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ABSTRACT The Labor Compensation Share (LS) as a crucial indicator measuring a household's share in the primary income allocation has the important influence on both the structure of final demand and household welfare. As a sequence, LS has attracted widely attention from policy-makers and researchers in China. With the development of the digital economy, the factors related to digitalization have become inevitable to participate in the primary income allocation. Whether or not digitizing economy would reduce LS by replacement effect is worthy of study. This paper distinguishes the digital economy and traditional economy components related matrix of input coefficients, final demand sector structure matrix, and employee compensation coefficients vector under the digital economy input-output framework and proposes a structural decomposition analysis to explore the impact path of the development of the digital economy on the evolution of overall LS in China. An empirical analysis has been done based on the compiled non-competitive digital economy input-output tables of China in 2012, 2017, and 2020. The results show: (1) Holding all other factors constant, the changes of factors related to the digital economy decreased overall LS by 17.72% between 2012 and 2017; and increased overall LS by 11.69% between 2017 and 2020; (2) Among all factors related to the digital economy, the most important driving force of changing LS is production technology changes related to the digital economy rather than changes in employee compensation coefficient of digital economy sectors; (3)There exists a small number of important sectors and important coefficients who could determine the contributions of the changes in driving factors on LS changes. This study discovers how the development of the digital economy affects overall Labor Compensation Share in China from the perspectives of comparative static analysis and multi-sector dependency relationships and could provide some implications for the formulation of Income Distribution policies.

Keywords: Non-competitive Digital Economy Input-output Table; Labor Compensation Share;Structural Decomposition Analysis; Primary Income Distribution.

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1. Introduction

Employee Compensation is the main source of income for Chinese residents. The share of labor compensation (LS) directly measures the proportion of compensation of employees in the primary income allocation, which is crucial to China's allocation of primary income issue. The LS in the primary allocation determines the share that residents can ultimately obtain in income allocation. As income allocation is a critical link between the generation of income and the use of income in the economic cycle, the ability to increase the proportion of labor compensation in the Primary allocation will directly impact the share of residents' consumption in the use of income. The continuous growth of LS is not only an important driving force for high-quality economic development but also a crucial guarantee for promoting social equity. However, according to calculations, from 1978 to 2020, the average LS in China still lags behind developed countries such as the UK and France. Hence, China pays close attention to and significantly emphasizes the evolution of the LS. It is explicitly stated in multiple key policies that there is a commitment to increase the LS in the primary distribution.

With the rapid development of the digital economy, the factors related to digitalization has become inevitable to participate in the primary income allocation. This raises a significant research question: Will the development of the digital economy promote or suppress the increase in LS? Examining the actual evolution of LS in China, it generally follows an inverted U-shaped pattern, declining initially and then rising (Feng et al., 2022; Zhang, 2022; Liu, 2021; Lan et al., 2019; Hu, 2016; Li et al., 2009). However, since 2017, there has been a stagnation in the upward trend, coinciding with a period of rapid development in the digital economy. While simple correlation is insufficient to establish causation, it is necessary to increase attention to the relationship between the development of the digital economy and the LS.

The literature reviewed in this article primarily falls into two main streams: one focuses on the factors influencing the evolution of LS, and the other examines the impact of digital economic development or digital transformation on the labor market.

In terms of factors influencing changes in LS, existing research can be broadly categorized into three main types: The first， industrial structural transformation is a crucial factor propelling macro-level changes in the LS (Qi et al., 2021). The second, operating at the micro-level and employing a technical framework, asserts that biased technological progress is a significant driver of fluctuations in the LS (Shen&Zheng, 2022; Wang&Yuan, 2018). Biased technological progress not only impacts the inter-industry structure but also generates asymmetrical effects on marginal output within industries, leading to changes in the pattern of factor income distribution. The third category of research focuses on institutional factors, such as globalization under the new development pattern (Liu, 2022), adjustments in income distribution policies (Jiang, 2020; Zhan et al., 2020), and changes in labor bargaining power (Bai et al., 2019). These factors are considered to impact the LS significantly.

The impact of the digital economy on the labor market has become a focal point of domestic and international research in recent years. Within this literature, most studies concentrate on the effects of the digital economy on employment scale or structure. Researchers have identified two main impact pathways: the substitution effect and the creation or pull effect.

The substitution effect refers to the significant improvement in capital accumulation efficiency represented by the technological revolution of the digital economy. This effect reduces the comparative advantage of labor, manifesting in the labor market as the substitution of machines for human labor, leading to substantial unemployment (Acemoglu and Restrepo, 2020; Wang et al., 2020; Shen&Qiao, 2022). The creation or pull effect, on the other hand, involves the development of the digital economy, such as the application of intelligent technologies, creating new positions that require higher education or specific skills (Yin et al., 2022) or unconventional task positions (He &Liu, 2023).

To verify the existence of employment substitution effects, creation effects, and resulting structural changes in employment, particularly the phenomenon of employment polarization, existing literature employs empirical testing from various perspectives using enterprise-level microdata. He&Liu (2023) utilize the China Industrial Enterprise Database and matching data on robot imports to confirm that robots replace conventional task positions while simultaneously creating unconventional positions, leading to employment polarization. Yin&Li (2022) find that with intelligent manufacturing policies, intelligent machine equipment gradually replaces procedural and process-oriented low-skilled positions. Simultaneously, the application of intelligent technology increases enterprises' demand for highly educated and skilled labor and enhances on-the-job training, optimizing the human capital structure of enterprises.

While there is no conclusive evidence regarding whether the digital economy will lead to overall employment growth (Wang et al., 2023; Humlum, 2020), the verified substitution effects of "machines replacing humans" and the creation effects of generating new employment positions have been shown to result in changes in employment structure, such as employment polarization.

Compared to its impact on employment positions, the influence of the digital economy on workers' income is more intricate. Yu et al. (2021) discovered that industrial robots significantly increased the wages for unconventional tasks. While the development of the digital economy has encroached upon the relative income rights of low-skilled workers, it has safeguarded their relative welfare rights (Bai et al., 2021). The impact pathways studied primarily focus on three perspectives. Firstly, by establishing an improved neoclassical model, Hemous&Isen (2022) found that artificial intelligence accelerates the increase in capital income compared to labor income, widening the income gap between high-skilled workers and those with middle to low skills. Secondly, from the perspective of digital transformation, it is concluded that the benefits of digital technologies will improve enterprises' ability to increase workers' income (Xue, 2021). The comprehensive impact of the digital economy on employment positions and income is bound to have implications for the LS. The overall LS in an economic system can be written as the sum of the products of various job quantities and the average income per job, expressed as a proportion of the total value added. Changes in the scale of positions at different income levels and variations in average income will collectively influence the total employee compensationin the economy. Moreover, the development of the digital economy will affect the denominator, value-added, through measures such as efficiency enhancement. Consequently, the influence of the digital economy on the LS constitutes a more intricate issue than its impact on employment positions and income. The literature addressing this matter is relatively limited, and substantial divergence exists in conclusions.

Representative studies, such as Acemoglu and Restrepo (2020), utilizing data up to 2007, found that the substitution effect of industrial automation was more pronounced, thereby reducing employment and labor compensation share in OECD countries. On the other hand, Aghion et al. (2020) discovered a positive impact of industrial automation on the labor compensation share, which gradually increased over time. This suggests that increasing industrial automation is conducive to raising the labor compensation share.

Some scholars provide empirical evidence from a micro-level perspective regarding the impact of digital technology on the LS. Cong& Chen (2022), based on dynamic panel data of A-share listed companies from 2007 to 2020, found that the digital technology transformation and digital business transformation in the process of industrial digitization have a significant negative impact on the proportion of labor compensation. Xiao et al. (2022), using text analysis methods to construct digitalization indicators, discovered that enterprise digital transformation can significantly increase labor income share.

Currently, empirical analyses of the relationship between the development of the digital economy and the evolution of ls in the literature predominantly employ econometrics as the research tool. The measurement indicators for the degree of digital transformation or digital economic development often include actual payments made by enterprises to employees, the usage of robots, digital inputs, or the frequency of digital-related terms in corporate annual reports. However, this research methodology has two main areas for improvement. Firstly, income initial distribution follows a factor-based allocation, excluding transfer payments such as income tax and social security contributions. Actual worker compensation is derived by subtracting income tax and social security contributions from the payable income. Consequently, using actual payroll divided by value-added fails to accurately depict the proportion of labor compensation in the initial income distribution. Secondly, the development of the digital economy alters the input structure of enterprises and sectors, thereby changing the interdependence among industries and resulting in complex indirect impacts on LS. For instance, the digital transformation of traditional enterprises often involves the construction of data platforms and the digitization of marketing. The establishment of data platforms is frequently outsourced to information technology companies providing such services, increasing the enterprise's consumption of products from the information sector. Simultaneously, digital marketing increases the consumption of products from the e-commerce sector. Changes in these intermediate input coefficients not only affect the LS of the enterprise itself but also alter the pulling relationships of the industry where the enterprise operates with other sectors. Consequently, by reshaping sector structures, these changes impact the overall LS in the economy. Econometric models must be more adequate in effectively measuring such indirect impacts of digital economic development.

Compared to existing research, this paper adopts a distinct methodological approach to investigate the impact of digital economic development on the LS. The study focuses on the overall

LS in the Chinese economy. By constructing a Structural Decomposition Analysis (SDA) based on a digital economic input-output model, this paper decomposes the changes in the LS into contributions from digital economy-related factors and contributions from non-digital economy factors, aiming to identify the influence of digital economic development on the LS.

