

Retraction

Retracted: Economic Development Analysis of China's Coastal Industries Based on Deep Learning and SDA Model Weighting

Wireless Communications and Mobile Computing

Received 11 July 2023; Accepted 11 July 2023; Published 12 July 2023

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] Z. Li, "Economic Development Analysis of China's Coastal Industries Based on Deep Learning and SDA Model Weighting," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5212585, 7 pages, 2022.

Research Article

Economic Development Analysis of China's Coastal Industries Based on Deep Learning and SDA Model Weighting

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Received 21 March 2022; Accepted 16 April 2022; Published 9 June 2022

Academic Editor: Zhiguo Qu

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China's coast is the main spatial carrier and important geographical unit for future industrial development in China. We propose a weighted average decomposition method based on three basic problems in the theory of SDA model decomposition method, investigate the relevant properties of this method, and prove that two decomposition methods widely used in the literature—bipolar decomposition method and midpoint power decomposition method—are the approximate solutions of this decomposition method. Based on the idea of the Wasserstein distance algorithm for machine learning, the Wasserstein distance algorithm and its solution are improved by using the matrix expansion Sinkhorn algorithm and the entropy regularization constraint method, and the industry copolymerization index is constructed through hypothesis testing and Monte Carlo simulation to measure the level of industry copolymerization in coastal China. The results show that the level of industry copolymerisation within the same quantile industry is greater than that between industries across quantile industries in China's coasts.

1. Introduction

In the new era, the new form of industrial space is breaking through the traditional administrative boundaries and gradually forming a new pattern of industrial space with core cities as the hubs and multicity industries developing in a coordinated manner [1]. The transformation and upgrading of industrial structure and high-quality industrial development in China's coastal space will be an important tool to promote quality change, efficiency change, and power change in regional economic development. The difficulty in the spatial governance of China's coastal industry lies in the fact that the regional level requires both “planning the overall situation” and “planning a region,” and the industrial level requires both “taking care of the whole” and “grasping the focus” [2]. The difficulty lies in the fact that at the regional level, it is necessary to “plan the whole picture” as well as “plan a region,” and at the industrial level, it is necessary to “take care of the whole” as well as “focus.” In many places, the industrial system has been restructured and reorganised in such a way that there is a mishmash of industrial zones and industrial silos, and there are also uncoordinated

industrial policies, regional inefficiencies, and excessive competition between governments within China's coastal regions [3]. An accurate judgment of the spatial connection and interaction of different industries within the industrial system is an important prerequisite and a fundamental task to solve the above problems and improve the spatial governance of China's coastal industries [4]. It is of great theoretical value and practical significance to understand the direction of spatial restructuring of the industrial system and to formulate layout optimisation strategies among and within China's coasts [5].

The spatial coalescence of industries or cluster complexes is important for the formulation of industrial policies and the location choice of enterprises (Porter, 1998). It is important to note that coagglomeration differs from agglomeration in that it emphasises the dependencies, linkages, and interactions across the spatial distribution of industries, whereas agglomeration focuses on the spatial distribution patterns of industries in general or of individual industries [6]. From this perspective, the study of industry-spatial colocation is the core of industrial clusters and industrial structure.

In recent years, the SDA model has become a mainstream economic analysis tool in the field of input-output technology and has been widely used in economic analysis of economic growth [7], trade [8], labour [9], prices [10], energy [11], and environmental protection [9]. Much classical work has been done on the theoretical foundations of the SDA model [12]. However, there are some problems with the SDA model, mainly the uniqueness of the measurement results, the comparability of factor weights, and the decomposition method of interaction effects. To solve these problems, a weighted average decomposition method of SDA is proposed here, and the relevant properties of the method are investigated. It is shown that two decomposition methods widely used in the input-output technology literature—the bipolar decomposition method and the midpoint weight decomposition method—are approximate solutions of this decomposition method [13].

2. Review of the Literature

The empirical research of foreign scholars on industrial spatial coalescence has basically developed in two directions: first, to continuously innovate and improve the measurement indicators of industrial coalescence at the delimited geographical scope and industry level; second, to test the micromechanisms affecting industrial spatial coalescence based on different indicators [14].

