	0.5%	-1.8%	0.0%
22	52.0%	45.3%	52.1%	58.6%	2.8%	1.5%	1.0%

23	42.5%	41.5%	41.3%	44.7%	1.7%	-0.1%	1.0%
24	2.6%	3.0%	2.8%	2.1%	-0.4%	-1.7%	-4.4%
25	9.0%	10.0%	8.9%	8.0%	-1.5%	-1.7%	0.4%
26	8.9%	8.1%	10.5%	8.3%	0.0%	2.4%	-5.8%
27	9.3%	5.6%	11.6%	10.8%	-3.6%	10.4%	-5.7%
28	1.2%	1.4%	1.2%	1.2%	-8.7%	-1.2%	1.9%
29	13.9%	13.9%	14.8%	13.1%	0.1%	-0.5%	-0.7%
30	30.8%	21.9%	34.5%	36.0%	-0.7%	7.4%	-2.7%
31	9.1%	7.4%	12.6%	7.3%	10.5%	-0.9%	-8.3%
32	9.8%	9.5%	8.5%	11.5%	-5.6%	2.6%	2.1%
33	22.6%	17.2%	24.6%	26.1%	-4.0%	7.2%	-2.6%
34	11.5%	14.8%	12.6%	7.2%	0.6%	-7.6%	1.9%
35	10.8%	14.9%	9.1%	8.6%	-5.4%	-5.0%	1.6%
36	6.0%	4.3%	6.5%	7.4%	-3.1%	1.1%	1.6%
37	8.4%	7.4%	8.4%	9.5%	0.6%	-2.2%	5.9%

The first column of Table 2 shows the mean values for the mechanization indicator over the entire period from 1981-2010. The results show that the indicators for some manufacturing sectors and tertiary sectors are high, such as sectors with IDs 3, 19, 21, 22, 23, 30, and 33. All of these sectors have a high level for the indicator, as shown in columns 2 to 4 in Table 2. According to the columns 5 to 7 in Table 2, the manufacturing sectors with IDs 19, 21, 22, and 23 were growing in the 1980s and 2000s, while they did not grow in the 1990s. On the other hand, the tertiary sectors with IDs 30 and 33 were growing in 1990s. These results indicate that there are differences in the characteristics of mechanization between manufacturing sectors and tertiary sectors.

Table. 3 Average value and growth of ICT indicator

ID	Average value (1981-2010)	Average value (1981-1990)	Average value (1991-2000)	Average value (2001-2010)	Growth rate (1982-1990)	Growth rate (1991-2000)	Growth rate (2001-2010)
1	3.8%	4.2%	4.2%	3.0%	5.7%	-2.1%	-3.9%
2	6.7%	4.5%	6.6%	8.8%	0.3%	6.0%	-1.0%
3	6.1%	5.5%	6.6%	6.3%	6.3%	1.6%	-3.7%
4	6.6%	4.9%	8.0%	7.1%	-5.4%	6.0%	-0.2%
5	9.0%	5.2%	11.3%	10.6%	-2.7%	9.6%	-3.4%
6	2.9%	4.3%	2.0%	2.2%	5.1%	0.0%	-3.7%
7	3.2%	3.6%	2.0%	3.9%	9.4%	-1.0%	4.0%
8	1.4%	1.9%	1.2%	0.9%	-0.6%	-0.4%	-5.3%
9	1.7%	1.8%	1.5%	1.8%	-0.3%	6.0%	-4.7%
10	2.3%	3.2%	2.1%	1.7%	2.0%	-3.7%	-4.2%
11	3.5%	4.0%	3.2%	3.3%	-9.0%	3.7%	-4.7%
12	3.6%	3.5%	3.6%	3.8%	2.9%	4.1%	-4.8%
13	6.0%	8.6%	5.4%	4.1%	-3.4%	-1.7%	-5.5%
14	3.9%	3.9%	3.9%	3.7%	-1.1%	1.9%	-2.9%
15	2.6%	2.8%	2.5%	2.5%	-3.1%	3.5%	-5.0%
16	5.7%	5.5%	6.4%	5.3%	-6.1%	3.5%	-4.4%
17	3.7%	4.0%	4.0%	3.1%	-7.2%	3.5%	-5.4%
18	3.7%	3.6%	4.1%	3.2%	0.3%	2.9%	-5.8%
19	5.2%	5.1%	5.4%	5.1%	0.2%	1.4%	-2.1%
20	5.7%	4.5%	5.6%	6.9%	1.0%	3.5%	0.9%
21	39.1%	49.7%	33.5%	34.0%	0.6%	-4.5%	1.5%
22	33.6%	24.5%	31.7%	44.6%	2.3%	4.1%	1.7%
23	4.5%	4.8%	4.4%	4.4%	0.5%	-0.4%	-1.6%