The innovative aspects and value of this methodological approach are as follows: (1) Analyzing the impact of the digital economy from a general equilibrium perspective, the input-output model serves as a multi-sector model characterized by general equilibrium properties. Leveraging this model, a comprehensive examination from a multi-sector viewpoint becomes possible. It allows for the analysis of the changing interdependence between digital and traditional sectors, including variations in the level of digital integration, alterations in the composition of final demand between digital and traditional sectors, and the influence of changes in employee compensation coefficients across sectors on the overall LS. These factors are challenging to incorporate into the framework of econometric models effectively, yet within the input-output analysis framework, they can be seamlessly integrated. Current literature typically adopts several indicators to characterize the level of digitization. In contrast, the structural indicators of digital economic development introduced in this study are novel and not considered in the existing literature examining the impact of the digital economy on LS. Furthermore, with its well-defined economic theory foundation, the input-output model specifies clear causal pathways, making identifying causal relationships no longer a formidable challenge. (2) To better analyze the impact of digital sectors, this study, building upon the classical non-competitive input-output model, compiled a time-series digital economic input-output table encompassing 55 sectors, including 16 digital economic sectors, according to the classification standards of the National Bureau of Statistics. This table accurately depicts the relationships between digital and tangible sectors, yielding scientifically reliable conclusions. (3) To further elucidate the contributions of various factors influencing changes in LS, this paper introduces a method to calculate the contribution of each coefficient change represented in matrix or vector form. This approach enables the representation of the contribution of coefficient changes as the product of the magnitude of coefficient changes and a weighting coefficient. Consequently, it allows for the deconstruction of the black box, providing a better explanation of the structure obtained by the Structural Decomposition Analysis (SDA).

The remaining sections of the paper are organized as follows: Section 2 introduces the Structural Decomposition Analysis (SDA) method, which is based on a non-competitive digital economic input-output model, to examine the impact of digital economic development on the evolution of employee compensation. Section 3 provides a brief overview of the data sources, detailing the compilation method for the non-competitive digital economic input-output table and explaining the changes in LS and its influencing factors reflected in this table. Section 4 discusses the results of the structural decomposition of changes in LS. Finally, the paper concludes with a summary and prospects for future research.

2. Methodology

The Structural Decomposition Analysis (SDA) is a method used in a multi-sector framework to decompose the changes in the target variable into the sum of contributions from its determining factors. It has been widely applied in various fields such as resource and environment, energy, and labor economics to analyze the contributions of different influencing factors driving the evolution of the target variable.

Structural Decomposition Analysis is generally conducted based on input-output models or demand-driven models. This section will first provide the decomposition formula for the overall LS changes. Building upon this, we will further conduct a secondary decomposition of the factors in the primary decomposition based on the digital economic input-output model, distinguishing between digital and traditional sectors. This will enable us to identify the contributions and pathways of digital economic development in the evolution of employee compensation. To better interpret the obtained results, this section also introduces a method to calculate the contribution rates of elements in each influencing factor matrix, facilitating the identification of critical impact coefficients.

2. 1 Non-competitive Input-Output Table for the Digital Economy

The structure of the non-competitive input-output table for the digital economy used in this paper is presented in Table 1. The non-competitive input-output table assumes that imported and domestic products are not perfect substitutes, indicating non-competitiveness. It divides intermediate and final use into two major components: domestic products and imported products (Liang & Guo, 1990),

Table 1 Non-competitive Input-Output Table for the Digital Economy

Output \ Input		Intermediate Input		Final Demand					Gross output/ input
		Ssector D	Ssector T	Consumption	Fixed capital investment	Inventory changes	Export	Total	
Domestic products	Ssector D	dz_{ij}^{DD}	dz_{ij}^{DT}	dc_i^D	dg_i^D	$dinv_i^D$	de_i^D	dy_i^D	x_i^D
	Ssector T	dz_{ij}^{TD}	dz_{ij}^{TT}	dc_i^T	dg_i^T	$dinv_i^D$	de_i^T	dy_i^T	x_i^T
Imported products	Ssector D	mz_{ij}^{DD}	mz_{ij}^{DT}	mc_i^D	mg_i^D	$minv_i^D$	me_i^D	my_i^D	m_i^D
	Ssector T	mz_{ij}^{TD}	mz_{ij}^{TT}	mc_i^T	mg_i^T	$minv_i^T$	me_i^T	my_i^T	m_i^T
Value Added		v_i^D	v_i^T						
Gross output		x_i^D	x_i^T						

where x is the vector of gross output, dy is the vector of final demand, comprising domestic final consumption (dc), the total of domestic fixed capital formation (dg), changes in domestic inventory $(dinv)$, and exports of domestic products (de). my represents the final demand for imports, encompassing import final consumption (mc), the total of import fixed capital formation (mg), changes in import inventory $(minv)$, and the export of import products (me). On the other hand, dz denotes the domestic intermediate flow, and mz represents the import intermediate flow. v denotes value-added. In the notation used, the superscript D represents digital economy sectors, T represents traditional economy sectors, and the subscript denotes the specific sector.

2. 2 Structural Decomposition Analysis of Changes in LS

2. 2. 1 The formula for LS and its determination based on the demand-driven model

The objective of this study is to decompose the overall labor share of the economy(LS), defined as the aggregate employee compensation （W_i） divided by the aggregate value-added of all sectors （$\boldsymbol{V_i}$） , which is equivalent to the ratio of total domestic employee compensation to the gross domestic product $(\boldsymbol{GDP})$. That is,

$$LS = \frac{\sum W_i}{\sum V_i} = \frac{\sum W_i}{GDP} \tag{1}$$

The numerator of the overall labor share is determined by summing the employee compensation for each sector, calculated as the product of each sector's employee compensation coefficient (the ratio of sectoral employee compensation to total output) and the sector's total output. This is based on the input-output demand-driven model, where total output is further determined by the total final demand, the structure of final demand, and the Total requirements matrix. For the LS, we have,

$$LS = R'BMDL\frac{1}{GDP} \qquad (2)$$

where R represents the column vector of employee compensation coefficients, r_i indicating the proportion of employee compensation received by employees in sector i relative to the total output of that sector; B represents the Total requirements matrix; M represents the matrix of sectoral structure coefficients for final demand, where the element M_{ik} signifies the proportion of sector i in the k category of final demand. In the input-output table, final demand is divided into four categories: consumption, total fixed capital formation, inventory changes, and exports. D is the column vector representing the distribution of final demand types, with its elements d_k representing the proportion of the total domestic final demand accounted for by the k^{th} category of final demand. L stands for the total domestic final demand.

By input-output theory, the sum of value-added equals the total final demand. The basic balance equation for a non-competitive input-output model is: the total domestic final demand (L) equals the GDP plus imports minus the final demand for imports. That is,

$$\frac{L}{GDP} = 1 + \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} mz_{ij}}{GDP} \qquad (3)$$

Consequently, Eq. (3) denotes the import dependency of intermediate goods, which is determined by the ratio of intermediate input imports to GDP. Let θ as L/GDP. That is,

$$LS = R'BMD\theta \qquad (4)$$

2. 2. 2 Decomposition of Changes in LS: The first layer

Utilizing superscripts "0" and "1" to denote the reference period and the computation period, respectively, and employing the symbol Δ to signify the change. For the ΔLS, we have,

$$\Delta LS = LS^1 - LS^0 = R^{1'}B^1M^1D^1\theta^1 + R^{0'}B^0M^0D^0\theta^0 \qquad (5)$$

In this regard, the change in the LS from year 0 to 1 could be decomposed as the contributions of changes in these five factors. For n factors, there are n! ways to decompose the contributions of each factor (Dietzenchaer & Los, 1998). That is,

$$\Delta LS = \tfrac{1}{2}(\Delta R'B^1M^1D^1\theta^1 + \Delta R'B^0M^0D^0\theta^0) \qquad (6.\ a)$$

$$+\tfrac{1}{2}\left(R^{0'}\Delta BM^1D^1\theta^1 + R^{1'}\Delta BM^0D^0\theta^0\right) \qquad (6.\ b)$$

$$+\tfrac{1}{2}\left(R^{0'}B^0\Delta MD^1\theta^1 + R^{1'}B^1\Delta MD^0\theta^0\right) \qquad (6.\ c)$$

$$+\tfrac{1}{2}\left(R^{0\prime}B^0M^0\Delta D\theta^1 + R^{1\prime}B^1M^1\Delta D\theta^0\right) \tag{6. d}$$

$$+\tfrac{1}{2}\left(R^{0\prime}B^0M^0D^0\Delta\theta + R^{1\prime}B^1M^1D^1\Delta\theta\right) \tag{6. e}$$

$$= \underbrace{C(R)} + \underbrace{C(B)} + \underbrace{C(M)} + \underbrace{C(D)} + \underbrace{C(\theta)} \tag{6}$$

where Eq. (6. a) denotes the contributions to changes in employee compensation coefficients; Eq. (6. b) denotes the contributions to changes in production technology coefficients represented by the Total requirements matrix, Eq. (6. c) denotes the contributions to changes in the composition of final demand, Eq. (6. d) denotes the contributions to changes in the composition of final demand types, Eq. (6. e) denotes the contributions to changes in the dependence on imported intermediate goods.