In [15], the current mainstream industry coalescence measurement indicators are divided into two categories based on discrete spatial units and continuous spatial units indicators. The first category is represented by the EG index [16], which is based on the locational choice model theory. The main problem with this category is that industries coalescing at any spatial scale will lead to spurious correlations among all coalescing variables. The second type of indicator is represented by the DO index. In [17], an index of industrial agglomeration was constructed based on microgeographic distance, Gaussian linear kernel density function, and counterfactual samples, and on this basis, an index of interindustry coalescence was extended

In view of the main problems of the above two types of indexes, [18] proposed a measure of industrial coalescence based on the idea of the Wasserstein distance algorithm, which is an important breakthrough in industrial coalescence research in recent years. The algorithm is different from the two existing methods mentioned above. In [19], the Wasserstein distance was introduced to GAN (generative adversarial network) training in the field of machine learning, creating the sensational WGAN (Wasserstein generative adversarial network) algorithm, which has been widely used in the field of face recognition, image analysis, and other machine learning training. The algorithm was developed in [20] as an “unbiased feature for arbitrary spatial classification changes,” but in the actual measurement process, a certain spatial scale still needs to be chosen for measurement. In the process of applying the geographic information of Chinese enterprises to measure the spatial distribution of industries, this paper considers that it is more appropriate to measure at the spatial scale of China’s coast.

3. SDA Model

3.1. Empirical Analysis. Consider the simplest case of the input-output model: $X = BF$, where X , B , and F denote the total output vector, the Leontief inverse matrix, and the final demand vector, respectively. The footnotes 1,0 denote the calculation period and the base period, respectively. In order to quantify the magnitude of the factors affecting the change in total output in the two periods, we have

$$X_1 - X_0 = B_1 F_1 - B_0 F_0 = (B_1 - B_0) F_0 + B_0 (F_1 - F_0) + (B_1 - B_0) (F_1 - F_0). \quad (1)$$

Let $\Delta X = X_1 - X_0$, $\Delta B = B_1 - B_0$, and $\Delta F = F_1 - F_0$; then

$$\Delta X = (\Delta B) F_0 + B_0 (\Delta F) + (\Delta B) (\Delta F), \quad (2)$$

where $(\Delta B) F_0$, $B_0 (\Delta F)$, and $(\Delta B) (\Delta F)$ denote the impact of technological change, the impact of final demand change, and the interaction of the two, respectively. Equation (1), which retains the interaction effects, is a form of the usual SDA. Since the interaction effects are generally large in practical empirical analysis, they are often attributed to the respective variables in order to clearly explain the causes of changes in aggregate output, so that equation (1) can be combined in the following two ways:

$$\Delta X = (\Delta B) F_1 + B_0 (\Delta F), \quad (3)$$

$$\Delta X = (\Delta B) F_0 + B_1 (\Delta F). \quad (4)$$

Equations (3) and (4) are two forms of the usual SDA model. Since both $(\Delta B) F_1$ and $(\Delta B) F_0$ can represent the effect of a change in the independent variable B on a change in the dependent variable X , it is clear that the two results are inconsistent, i.e., the effect of a change in the independent variable B is not measured uniquely here. In equation (4), ΔB and ΔF are weighted by F and B in different periods, respectively, and the weights do not match, which is due to the unscientific decomposition method of the interaction effects. To overcome these problems, a more scientific decomposition method should be considered.

3.2. Weighted Average Solution Method. In general, if $x_i (i = 1, 2, \dots, n)$ are n independent variables, and

$$y = \prod_{i=1}^n x_i. \quad (5)$$

Using the second footnotes 1 and 0 to indicate the calculation period and base period, respectively, the

$$\Delta y = \prod_{i=1}^n x_{i1} - \prod_{j=1}^n x_{j0}. \quad (6)$$

The decomposition from the base or calculation period, respectively, has

$$\begin{aligned} \Delta y = & (\Delta x_1) \prod_{i=2}^n X_{i0} + X_{11}(\Delta x_2) \prod_{j=3}^n X_{j0} + \dots \\ & + \prod_{k=1}^{n-2} X_{k1}(\Delta x_{n-1})X_{n0} + \prod_{l=1}^{n-1} X_{l1}(\Delta x_n), \end{aligned} \quad (7)$$

$$\begin{aligned} \Delta y = & (\Delta x_1) \prod_{j=2}^n x_{1j} + x_{10}(\Delta x_2) \prod_{j=3}^n x_{j1} + \dots \\ & + \prod_{k=1}^{n-2} x_{k0}(\Delta x_{n-1})x_{n1} + \prod_{j=1}^{n-1} x_{10}(\Delta x_n). \end{aligned} \quad (8)$$