24	3.5%	4.0%	3.6%	2.8%	-5.0%	2.7%	-7.2%
25	6.8%	5.2%	7.0%	8.1%	-1.3%	2.0%	3.4%
26	6.7%	9.1%	7.6%	3.4%	-7.4%	-0.7%	-12.4%
27	20.9%	12.0%	20.1%	30.6%	17.0%	-6.3%	10.2%
28	3.5%	4.7%	3.0%	2.8%	-7.4%	3.6%	-4.2%
29	17.8%	16.9%	18.7%	17.9%	-8.1%	10.2%	-5.1%
30	19.3%	17.3%	16.7%	23.8%	-3.7%	3.1%	2.4%
31	25.6%	27.8%	24.2%	24.7%	-3.2%	1.5%	-0.3%
32	12.3%	8.5%	13.2%	15.3%	3.6%	4.6%	-1.8%
33	22.0%	24.3%	23.9%	17.8%	-0.4%	0.5%	-4.1%
34	20.6%	26.2%	21.5%	14.2%	-0.8%	-3.4%	-1.3%
35	14.6%	15.9%	15.0%	12.9%	-2.8%	0.4%	0.0%
36	3.0%	4.6%	2.5%	1.9%	-11.3%	-1.8%	-3.0%
37	8.7%	10.2%	7.5%	8.3%	-3.4%	0.3%	1.4%

The first column of Table 3 shows the mean values for the ICT indicator over the entire period from 1981-2010. The results show that the indicators for some manufacturing sectors and tertiary sectors are high, such as sectors with IDs 21, 22, 29, 30, 31, 33, 34, and 35. All of these sectors have a high level for the indicator, as shown in columns 2 to 4 in Table 3. According to columns 5 to 7 in Table 3, the manufacturing sectors with IDs 21 and 22 were growing in the 1980s and 2000s. In contrast, the sector with ID 21 did not grow in the 1990s, though the sector with ID 22 did. Furthermore, most of the tertiary sectors except for sector 34 grew in the 1990s. The growth rates for the indicators show that the growth in the degree of included ICT slowed down in the 2000s in many of the sectors.

According to existing studies, FDI in China promoted sophistication in some sectors. Some characteristics can be gleaned about the transition of FDI in China from 1983 to 2010[1] (Figure 21). As the reason of the sharp increase in the amount of FDI in China in 1992, the Lecture in Southern Tour is thought to be in the same year. In 1998, FDI growth stopped, and the amount was reduced in 1999, which is consistent with the Asian currency crisis. Furthermore, owing to infectious diseases such as Severe Acute Respiratory Syndrome (SARS) and Avian influenza, the growth rate of FDI in China has decreased. After the Global Financial Crisis in 2007, a negative growth rate is observed in only one year; however, the growth rate instantly recovered thereafter.

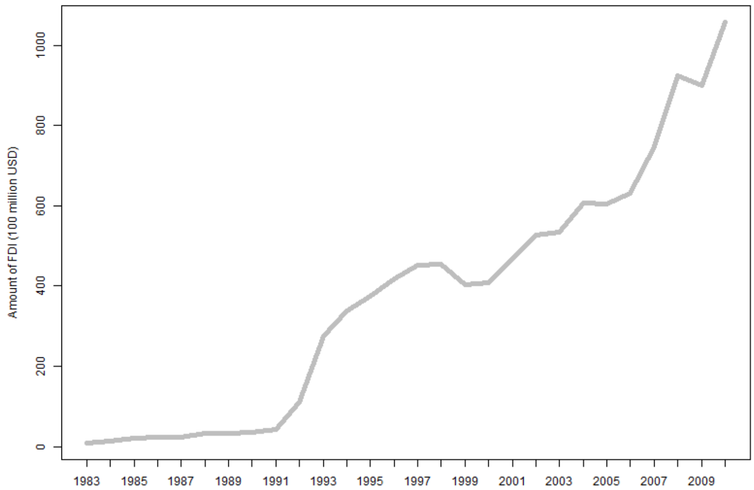

Figure. 21 The amount of foreign direct investment (unit: 100 million USD)

Table. 4 Correlation test for between FDIs and degree of Mechanization and ICT[2]

ID	Test Value for Mechanization indicator	P-Value for Mechanization indicator	Test Value for ICT indicator	P-Value for ICT indicator	Examinations for Mechanization	Examinations for ICT
1	0.172	0.391	-0.017	0.932	0	0

[1] Data from the Ministry of Commerce of the People's Republic of China are used here, and data are available from about 1983 to 2017.
http://data.mofcom.gov.cn/lywz/inmr.shtml
[2] The values of Examination column show 1 when test value shows positive sign and P-value shows less than 0.05, otherwise show 0.