2.2.3 Decomposition of LS changes: Distinguishing the Digital Economy

Based on the non-competitive digital economy input-output model used in this paper, the employee compensation coefficient can be divided into the employee compensation coefficient for the digital economy sector （r^D） and the employee compensation coefficient for the traditional economy sector （r^T）. r^D is a column vector formed by setting the employee compensation coefficients for the 16 digital economy sectors to their actual values while assigning zero values to the employee compensation coefficients of traditional economy sectors. On the other hand, r^T is a column vector formed by setting the employee compensation coefficients for digital economy sectors to zero and assigning the actual values to the employee compensation coefficients of traditional economy sectors. Therefore, it can be expressed as follows:

$$\Delta R = \Delta R^D + \Delta R^T \tag{7}$$

Similarly, the direct input coefficient matrix can be expressed as the sum of four matrices: the direct input coefficient matrix of digital sectors by digital sectors(A^{DD}), the cross-sector direct coefficient matrix from digital sectors to traditional sectors(A^{DT}), the direct input coefficient matrix of traditional sectors by digital sectors (A^{TD}), and the direct input coefficient matrix of traditional sectors by traditional sectors(A^{TT}). That is,

$$\Delta A = \Delta A^{DD} + \Delta A^{DT} + \Delta A^{TD} + \Delta A^{TT} \tag{8}$$

However, the influencing factor is the Total requirements matrix determined by the direct input coefficient matrix. In this paper, we follow the decomposition proposed by Lin and Polenske (1995) to decompose changes in the Total requirements matrix based on the division between digital economy sectors and traditional economy sectors. The change in the Total requirements matrix (ΔB)

can be written as follows:

$$\Delta B = B^1 - B^0 = B^1 \Delta A B^0 \tag{9}$$

Similar to intermediate goods, the M matrix representing the structure coefficients of final demand sectors can also be further divided into two sub-matrices: M^D matrix the composition of final demand in the digital sectors, and M^T matrix matrix the composition of final demand in traditional sectors. The approach for defining these sub-matrices is the same as that for the intermediate input matrix:

$$\Delta M = \Delta M^D + \Delta M^T \tag{10}$$

Thus, combining Eqs. (7)-(10) and (6. a)-(6. e), the change ΔLS can be further decomposed from a demand-side perspective as follows:

$$\Delta LS = \tfrac{1}{2}\left(\Delta R^{D'} B^1 M^1 D^1 \theta^1 + \Delta R^{D'} B^0 M^0 D^0 \theta^0\right) \quad (11.\ \mathrm{a})$$

$$+ \tfrac{1}{2}\left(\Delta R^{T'} B^1 M^1 D^1 \theta^1 + \Delta R^{T'} B^0 M^0 D^0 \theta\right) \quad (11.\ \mathrm{b})$$

$$+ \tfrac{1}{2}\left(R^{0'} B^1 \Delta A^{DD} B^0 M^1 D^1 \theta^1 + R^{1'} B^1 \Delta A^{DD} B^0 M^0 D^0 \theta^0\right) \quad (11.\ \mathrm{c})$$

$$+ \tfrac{1}{2}\left(R^{0'} B^1 \Delta A^{DT} B^0 M^1 D^1 \theta^1 + R^{1'} B^1 \Delta A^{DT} B^0 M^0 D^0 \theta^0\right) \quad (11.\ \mathrm{d})$$

$$+ \tfrac{1}{2}\left(R^{0'} B^1 \Delta A^{TD} B^0 M^1 D^1 \theta^1 + R^{1'} B^1 \Delta A^{TD} B^0 M^0 D^0 \theta^0\right) \quad (11.\ \mathrm{e})$$

$$+ \tfrac{1}{2}\left(R^{0'} B^1 \Delta A^{TT} B^0 M^1 D^1 \theta^1 + R^{1'} B^1 \Delta A^{DT} B^0 M^0 D^0 \theta^0\right) \quad (11.\ \mathrm{f})$$

$$+ \tfrac{1}{2}\left(R^{0'} B^0 \Delta M^D D^1 \theta^1 + R^{1'} B^1 \Delta M^D D^0 \theta^0\right) \quad (11.\ \mathrm{g})$$

$$+ \tfrac{1}{2}\left(R^{0'} B^0 \Delta M^T D^1 \theta^1 + R^{1'} B^1 \Delta M^T D^0 \theta^0\right) \quad (11.\ \mathrm{h})$$

$$+ \frac{1}{2}\left(R^{0'} B^0 M^0 \Delta D \theta^1 + R^{1'} B^1 M^1 \Delta D \theta^0\right) \quad (11.\ \mathrm{i})$$

$$+ \frac{1}{2}\left(R^{0'} B^0 M^0 D^0 \Delta \theta + R^{1'} B^1 M^1 D^1 \Delta \theta\right) \quad (11.\ \mathrm{j})$$

$$= \underbrace{C(R^D)} + \underbrace{C(R^T)} + \underbrace{C(A^{DD})} + \underbrace{C(A^{DT})} + \underbrace{C(A^{TD})} + \underbrace{C(A^{TT})} + \underbrace{C(\mathrm{D})} + \underbrace{C(\theta)} \tag{11}$$

The changes in the LS in China can be decomposed into contributions from 10 factors. Among them, the factors related to the digital economy include Eq. (11.a) denotes the change in the employee compensation coefficient in digital economy sectors; Eq. (11.c) denotes the change in the input coefficient from digital sectors to digital sectors, Eq. (11.d) denotes the change in the input coefficient from digital to traditional sectors, Eq. (11. e) denotes the change in the input coefficient from traditional to digital sectors, and Eq. (11. g) denotes the change in the composition of final demand of digital sectors. The matrices A^{DT} and A^{TD} directly measure the degree of numerical and real integration. Non-digital economy factors include Eq. (11.b) denotes the change in the employee compensation coefficient in traditional economy sectors; Eq. (11.f), which denotes the change in the input coefficient from traditional sectors to traditional sectors; Eq. (11.j) denotes the change in intermediate goods import dependence, Eq. (11.i) denotes the change in the structure of final demand types, and Eq. (11.h) denotes the change in the composition of final demand of traditional sectors. These five factors represent other non-digital economic influences.

2.3 Decomposition of changes in the LS in traditional sectors

To better understand the mechanism of the impact of the digital economy on changes in the LS, this study undertakes a similar structural decomposition analysis of changes in the LS in traditional sectors. According to the definition, the LS in traditional sectors (LS^T) is equivalent to the proportion of employee compensation (W^T) to value added (V^T) in traditional economic sectors. The digital economy's contribution (theta) is the reciprocal ratio of value added in traditional economic sectors to GDP, reflecting the digital economy's contribution to the overall economy. The decomposition formula for changes in the LS in traditional economic sectors can be expressed as:

$$LS^T = \frac{W^T}{V^T} = R^{T'}BMD\theta * \frac{GDP}{V^T} = R^{T'}BMD\theta\gamma \tag{12}$$

Building on the previous analytical process, the structural decomposition of changes in the LS in traditional sectors is as follows:

$$\begin{aligned}\Delta LS^T = &\tfrac{1}{2}(\Delta R'B^1M^1D^1\theta^1\gamma^1 + \Delta R'B^0M^0D^0\theta^0\gamma^0) + \tfrac{1}{2}\left(R^{0'}\Delta BM^1D^1\theta^1\gamma^1 + R^{1'}\Delta BM^0D^0\theta^0\gamma^0\right) \\ &+ \tfrac{1}{2}\left(R^{0'}B^0\Delta MD^1\theta^1\gamma^1 + R^{1'}B^1\Delta MD^0\theta^0\gamma^0\right) + \tfrac{1}{2}\left(R^{0'}B^0M^0\Delta D\theta^1\gamma^1 + R^{1'}B^1M^1\Delta D\theta^0\gamma^0\right) \\ &+ \tfrac{1}{2}\left(R^{0'}B^0M^0D^0\Delta\theta\gamma^1 + R^{1'}B^1M^1D^1\Delta\theta\gamma^0\right) \\ &+ \tfrac{1}{2}\left(R^{0'}B^0M^0D^0\theta^0\Delta\gamma + R^{1'}B^1M^1D^1\theta^1\Delta\gamma\right)\end{aligned} \tag{13}$$

Taking into account the influencing factors of the digital economy, a similar breakdown of the direct input coefficients and the final demand sector structure coefficients allows for the structural decomposition of the LS in traditional sectors distinguished by digital sectors:

$$\begin{aligned}\Delta LS^T = &\tfrac{1}{2}\left(\Delta R^{T'}B^1M^1D^1k^1\gamma^1 + \Delta R^{T'}B^0M^0D^0k^0\gamma^0\right) \\ &+ \tfrac{1}{2}\left(R^{0'}B^1\Delta A^{DD}B^0M^1D^1\theta^1\gamma^1 + R^{1'}B^1\Delta A^{DD}B^0M^0D^0\theta^0\gamma^0\right) \\ &+ \tfrac{1}{2}\left(R^{0'}B^1\Delta A^{DT}B^0M^1D^1\theta^1\gamma^1 + R^{1'}B^1\Delta A^{DT}B^0M^0D^0\theta^0\gamma^0\right) \\ &+ \tfrac{1}{2}\left(R^{0'}B^1\Delta A^{TD}B^0M^1D^1\theta^1\gamma^1 + R^{1'}B^1\Delta A^{TD}B^0M^0D^0\theta^0\gamma^0\right)\end{aligned}$$

$$+\frac{1}{2}\left(R^{0\prime}B^{1}\Delta A^{TT}B^{0}M^{1}D^{1}\theta^{1}\gamma^{1}+R^{1\prime}B^{1}\Delta A^{DT}B^{0}M^{0}D^{0}\theta^{0}\gamma^{0}\right)$$

$$+\frac{1}{2}\left(R^{0\prime}B^{0}\Delta M^{D}D^{1}\theta^{1}\gamma^{1}+R^{1\prime}B^{1}\Delta M^{D}D^{0}\theta^{0}\gamma^{0}\right)$$

$$+\frac{1}{2}\left(R^{0\prime}B^{0}\Delta M^{T}D^{1}\theta^{1}\gamma^{1}+R^{1\prime}B^{1}\Delta M^{T}D^{0}\theta^{0}\gamma^{0}\right)$$

$$+\frac{1}{2}\left(R^{0\prime}B^{0}M^{0}\Delta D\theta^{1}\gamma^{1}+R^{1\prime}B^{1}M^{1}\Delta D\theta^{0}\gamma^{0}\right)$$

$$+\frac{1}{2}\left[R^{0\prime}B^{0}M^{0}D^{0}\Delta\theta\gamma^{1}+R^{1\prime}B^{1}M^{1}D^{1}\Delta\theta\gamma^{0}\right]$$

$$+\frac{1}{2}\left[R^{0\prime}B^{0}M^{0}D^{0}\theta^{0}\Delta\gamma+R^{1\prime}B^{1}M^{1}D^{1}\theta^{1}\Delta\gamma\right] \qquad (14)$$

2.4 Decomposition at matrix elements level and economic interpretion of contributions

Based on the decomposition formula proposed in Section 2.2, the change in the LS between two years can be decomposed into the contributions of 10 factors effect. However, the mere calculation at the matrix level cannot provide a deep explanation for why a certain factor has such a contribution. This section further decomposes the contribution of each factor measured at the matrix or vector level into the matrix elements, i.e., the coefficient level. The calculation formula for the contribution of each coefficient change is written as the product of the coefficient change magnitude and the corresponding specific weight coefficient. Thus, the contribution of each factor measured at the matrix or vector level can be represented as the sum of the products of the change magnitudes of all constituent coefficients and their respective weight coefficients. This element-level decomposition formula has two advantages in application: firstly, it can be used to identify importentcoefficients. A matrix or vector generally contains many coefficients, but only a few of them will decisively influence the direction and magnitude of the contribution of the influencing factors. Identifying these coefficients is crucial for understanding the key chains determining the change in the LS. Secondly, it facilitates the economic interpretation of the decomposition results. The contribution of any coefficient is determined by the change magnitude of the coefficient between the base period and the reporting period, as well as the weight coefficient. Since weight coefficients generally have clear economic meanings, the reason why importentcoefficients are critical can be clearly explained, and thus the contribution of a certain influencing factor represented by a matrix or vector can be explained.