Thus, there are n independent variables in the model, and all the different decompositions like (7) and (8) have $n!$. Find the arithmetic mean of these $n!$ equations, and note that the effect of a change in x_i on Δy is $E(\Delta x_i)$, then

$$\Delta y = \sum_{i=1}^n E(\Delta x_i). \quad (9)$$

Here, $E(\Delta x_i)$ is the arithmetic mean of the $n!$ -different decompositions containing Δx_i , for which we combine like terms and have

$$E(\Delta x_i) = \sum_s f(s) \prod_{\substack{j \\ j \neq i}}^n x_{jt}(\Delta x_i), \quad (10)$$

where $t = 0$ or 1 , $\sum_s f$ summing over all $\{X_{1t}, X_{2t}, \dots, X_{i-1,t}, X_{i+1,t}, \dots, X_{nt}\}$ combinations of t , $|s|$ is the number of combinations with $t = 1$, and

$$f(s) = \frac{L_s!(n-1-s)!}{n!}. \quad (11)$$

In most studies of empirical economic analysis, the dependent variable is often closely related to only 2 or 3 factors, i.e., when $n = 2, 3$, according to definition (9), there are the following cases.

In scenario 1 (two independent variables), if for two independent variables x and y , there is $z = xy$, then, $\Delta z = (\Delta x)y/2 + x - 1/2(\Delta y)$, where

$$\begin{aligned} \frac{y}{2} &= \frac{1}{2}y_0 + \frac{1}{2}y_1, \\ \frac{x}{2} &= \frac{1}{2} \times 0 + \frac{1}{2} \times 1. \end{aligned} \quad (12)$$

That is $E(\Delta x) = (\Delta x)y - 1/2$, $E(\Delta y) = x - 1/2(\Delta y)$.

This decomposition is not approximate and the two Δ terms have the same type of weights, i.e., the weights match.

In scenario 2 (three independent variables), if $a = xyz$, then, $\Delta a = E(\Delta x) + E(\Delta y) + E(\Delta z)$, where

$$E(\Delta x) = \frac{1}{3}(\Delta x)y_0z_0 + \frac{1}{6}(\Delta x)y_0z_1 + \frac{1}{6}(\Delta x)y_1z_0 + \frac{1}{3}(\Delta x)y_1z_1, \quad (13)$$

$$E(\Delta y) = \frac{1}{3}x_0(\Delta y)z_0 + \frac{1}{6}x_0(\Delta y)z_1 + \frac{1}{6}x_1(\Delta y)z_0 + \frac{1}{3}x_1(\Delta y)z_1, \quad (14)$$

$$E(\Delta z) = \frac{1}{3}x_0y_0(\Delta z) + \frac{1}{6}x_0y_1(\Delta z) + \frac{1}{6}x_1y_0(\Delta z) + \frac{1}{3}x_1y_1(\Delta z). \quad (15)$$

The nature theorem contains that the various decompositions of Δx_i converge to a weighted mean decomposition $E(\Delta x_i)$.

Since $E(\Delta x_i)$ is the mathematical expectation of the various decompositions containing Δx_i , the large number theorem is satisfied. That is, when x_i is an independent variable, the arithmetic mean of the effects of each x_i change is infinitely close to $E(\Delta x_i)$ as long as n is large enough.

4. Machine Learning Methods in This Paper

4.1. SVM. Support vector machines (SVMs) are advantageous in solving small samples, non-linearly differentiable and Kor-dimensional data and can be generalised to other machine learning problems such as function fitting. The best generalisation capability (or generalisation ability) over a small sample space is expected to be obtained by finding the best compromise between the complexity of the model (i.e., the learning accuracy for a given training sample) and the learning ability (i.e., the ability to identify arbitrary samples without errors).