2	-0.484	0.011	0.166	0.409	0	0
3	-0.211	0.290	-0.129	0.521	0	0
4	0.088	0.664	0.565	0.002	0	1
5	-0.096	0.633	0.585	0.001	0	1
6	-0.035	0.864	-0.104	0.606	0	0
7	0.087	0.665	-0.245	0.217	0	0
8	0.096	0.632	0.037	0.856	0	0
9	0.504	0.007	0.002	0.991	1	0
10	-0.061	0.762	-0.363	0.062	0	0
11	-0.522	0.005	-0.225	0.258	0	0
12	0.435	0.023	-0.083	0.680	1	0
13	0.507	0.007	-0.196	0.326	1	0
14	-0.156	0.437	0.120	0.551	0	0
15	0.437	0.023	-0.057	0.779	1	0
16	-0.160	0.424	0.326	0.097	0	0
17	-0.051	0.800	0.310	0.116	0	0
18	-0.103	0.610	0.432	0.024	0	1
19	-0.347	0.077	0.248	0.213	0	0
20	-0.467	0.014	0.493	0.009	0	1
21	-0.486	0.010	-0.588	0.001	0	0
22	0.359	0.066	0.408	0.035	0	1
23	-0.219	0.273	-0.345	0.078	0	0
24	-0.015	0.940	0.218	0.276	0	0
25	0.044	0.827	0.404	0.036	0	1
26	0.177	0.376	0.060	0.764	0	0
27	0.532	0.004	-0.004	0.986	1	0

28	0.019	0.926	0.339	0.084	0	0
29	0.221	0.267	0.397	0.040	0	1
30	0.603	0.001	0.055	0.784	1	0
31	0.102	0.614	-0.005	0.979	0	0
32	0.069	0.734	-0.069	0.731	0	0
33	0.571	0.002	0.453	0.018	1	1
34	-0.021	0.916	-0.055	0.785	0	0
35	-0.523	0.005	0.413	0.032	0	1
36	0.011	0.956	0.010	0.962	0	0
37	-0.040	0.844	-0.157	0.434	0	0

In each sector, the correlation between FDI series and the industry sophistication indicators is examined. To test the correlation, we calculated Pearson's correlation coefficients and conducted statistical tests. The results of the statistical tests are shown in Table 4. Both series of FDI and indicators of industry sophistication are considered to follow persistent time series, and Pearson's test is applied on the rate of change in FDI and the indicators. The result of Pearson's test show that the positive correlations between FDI and the mechanization indicator are supported at the significance of level 5% in sectors with IDs 9, 12, 13, 15, 27, 30, and 33. These sectors include sectors in the light industry and tertiary sectors. Similarly, the positive correlations between FDI and the ICT indicator are supported at a significance level of 5% in sectors with IDs 4, 5, 18, 20, 22, 25, 29, 33, and 35. These sectors include the sectors in heavy industries and tertiary sectors. A correlation between FDI and both sophistication indicators is found only for the sector with ID 33. Other sectors show correlations between FDI and the mechanization indicator but not the ICT indicator and vice versa. Therefore, the results suggest that FDI has increased sophistication in some sectors; however, the paths to sophistication are not unified among the sectors.

5. Conclusions

This paper suggests that an evaluation indicator for industrial structure based on an arbitrary economy with an IO table. The results of the examination of the indicator shows that the matrix of input coefficients presents a bias, where the difference in the value-added rate between the objective and comparison is too large. In this way, the matrix of input coefficients may have a downward bias in sectors with a high value-added rate. As this paper demonstrates, the industry structure matrix shows an input structure that does not depend on the value-added rate or the ratio of intermediate to final demand. In other words, the industry structure matrix shows the technical structure at the supply side.

The present paper overviews the sophistication of industries in China from the viewpoint of the mechanization and the input of ICT in industry. The levels of the indicators show that some manufacturing sectors and tertiary sectors have a high level in both measures of sophistication; however, the growth rates of the indicators show that the characteristics of sophistication in these manufacturing sectors and tertiary sectors differ. Regarding mechanization, the mechanized manufacturing sectors showed increases in sophistication in the 1980s and 2000s; however, mechanized tertiary sectors showed increases in sophistication in the 1990s. Regarding ICT input, while manufacturing sectors showed a high level of sophistication in ICT input in the 2000s, tertiary sectors showed a high level of sophistication in ICT input in the 1990s.

Furthermore, the correlations between FDI and the sophistication indicators were examined. The results show that although some light industry sectors and tertiary sectors show a positive correlation between FDI and mechanization, some heavy industry sectors and tertiary sectors show a positive correlation between FDI and ICT input. It is noteworthy that the effects of FDI in each sectors are not uniform.

Finally, the method used in this paper to examine or compare an arbitrary economy is not limited to time-series IO tables. Indeed, the method can be also applied to cross-country or cross-regional comparisons.

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