Among the five primary factors influencing the LS, the elements involved in the coefficient matrices representing the A matrix for production technology and the M matrix are the most numerous and complex. Therefore, this study focuses on these two influencing factors, proposing formulas for their coefficient-level contributions and providing economic explanations.

2.4.1 Decomposition of the Contribution of Composition of Final Demand Coefficients

Taking the structural changes in the final demand sectors as an example, and based on the segmentation of departmental scale and final demand types in the table, the matrix comprises $(n \times 4)$ coefficients. The formula for calculating the contribution at the matrix level, denoted as

$C(M)$, using:

$$C(\Delta M) = \frac{1}{2}\left(R^{0\prime}B^{0}\Delta M D^{1}\theta^{1} + R^{1\prime}B^{1}\Delta M D^{0}\theta^{0}\right) \tag{15}$$

Decomposing matrix multiplication to the elemental level representation, Eq.(15) then becomes

$$C(\Delta M) = \begin{bmatrix} l_1 & \cdots & l_n \end{bmatrix} \begin{bmatrix} \Delta m_{11} & \cdots & \Delta m_{14} \\ \vdots & \ddots & \vdots \\ \Delta m_{n1} & \cdots & \Delta m_{n4} \end{bmatrix} \begin{bmatrix} d_1\theta \\ \cdots \\ d_4\theta \end{bmatrix} \tag{16}$$

where d_k denotes the proportion of the k-th type of final demand, l_i is calculated as $l_i = \sum_{h=1}^{n} r_h b_{hi}$ and l_i、$d_k\theta$ are calculated as the arithmetic mean between the base period and the given period.

The expansion of the formula can be expressed as:

$$C(\Delta M) = \sum_{i=1}^{n}\sum_{k=1}^{4} l_i d_k \theta \Delta m_{ik} \tag{17}$$

The contribution of any coefficient Δm_{ik} in the ΔM matrix to the change in the LS is:

$$C(\Delta m_{ik}) = l_i d_k \theta \Delta m_{ik} \tag{18}$$

From Eq. (17), it can be clearly seen that the contribution of the factor of changes in the composition of final demand can be additively decomposed into the sum of contributions from all coefficients in the ΔM matrix. The contribution of any coefficient is equal to the product of the coefficient change magnitude and the corresponding weight coefficient. As Eq.(18) shows, the weight coefficient can be further decomposed into the product of two coefficients. The coefficient m_{ik} is independent of k and varies only with the different rows i in which the composition of final demand coefficient is located. Therefore, it can be defined as the row weight coefficient.Similarly, $d_k\theta$ varies only with the different columns k in which the composition of final demand coefficient is located, so it can be defined as the column weight coefficient. The economic meaning of the row weight coefficient is the total LS, which is the increase in the overall economic labor compensation resulting from one unit increase in the final demand for the i sector. The economic meaning of the column weight coefficient is the proportion of the k category of domestic final demand to GDP, if domestic consumption accounts for the proportion of GDP. The essence of weight coefficients is derivatives. The larger the weight coefficient, the greater the impact of a one-unit change in the corresponding composition of final demand coefficient on the change in the LS. From this perspective, weight coefficients are similar to leverage ratios in econometrics and can be used to identify highly impactful leverage points.

If constructing a matrix where each element represents the contribution of the change in that element, according to Eq. (16), this matrix can be expressed as:

$$C(\Delta M)_{n\times 4} = [(D\theta) \otimes (R'B)]' \circ \Delta M \tag{19}$$

In Eq.(19), the symbol ∘ represents the Hadamard product, which is the element-wise multiplication of two matrices of the same order, and ⊗ represents the Kronecker product.

2.4.2 Decomposition of the Contribution of Composition of Direct Input Coefficients

Based on the table's sector scale, the ΔA matrix has a total of n×n coefficients. The formula for calculating the contribution of this factor's change at the matrix level, denoted as :

$$C(\Delta A)=\frac{1}{2}\left(R^{0\prime}B^{1}\Delta AB^{0}M^{1}D^{1}\theta^{1}+R^{1\prime}B^{1}\Delta AB^{0}M^{0}D^{0}\theta^{0}\right) \qquad (20)$$

Similarily, we have

$$C(\Delta A)=\sum_{i=1}^{n}\sum_{j=1}^{n}\left[\left(\sum_{h=1}^{n}r_{h}b_{hi}^{1}\right)\left(\sum_{g=1}^{n}b_{jg}^{0}\left(\sum_{k=1}^{4}m_{gk}\,d_{k}\theta\right)\right)\Delta a_{ij}\right] \qquad (21)$$

where r_h denotes the employee compensation coefficient of h sector， b_{hi}^{1} is the $hi-th$ element in the Leontief inverse matrix for the given period; b_{jg}^{0} is the $jg-th$ element in the Leontief inverse matrix for the base period, and other variables are defined as before. For simplification, $r_h\sum_{g=1}^{n}b_{jg}^{0}\left(\sum_{k=1}^{4}m_{gk}\,d_{k}\theta\right)$ are defined as the arithmetic mean of the base period and given period.

The contribution of any coefficient Δa_{ij} in the ΔA matrix to the change in the LS is:

$$C(\Delta a_{ij})=\left(\sum_{h=1}^{n}r_{h}b_{hi}^{1}\right)\left(\sum_{g=1}^{n}b_{jg}^{0}\left(\sum_{k=1}^{4}m_{gk}\,d_{k}\theta\right)\right)\Delta a_{ij} \qquad (22)$$

The matrix expression that reflects the contribution of elements is:

$$C(\Delta A)_{n\times n}=[(R'B^{1})\otimes(B^{0}MD\theta)]'\circ\Delta\mathrm{A} \qquad (23)$$

Eq. (21) denotes that the contribution of the direct input coefficient change can also be additively decomposed into the sum of contributions from all coefficients in the matrix. Eq.(22) shows that its weight coefficient can also be further decomposed into the product of two coefficients. $\sum_{h=1}^{n}r_{h}b_{hi}^{1}$ is the row weight coefficient, representing the total employee compensation coefficient of i sector calculated based on the total requirements coefficients and the average employee compensation coefficients for the base period and given period. $\sum_{g=1}^{n}b_{jg}^{0}\left(\sum_{k=1}^{4}m_{gk}\,d_{k}\theta\right)$ is the column weight coefficient, which represents the proportion of the domestic total output and GDP driven by the domestic final demand of sector j in the base period to the proportion of the domestic total output and GDP driven by the domestic final demand of sector j in the given period. This reflects the size of the multiplier effect of each sector.

3. Descriptive analysis

3.1 Compilation of Non-Competitive Input-Output Tables for Digital Economy

Based on the "Classification of Digital Economy and Its Core Industries (2021)" published by the State Statistics Bureau, and utilizing the Input-Output Tables and Extended Input-Output Tables compiled by the National Bureau of Statistics of China, along with other available statistical data, we systematically compiled the Input-Output Tables for the years 2012, 2017, and 2020. To ensure comparability in the number of industries and calculation results across the years 2012 to 2020, we adjusted the Input-Output Tables for each year to standardize them to 41 sectors.

Given that each sector in the Input-Output Tables corresponds to one or more sub-sectors in the national economic industry classification, we found that some sectors encompass both digital and non-digital economic industries. Therefore, referring to the "Classification of Digital Economy and Its Core Industries (2021)" and the "National Standard Industry Classification (GB/T4754—2017)", we identified and disaggregated the sectors related to the digital economy in China's Input-Output Tables, organizing the corresponding types of digital economy industries for each sector in the Input-Output Tables.

Table 2 The correspondence between digital economy types and sectors in the input-output table

Type	Sectors
Digital Product Manufacturing (7 sectors)	Paper Printing and Educational, Sports, and Cultural Supplies*; Chemical Products*; General Equipment*; Special Equipment*; Electrical Machinery and Equipment*; Communications Equipment, Computers and Other Electronic Equipment; Instruments and Apparatus*
Digital Product Services (3 sectors)	Wholesale and Retail *; Leasing and Business Services*; Residential Services*
Digital Technology Application (2 sectors)	Information Transmission, Software and Information Technology Services; Comprehensive Technical Services *
Digital Factor-driven (4 sectors)	Construction*, Finance *, Research and Experimental Development *, Culture, Sports and Entertainment *
Traditional sectors (39 sectors)	Traditional Sectors (See Appendix)

Note: * indicates that it simultaneously includes content from both the digital economy and the traditional economy. According to the “Statistical Classification of Digital Economy and Its Core Industries (2021)”, the wholesale industry includes both digital product services and digital technology application industries; Internet-related services exist in both digital technology application and digital element-driven categories; In line with the principle of more merging and less splitting, all digital economic core industries in the wholesale industry are classified into digital product services here. At the same time, Internet-related services are classified into the digital technology application industry.