The general principle of a support vector machine is as follows: first, the points in the vectorised sample space are mapped into a higher or even infinite dimensional feature space (Hilbert space) through a nonlinear mapping f . This transforms a linearly indistinguishable problem in a low-dimensional sample space into a linearly distinguishable problem in a higher dimensional feature space, in short, ascending and linearising. Mapping the points in the sample space to a higher dimensional space is a process of dimensionalisation, which increases the computational complexity of the vector representing the sample points, and can even cause a ‘‘combinatorial explosion.’’ By applying the expansion theorem of the kernel function, SVM cleverly solves the problem of excessive computational complexity after dimensionality increase, without the need to know the explicit expression of the nonlinear mapping f . Compared with linear models, SVM adds little computational complexity and avoids the ‘‘combinatorial explosion,’’ so it is highly efficient in classification. Different kernel functions can generate different SVM, and the following kernel functions are commonly used.

It has been observed that for units with only a single economic activity in the business scope description, the

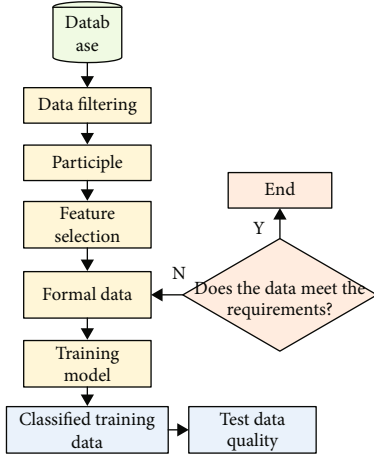


FIGURE 1: Iterative optimization of the training set using a manually annotated corpus.

manually marked accuracy rate of the annotated industry numbers is higher. These relatively high-quality corpora can be extracted to train classifiers, then classify them on the rest of the corpus, and use the classifier’s classification results as the new industry number for each record. The specific steps are shown in Figure 1.

As shown above, the process of correcting the training set is in fact an iterative process. First, each industry number of each record is initialized to the manually annotated industry number in the code centre database; then, the entire data is then disambiguated and selected as the training set for the initial iteration, features are selected, and the data is formalized into the classifier input form. The next step is to train the classifier and use the trained classifier to classify the training data, replacing the industry numbers in the original records with the classifier classification results; finally, the training set is analyzed to see if it meets the accuracy requirements, and if it does not, the next iteration is performed. If the training set does not meet the accuracy requirement, it will proceed to the next iteration until the training set meets the accuracy requirement. The iteration of the training set is performed as follows:

- (1) The training set is extracted from the entire database of the code centre, the records with typos are filtered out, and the stanford segmenter is used for word separation
- (2) After segmentation, the word frequencies of all words in the training set are counted and stop words and punctuation are removed; then, the remaining words are arranged in descending order of word frequency, the last 10% are eliminated, and the rest are used as the classifier training feature set. This step yields a list of feature words for training the classifier
- (3) Based on the word list, the training set is formalized. The words in the word list are first numbered according to their position in the word list (line number); then, for each word in the training set after the word separation, the word is replaced by the

TABLE 1: Table of the training set after each iteration.

Number of iterations	Closed test accuracy	Manual test accuracy (100 records)
1	75.8%	47%
2	89.5%	63%
3	92.4%	68%
4	94.7%	72%
5	98.8%	75%
6	99%	76%

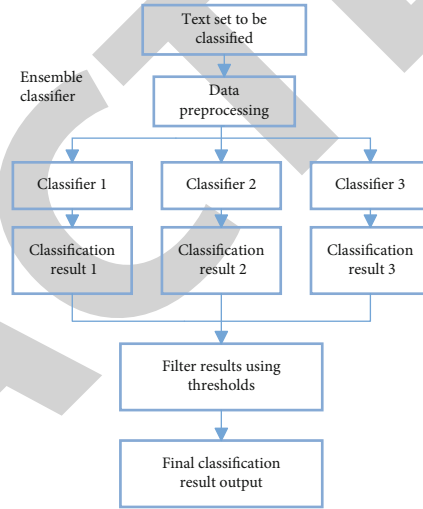


FIGURE 2: Workflow diagram of the automatic economic industry classification system.