As shown in Table 2, among the 41 sectors in the Input-Output Table, only two sectors, namely "Communications Equipment, Computers and Other Electronic Equipment", "Information Transmission, Software and Information Technology Services," belong entirely to the digital economy. Additionally, 14 sectors contain both digital and traditional economic content, requiring digital economy adjustment coefficients for disaggregation. Therefore, the Input-Output Table for the digital economy covers five types of digital economy, totaling 55 sectors, including 16 digital economy sectors and 39 non-digital economy sectors.

This study referred to the method proposed by Xu&Zhang (2020), using the proportion of value added in the digital economy part to the total value added of the sector as the adjustment coefficient. For sectors where it is not possible to obtain output data for the digital economy part, the study utilized various industry revenue data from databases such as the "China Statistical Yearbook," "China Economic Census Yearbook," "China Industrial Statistical Yearbook," and "China E-commerce Market Data Monitoring Report." It was assumed that the proportion of revenue for each sub-category industry within an industry is equal to the proportion of the total output of that sub-category industry, thereby estimating the adjustment coefficients for sectors. The National Bureau of Statistics published the non-competitive Input-Output Table for 2017. Based on this, the study directly used adjustment coefficients for disaggregation. For other years, disaggregation was conducted based on the competitive Input-Output Table. Then, the competitive Input-Output Table was adjusted to the non-competitive Input-Output Table according to the assumption of import ratio.

3.2 Analysis of changes in LS and various influencing factors

3.2.1 Changes in LS

From 2012 to 2020, the LS in China increased from 49.2% to 52.1%. Compared to the digital sectors, the LS is higher and grows faster in traditional sectors.

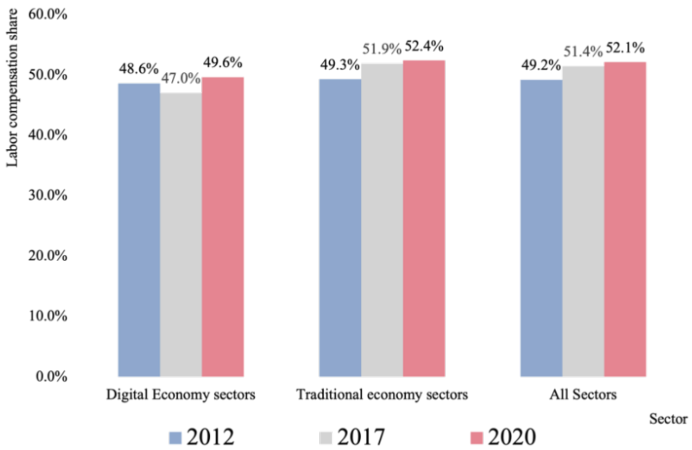

Fig. 1 The LS in the digital and traditional sectors in 2012, 2017, 2020.

Notes: Data are taken from the official website of National Statistical Bureau (www.stats.gov.cn)

Table 3 Changes in the LS in the digital and traditional sectors in two sub-periods

	2012-2017	2017-2020
Digital Product Manufacturing Sectors	0.05	-0.03
Digital Product Services Sectors	0.19	0.06
Digital Technology Application Sectors	0.05	0.01
Digital Factor-driven Sectors	0.18	-0.06
Traditional Sectors	0.52	-0.04

Notes: Data are taken from the official website of National Statistical Bureau (www.stats.gov.cn)

Although the LS in China showed a growth trend in both the 2012-2017 and 2017-2020 periods, the growth of LS at the sectoral level was uneven. Among the four classifications of the digital sectors, the LS in the digital service industry significantly increased, reflecting the driving effect of the digital economy. The proportion of value-added in the service industry has increased in the digital economy era, driving the overall labor share of income to rise. On the other hand, sectors where the LS o declined are mostly in the digital manufacturing industry. With the advancement of digital technology and the development of the digital economy, some traditional industries and jobs may be replaced by digitization and automation, leading to a decrease in the LS in the digital manufacturing industry, known as the "substitution effect" of the digital economy.

3.2.2 Changes in the proportion relationship between the digital sector and the traditional sector

To gain a clearer understanding of the development of the digital economy sector in China's economic structure from 2012 to 2020, we integrated both the digital economy and traditional economy sectors into a unified whole. We analyzed the changes in crucial proportion relationships within the framework of a 2×2 input-output table.

Fig.2 shows that both the value-added coefficients of the digital economy sector and the traditional economy sector are trending upwards, with the increase in the value-added coefficient of the digital economy sector being more pronounced. Regarding the interdependence between the digital economy sector and the traditional economy sector, the coefficient of production activities of the digital economy sector on the traditional economy sector shows a declining trend. In contrast, the coefficient on the digital economy sector itself tends to increase. This indicates a weakening overall pull of the development of the digital economy sector on the traditional economy sector while its self-pull is strengthening. The coefficient of production activities of the traditional economy sector on itself also tends to decrease, with little change observed in its coefficient on the digital economy sector. From the perspective of final demand, the changes in the input proportions of the digital sector appear relatively stable, with a slight upward trend.

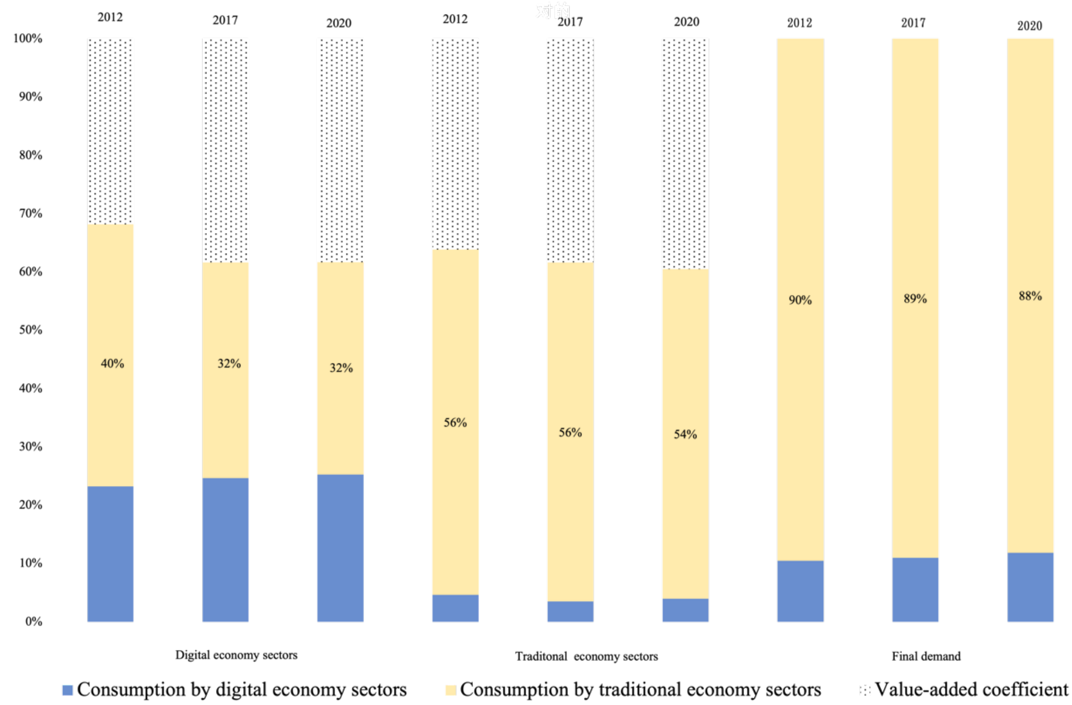

Fig. 2 Changes in aggregated coefficients for digital sectors and traditional sectors

3.2.3 The main characteristics of the changes in influencing factors

Changes in the direct input coefficient, changes in the composition of final demand, and changes in the employee compensation coefficient are important determinants of changes in the LS. Factors related to the digital economy are more likely to have a positive impact on changes in the LS, with the proportion of sectors showing positive changes generally higher than that for other factors. Looking at the period from 2012 to 2020 in two stages, changes with absolute values exceeding 0.01 are defined as significant changes. All coefficients of influencing factors show significantly more significant changes in the former stage than in the latter stage.

The LS in the national economy is on the rise, as shown in Table 3, with the proportion of sectors showing positive changes reaching 87.5%. The composition of final demand, on the other hand, shows a trend of negative growth. In the latter stage, the proportions of positive changes in both the employee compensation coefficient and the composition of final demand coefficient have decreased. In contrast, while most of the direct input coefficients showed negative changes, they mostly turned positive in the second stage, a point that will be further analyzed in the following sections.

Table 4 The main characteristics of the changes in influencing factors.

	2012-2017			2017-2020		
	Positive coefficients (%)	Significantly positive coefficient	Significantly negative coefficient	Positive coefficients (%)	Significantly positive coefficient	Significan negative coefficie
A^{DD}	34.77	3	11	45.31	3	1
A^{DT}	35.58	2	8	42.94	4	1
A^{TD}	25.80	13	92	54.17	8	8
A^{TT}	26.63	29	185	48.45	24	24
M^{D}	43.75	3	4	35.94	3	3
M^{T}	37.82	19	23	33.33	14	15
R^{D}	87.50	11	1	50.00	5	4
R^{T}	69.23	20	9	43.59	9	10

3.2.4 Primary characteristics of changes at the level of direct input coefficients

One of the significant determinants of LS is the direct input coefficient. We utilized heatmaps with a grid size of 55×55 to visually present the variations in the direct input coefficient matrix to examine further the details of changes in the direct input coefficient matrix. The left heatmap compares the changes in direct input coefficients between 2012 and 2017, while the right heatmap depicts the changes between 2017 and 2020. The dashed lines divide the heatmap into four quadrants: the upper-left quadrant represents internal input within the digital economy sector, the upper-right quadrant represents input by the digital sector on the traditional sector, the lower-left quadrant represents input by the traditional sector digital on the economy sector, and the lower-right quadrant represents internal input within the traditional sector. The color intensity indicates the magnitude of the difference, with red indicating positive changes and blue indicating negative changes.