number described previously; next, the number of times each word in the record occurs in this record is counted, and the counted word frequency is added to each word frequency number of the word; for all words that are not in the word list, a uniform number is used. For all words not in the word list, a single number is used instead. For example, if beauty is in row 260 of the word list and appears twice in that record, the formalized result is 2602, which means that beauty appears twice in the record

- (4) After formalizing all the records in the training set, the SVM classification model was trained, and the training set was closed-tested to analyze whether the classification results reached the threshold value. If the required classification accuracy is achieved, the model is withdrawn; otherwise, for each record in the training set, the existing markers in the training set are replaced with the results of this classification, and the operation in step (3) is carried out

The classification model used in this paper is based on SVM. Table 1 shows the results of the analysis of the training set after each iteration with 420,000 records (6 iterations).

TABLE 2: Structural changes in China's economy and rate of development, 1987-1995.

Year	Total output			GDP		
	1987	1995	Average annual growth rate	1987	1995	Average annual growth rate
Total	100	100	14.88	100	100	14.11
Primary industry	18.56	11.15	7.79	28.84	16.46	4.8
The secondary industry	58.45	74.34	18.39	39.67	67.17	20.06
Industry	49.07	66.43	19.31	33.12	62.9	21.79
Construction	9.39	7.91	12.46	6.55	4.27	6.57
The service sector; the tertiary industry	22.98	15.4	8.46	31.5	16.37	3.58
Transportation, post, and telecommunications	3.99	2.58	10.24	6.34	4.52	6.93
Commercial catering industry	8.5	4.22	5.25	9.53	3.43	-1.08
Other social services	6.16	4.16	9.38	7.98	4.41	4.44
Finance and insurance industry	2.01	1.31	8.88	4.25	1.97	2.08
Administrative organs and other industries	2.34	1.95	12.35	3.43	2.31	6.98

From Table 1, we can see that the higher the classification accuracy of the closed test in the training set, the more accurate the labeling of the training set. The reason for this phenomenon may be that more than half of the manually labeled corpus is labeled accurately, so the iterative process will move in the direction of accuracy, and if half of the initial iterative preliminaries are labeled incorrectly, it is likely that the iterative process will proceed in the direction of decreasing accuracy.

4.2. Construction of an Automated Economic Industry Classification System. The automatic economic industry classification system consists of three functional modules: data preprocessing, combined classification, and rule-based reordering. The reordering module is only rule-based. The only reordering module in the industry classification system is the rule-based one, which removes the use of organisation names for reordering. Figure 2 shows the workflow of the automatic economic industry classification system.

How the output of the combinatorial classifier was used for threshold filtering to obtain the output has been discussed in detail in China Coastal and will not be repeated. Similar to the industry classification system, the sample set was first fully disaggregated, and after selecting the features, the sample set was fully formalized into model-acceptable data types [21].

5. Empirical Analysis

5.1. Changes in the Structure of the Economy. In order to avoid the influence of price factors, the 30-sector input-output tables for 1987 and 1995, which were compiled and released by the National Bureau of Statistics, were used to measure the changes in the industrial structure of the Chinese economy, using the current year 1990 prices as the basis for comparable prices. As shown in Table 2, China's coastal industries can be divided into five sectors: transportation, posts and telecommunications (freight, passenger transport, and telecommunications), commerce and catering, other social services (culture, education, science, health, public

utilities, and residential services), finance and insurance, administration, and other industries.

As shown in Table 2, the structural changes reflected in the changes in the share of total output and GDP reflect the distinctive features and contradictions of China's industrialisation process. On the one hand, the decline in the share of primary industries and the rapid growth in the share of secondary industries, especially industry, are in line with the general pattern of the industrialisation process; on the other hand, the decline in the share of coastal industries in China is inconsistent with the direction of the highly industrialised structure.