Between 2012 and 2017, the changes in the direct input coefficients exhibited a clear pattern of homogeneity, where all sectors showed similar trends of increase or decrease in their output coefficients towards a particular sector. The direct output coefficient of digital sector 11 significantly decreased, which is characteristic of the flexibility and rapidity often seen in digital sectors. This decrease may be attributed to the rapid technological advancements in Information Transmission, Software, and Information Technology Services, leading to a reduction in the resources required per unit of product. On the other hand, traditional sector 23 showed a significant positive change, possibly due to the increase in resource demand driven by consumption under the backdrop of the government's strong push for consumption. The bottom-right corner, representing input of traditional sectors by traditional sectors, exhibited a distinct diagonal pattern, indicating industrial restructuring and changes in production methods. Similarly, in the latter stage, specific sectors, such as Sector 23 and the digital products and services sector, show positive changes towards Sector 51. Notably, some sectors exhibit reverse changes between the two intervals; for instance, Sector 11 transitions from negative to positive, while Sector 18 shifts from positive to negative. The bottom-right quadrant of the heatmap illustrates the adjustment characteristics of input structures within the traditional sectors.

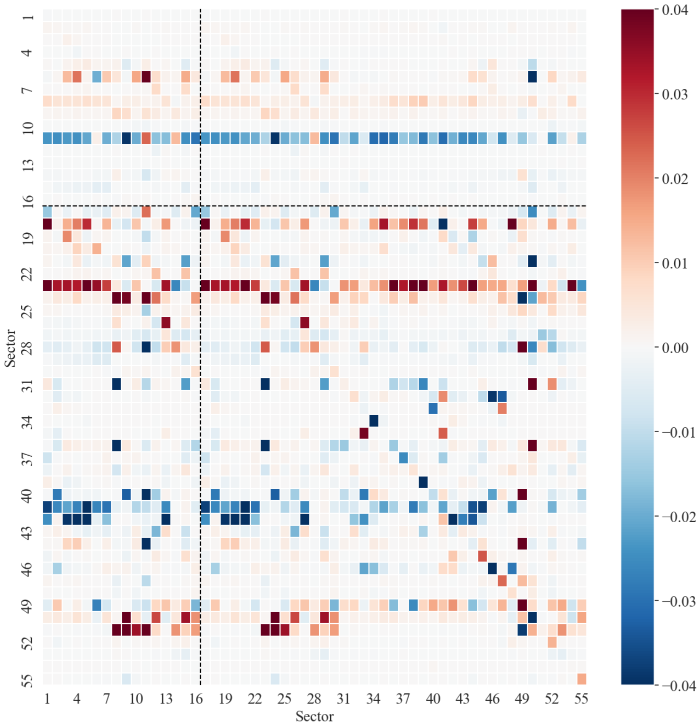

Fig. 3 Changes in direct input coefficients, 2012-2017

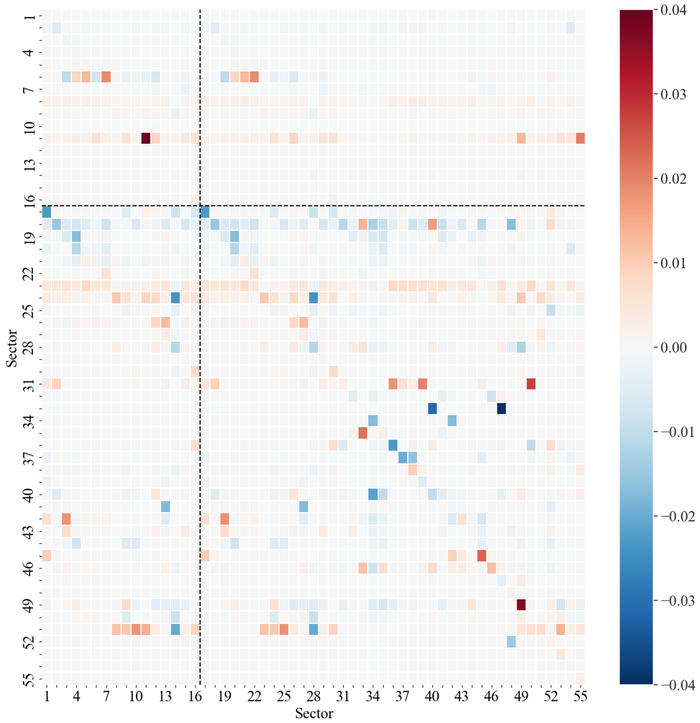

Fig. 4 Changes in direct input coefficients, 2017-2020

4. Decomposition results

Based on the compiled input-output tables of the non-competitive digital economy for the years 2012, 2017, and 2020, the results of the factor decomposition of the change in the share of China's overall employee compensation can be obtained according to the decomposition formulas proposed in Section 2 of this paper for the periods 2012-2017 and 2017-2020. The results of the empirical analysis are discussed in this section.

4.1 Structural decomposition results of cross-period changes in China's overall LS

The results of the decomposition for 2012-2017 are shown in Fig. 5. At the level of the first level of decomposition, changes in the employee compensation coefficients of the sectors, changes in the coefficients of production technology represented by the Total requirements matrix, changes in the structure of the final demand sectors, and changes in the structure of the types of final demand all contributed to the rise in the overall share of labor compensation, with changes in the coefficients of employee compensation of the sectors contributing the most, and changes in the coefficients of production technology having The smallest impact of the change in the production technology coefficient does not mean that the factor is unimportant, as can be seen from the secondary decomposition, where the small overall contribution of the production technology coefficient is because there have been increases and decreases in the complete needs coefficient, leading to their effects canceling each other out. The decline in the import dependence on intermediate goods during this period had a negative and larger impact on the LS, second only to the contribution of changes in the sectoral employee compensation coefficients. As seen in the formula for intermediate goods import dependence, the denominator of the LS, GDP, is also the denominator of intermediate goods import dependence, and the negative impact of this factor reflects the falling share effect of an increase in the denominator of the LS.

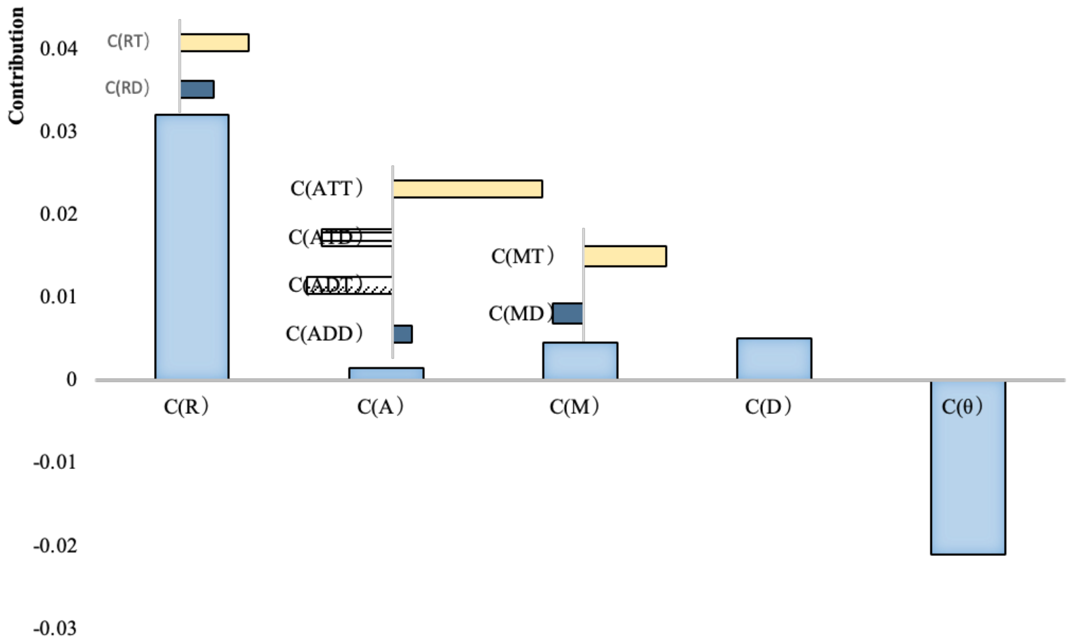

Fig. 5 Contribution to the LS decomposition in China, 2012-2017

In the secondary decomposition distinguishing between the digital sectors and traditional sectors y, the contribution of changes in the employee compensation coefficients of the traditional sector of the economy is larger than that of changes in the employee compensation coefficients of the digital sector of the economy; whereas in the impact component of the technology coefficients, both changes in A^{TT} and changes in A^{DD} contribute to the overall LS, with the former contributing significantly more than the latter, implying that both an overall This means that the overall decline in the consumption coefficient of the traditional sector on the digital sector and the overall increase in the consumption coefficient of the digital sector on the digital sector of the economy both contribute to the increase in the overall LS; while the changes in the technical coefficient matrices of A^{TD} and A^{DT}, which represent the relationship of the integration of the digital and real, during the period of 2012-2017 both make the share of employee compensation tend to decline, which means that the overall decline in the input coefficient of the traditional sector on the digital sector and the overall decline in the input coefficient of the digital sector on the traditional sector The overall decline in the input coefficient of the traditional economy over the digital economy sector and the overall decline in the consumption coefficient of the traditional sectors over the digital sector are both detrimental to the overall LS. In terms of the sectoral structure of final demand, the changes in the traditional sector of the economy favor an increase in the share of labor compensation while the changes in the digital sector of the economy (a small increase in the share of products from the digital sector in final demand) have a negative impact, which is related to the fact that the coefficient of labor compensation in the traditional sector is higher than in the digital sector of the economy in 2012 and 2017.

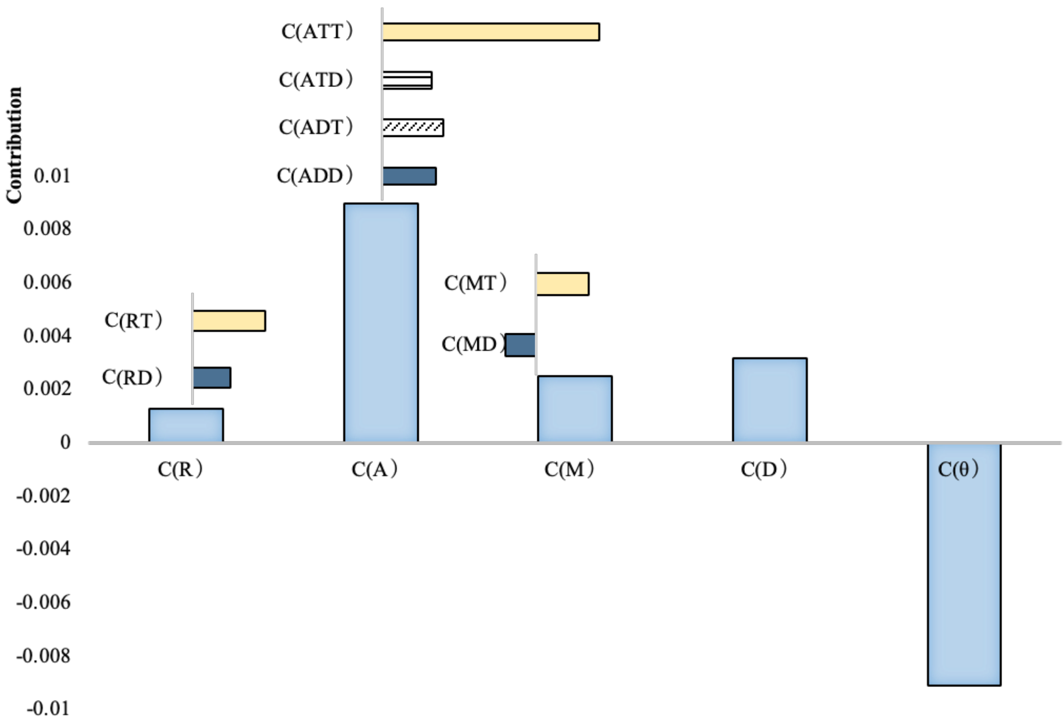

Fig. 6 Contribution to the LS decomposition in China, 2017-2020

The results of the decomposition for the period 2017-2020 are shown in Fig.6. At the level of the first level of decomposition, the most significant change is that the positive impact of changes in the technology coefficient increases significantly while the positive impact of the employee compensation coefficient decreases significantly in this period, with the contribution of the former having become much larger than that of the latter. This change is of great interest, as the impact of changes in the coefficient of employee compensation by sector has received more attention in the perspective of existing studies, while the impact of the coefficient of technology, or intersectoral dependence, on overall employee compensation, has received little attention.

At the level of secondary decomposition, the most noteworthy change is that the impact of changes in A^{TD} and A^{DT} on the overall LS has turned from negative to positive. Compared with 2017, the input coefficient of the digital sector to the traditional sector has increased significantly in 2020, and the degree of digital-real integration has increased in this period, and the positive impact of such an increase on the share of employee compensation has a role to play in the formulation of relevant policies.

Table 5 The decomposition of intertemporal changes in overall LS structure

		2012-2017		2017-2020	
		Contribution (%)	Contribution rate (%)	Contribution (%)	Contribution rate (%)
Digital Economic Factors	C(R^D)	1. 54	69. 44	0. 04	6. 48
	C(A^{DD})	0. 23	10. 31	0. 12	18. 24
	C(A^{DT})	-1. 01	-45. 77	0. 14	21. 14
	C(A^{TD})	-0. 85	-38. 23	0. 12	16. 85
	C(M^D)	-0. 30	-13. 47	-0. 35	-51. 02
Total		-0. 39	-17. 72	0. 07	11. 69
Other Factors	C(A^{TT})	1. 78	80. 31	0. 51	74. 86
	C(M^T)	0. 79	35. 83	0. 60	87. 46
	C(R^T)	1. 67	75. 75	0. 08	12. 3
	C(D)	0. 50	22. 76	0. 32	46. 49
	C(θ)	-2. 10	-95. 07	-0. 91	-132. 80
Total		2. 64	119. 58	0. 6	88. 31

Table 5 groups the influences on the overall LS according to the digital economy factors and other factors, giving the contribution of the development of the digital economy to the change in the LS through various pathways. As seen in Table 3, in 2012-2017, the development of the digital economy, in general, will make the LS decrease by 17.72%, in terms of the path of action, the change in the employee compensation coefficient of the digital economy sector, the change in the input coefficient of the digital economy sector on the digital economy sector contributed to the increase in the LS, while the other three paths have a negative impact, with the most significant impact being the change of the input coefficient of the traditional sector on the overall decline in the consumption coefficient of the digital sector and the decline in the input coefficient of the digital economy sector on the traditional economy sector. In the second stage of the study, although the contribution of the development of the digital economy to the LS is still significantly smaller than that of the traditional sector, the direction of the impact has turned from negative to positive, which is mainly attributable to the impact of the changes in A^{TD} and A^{DT} turning from negative to positive.

4.2 Structural decomposition results of cross-period changes in China's LS in traditional sectors

To further investigate the role of the digital economy in the evolution of LS, this study utilizes the decomposition results from Eq.19 to analyze the impact of various factors on the changes in LS in the traditional economy. A comparison is then made with the effects on the overall LS evolution.

Table 6 Decomposition of intertemporal changes in LS in traditional economics

		2012-2017		2017-2020	
		Contribution (%)	Contribution rate (%)	Contribution (%)	Contribution rate (%)
Digital Economic Factors	C(A^{dd})	0. 11	4. 23	0. 05	6. 78
	C(A^{dt})	-0. 32	-12. 31	0. 11	15. 08
	C(A^{td})	-0. 89	-34. 56	0. 10	14. 00
	C(M^{d})	-0. 13	-4. 99	-0. 37	-52. 49
	C(γ)	0. 13	4. 87	0. 68	94. 74
Total		-1. 1	-42. 76	0. 57	78. 11
Other Factors	C(A^{tt})	1. 54	59. 56	0. 27	38. 44
	C(M^{t})	0. 26	9. 90	0. 27	38. 00
	C(R)	3. 02	116. 99	0. 12	16. 33
	C(D)	0. 68	26. 34	0. 41	57. 73
	C(θ)	-2. 11	-81. 75	-0. 92	-128. 60
Total		3. 39	131. 04	0. 15	21. 9

From 2012 to 2020, the share of labor compensation in the traditional economy increased period by period. Interestingly, the development of the digital economy has played a dampening and then a boosting role, a trend similar to the change in the share of labor compensation in the country as a whole, which has contributed to the shift from negative to positive in the share of labor compensation in the traditional economy in specific periods. The main reason for this change is the increase in the share of value added to the digital economy sector in the aggregate. In addition, the increased integration of the digital economy with the traditional economy sectors has also been an essential factor in driving up the share of labor compensation in the traditional economy. Before 2017, the employee compensation factor was the dominant factor driving the increase in the share of labor compensation in the traditional economy. However, after 2017, reduced import dependence on intermediate goods dampened the momentum of further increases in the LS of the traditional economy. The increase in the value-added share of the digital economy sector became the main contributing factor to offset this negative impact. In addition, the negative impact of structural factors in the final demand sector of the digital economy has increased, a phenomenon that stems mainly from the adjustment of weights.

4.3 Analysis of the Important coefficients of the change in the LS in China

4.3.1 Important Coefficients in the A matrix

The concentration of the direct input coefficient matrix is high. As shown in Table 7, changes in a few coefficients can represent the changes in the entire matrix. From 2012 to 2017, the cumulative contribution error rate of the top 1% coefficients reached 51%. Furthermore, among the top 20 important coefficients, 90% of the coefficients inhibited the growth of the labor share in the former stage, while in the latter stage, they mostly changed to positive, explaining the increasing importance of production technology effects on the growth of the LS.

Table 7 Important Coefficients of A matrix

		2012-2017	**2017-2020**
Cumulative Contribution Error Rate	Top 1% coefficients	51.5%	35.0%
	Top 5% coefficients	19.7%	3.7%
	Top 10% coefficients	10.8%	2.3%
The composition of important coefficients	The percentage of coefficients with negative impacts.	90.0%	43.3%
	The percentage of coefficients on the diagonal	33.3%	20.0%

Among them, the coefficient with the largest contribution is $a_{31,36}$, which increased from -0.0150 in the former stage to 0.0021. In addition, the important coefficients on the diagonal account for 33.3% and 20%, respectively, indicating that sectors in the stage of structural adjustment also have an important impact on the LS.

Table 8 Top twenty important direct input coefficients for LS during two sub-periods

	2012-2017		2017-2020	
	Coefficients	Contribution	Coefficients	Contribution
1	$a_{31,36}$	-0.0150	$a_{31,36}$	0.0021
2	$a_{42,42}$	-0.0102	$a_{49,49}$	0.0019
3	$a_{41,27}$	-0.0080	$a_{36,36}$	-0.0017
4	$a_{18,18}$	-0.0078	$a_{41,27}$	-0.0017
5	$a_{42,27}$	-0.0074	$a_{26,27}$	0.0017
6	$a_{36,36}$	-0.0066	$a_{24,28}$	-0.0014
7	$a_{31,31}$	-0.0054	$a_{31,18}$	0.0013
8	$a_{36,31}$	-0.0041	$a_{11,11}$	0.0013
9	$a_{49,49}$	-0.0031	$a_{31,50}$	0.0010
10	$a_{24,28}$	-0.0031	$a_{23,27}$	0.0010
11	$a_{26,27}$	0.0028	$a_{18,18}$	-0.0009
12	$a_{26,26}$	-0.0025	$a_{23,36}$	0.0008
13	$a_{37,37}$	-0.0025	$a_{24,23}$	0.0007
14	$a_{6,11}$	-0.0022	$a_{24,49}$	0.0007
15	$a_{37,38}$	-0.0022	$a_{11,49}$	0.0007
16	$a_{46,46}$	-0.0021	$a_{23,18}$	0.0006
17	$a_{40,49}$	-0.0021	$a_{11,55}$	0.0006
18	$a_{19,19}$	0.0020	$a_{34,42}$	-0.0006
19	$a_{41,41}$	-0.0020	$a_{51,28}$	-0.0006
20	$a_{32,46}$	-0.0020	$a_{50,28}$	-0.0005

Further observation of the row weights and column weights of each sector reveals that most of the important coefficients are related to a few sectors, and there is a certain overlap in important coefficients between the two stages. For example, digital sectors 6 and 11, traditional sectors 27 and 31, compared to other sectors, have high row weights and column weights, and are located at the edges of the picture. Although some sectors have high row weights, their column weights are small. For example, the column weights of most digital sectors are almost zero, which also explains why the digital economy has not promoted a rapid increase in the LS.