In addition, during China's industrialisation process, changes in GDP have been less consistent with aggregate output, with the former having a greater magnitude, mainly due to changes in the ratio of intermediate demand to aggregate output. In order to explore the relationship between production, consumption, investment, and trade, input-output analysis based on changes in total output provides a clearer picture of the causes of structural changes in the economy than GDP-based analysis.

5.2. Analysis of the Decomposition of China's Coastal Industrial Structure. The analysis of demand factors for economic growth in China's coastal industries is based on the following input-output balance equations, $x_i = u_i(w_i + y_i) + e_i$, where x_i , w_i , y_i , and e_i denote total output, intermediate demand, final demand, and exports in sector i , respectively, and $y_i = c_i + v_i$, c_i and v_i denote consumption and fixed capital formation in sector i .

$u_i = x_i - e_i/w_i + y_i$ denotes the domestic supply rate of sector i , which is the ratio of domestic intermediate and final goods to aggregate demand in sector i . In terms of the matrix of moments, A denotes the input-output coefficient matrix, then, $w = vx$, \hat{u} is the diagonal array with $X = \hat{u}AX + \hat{u}Y + e$, i.e., $X = (I - \hat{u}A)^{-1}[\hat{U}(c^+v) + e]$. Let $R = (I - \hat{u}A)^{-1}$, $f = \hat{u}$, then $sX = sRf$, where s is the choice of diagonal array, consisting of 0, 1, 1 appears in the diagonal element position of the Chinese coastal industry sector, then, the change in output of the Chinese coastal industry sector

TABLE 3: Analysis of demand factors for economic growth in China's coastal industrial sector.

Department	Transportation, post, and telecommunications	Commercial catering industry	Other social services	Finance and insurance industry	Administrative organs and other industries	The service sector; the tertiary industry
Direct consumption coefficient	1.65	-23.31	4.48	-7.06	0	-24.24
Consumption	8.63	12.48	18.3	7.82	16.87	64.1
Fixed assets	7.26	15.49	6.28	4.45	0	33.49
Export	6.69	15.07	3.85	4.99	0.48	31.08
Import substitution	-1.76	0.38	-1.99	-0.78	-0.28	-4.43
Total impact	-1.76	0.38	-1.99	-0.78	-0.28	-4.43

$$\Delta(\widehat{X}) = \widehat{s}(X_1 - X_0) = \widehat{s} \left[R_1 \left(\widehat{u}_1 y_1 + e_1 \right) - R_0 \left(\widehat{u}_0 y_0 + e_0 \right) \right]. \quad (16)$$

The results in Table 3 are calculated by taking the arithmetic mean of the components of the four equations above.

Overall, the main reliance on economic growth in China's coastal industries is driven by domestic consumption (64.10%), followed by investment (33.49%) and exports (31.08%). The main impediment comes from the direct consumption coefficient (-24.24%), i.e., the reduction of intermediate service inputs per unit of product in all sectors, which is related to the country's particular industrialisation process. Import substitution is -4.43%, which means that instead of domestic services replacing imports, there is a greater dependence on imported services. In terms of the sectoral contribution structure, the other social service sector makes the largest contribution, followed by transport, post and telecommunications, and commercial catering. The financial and insurance sectors contribute the least. This indicates that, while the traditional post and telecommunications transport and commercial catering industries continue to develop, other social services, including tourism, information, advertising, and consulting, are emerging and beginning to change China's coastal industry, which is dominated by traditional industries. The contribution of consumption to other social services is nearly three times that of investment, and the direct consumption coefficient is 4.48%, the highest of all sectors.

6. Conclusions

In order to solve the three problems of the SDA model on the theoretical basis, this paper proposes the weighted average decomposition method and proves that the bipolar decomposition method and the midpoint power decomposition method, which are widely used in the literature, are the approximate solutions of this method. As empirical evidence, a quantitative analysis of the factors influencing the changes in the Chinese coastal industry in the Chinese economic structure is made. It is found that the economic growth of the Chinese coastal industry is mainly due to the pulling effect of domestic consumption; the decrease in the volume of services as an intermediate input is the main reason hindering its rapid development.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared no conflicts of interest regarding this work.

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