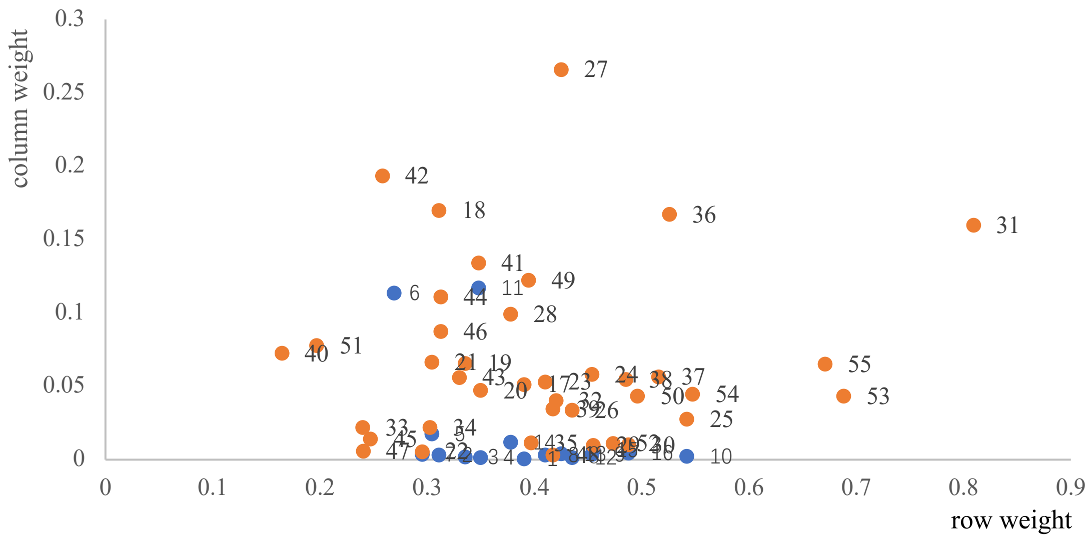

Fig. 7 Weights of direct input coefficients, 2012-2017

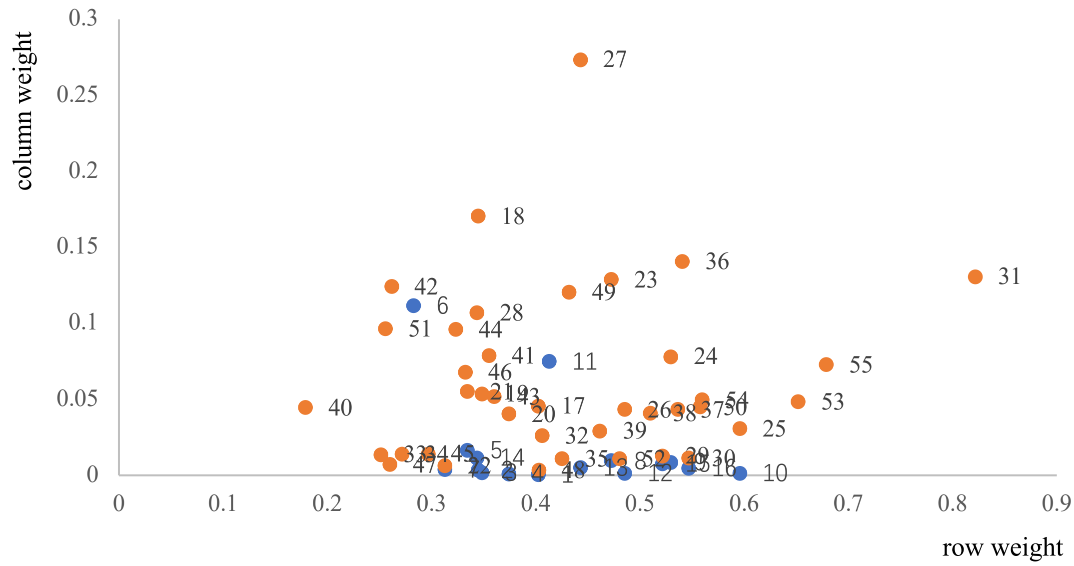

Fig. 8 Weights of direct input coefficients, 2017-2020

4.3.2 Important coefficients in the M matrix

According to the formula for the important coefficients, it is possible to calculate the contribution of changes in the structural coefficients of all final demand sectors (divided into four columns, consumption, capital formation, inventories, and exports, for a total of 55 x 4 coefficients) to the change in the share of labor compensation. After sorting the coefficients by the size of their absolute contribution, the size of the contribution of the 20 coefficients that contribute the most to the change in the LS is presented in the figure, as well as the size of the change in the coefficients and the two factors that determine the size of the contribution, namely, the size and the weight. The area of the circle represents the absolute value of the coefficient's contribution; the horizontal coordinate represents the size of the coefficient's change, and the vertical coordinate represents the coefficient's weight in the decomposition formula for employee compensation change. The different colors represent the four components of the final demand. A solid circle represents that the product belongs to the traditional sector, while a hollow represents that it belongs to the digital economy sector. From this figure, it is possible to visualize which coefficients are crucial and why they are critical.

Fig.9 shows that: among all 20 important coefficients, the fixed capital formation product composition coefficient accounts for the largest share of consumption formation product composition coefficients are the next largest, there are only four coefficients in the export column, and the coefficients in the inventory column do not have any significant impact on the change in the share of labor compensation; most of the important coefficients are the composition coefficients of the products of the traditional sectors in the various types of final demand, and there are only three composition coefficients for the sectors of the digital economy that are important coefficients, which are the coefficients of consumption products and fixed capital formation products for information transmission, software and information technology services1 and the coefficient of input for research and experimental development.1 Since the coefficients of the composition of input products in both sectors were negative in 2012-2017, the changes in both of them suppressed the increase in the share of labor compensation, and the coefficient of the composition of fixed capital formation products in information transmission, software and information technology services1 coefficient was positive, contributing to the increase in the LS; across all 20 important coefficients, the number of coefficients that showed an increase in the coefficient and the number of coefficients that showed a decrease in the coefficient were roughly the same, and since the weights were all positive, half of the important coefficients' changes led to an increase in the LS and half of the important coefficients' changes led to a decrease in the LS, which could explain why the overall change in the composition of the products of final demand contributed to the LS This also explains why the overall change in the composition of final demand products contributes less to the change in the LS; the coefficient that has the largest impact on the change in the LS is the coefficient on the ratio of fixed capital formation to total fixed capital formation for sector 27, construction2, which has a negative impact on the LS, and its large contribution is partly due to a large change in the coefficient itself.

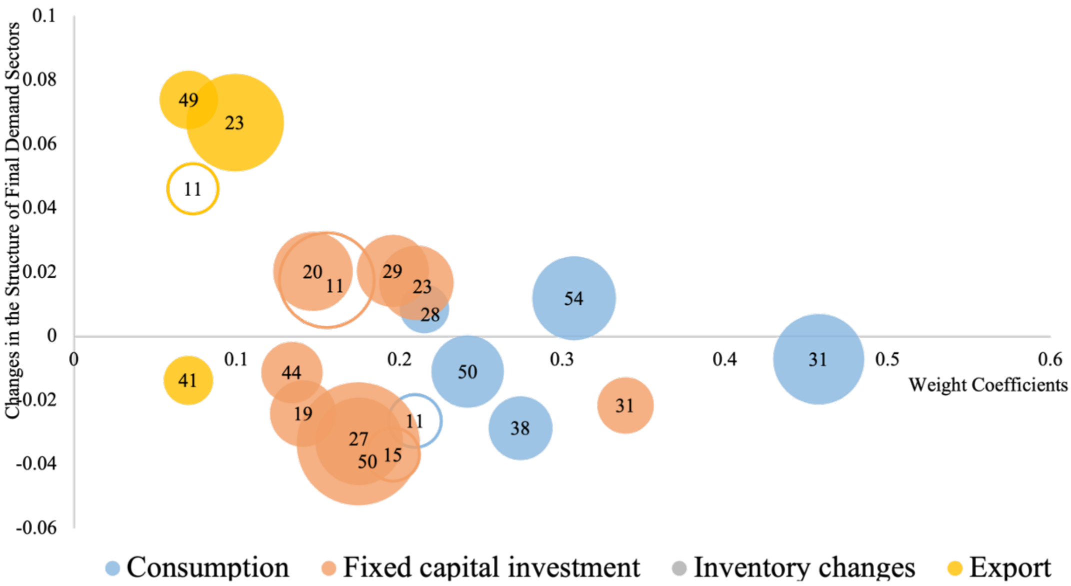

Fig. 9 Important coefficients in the M matrix,2012-2017

From 2017 to 2020, among all 20 important coefficients, the fixed capital formation product composition coefficient accounts for the largest share of consumption formation product composition coefficients are the next largest, there are only four coefficients in the export column, and the coefficients in the inventory column do not have any significant impact on the change in the LS; most of the important coefficients are the composition coefficients of the products of the traditional sectors in the various types of final demand, and there are only three composition coefficients for the sectors of the digital economy that are important coefficients, which are the coefficients of consumption products and fixed capital formation products for information transmission, software and information technology services1 and the coefficient of input for research and experimental development.1 Since the coefficients of the composition of input products in both sectors were negative in 2012-2017, the changes in both of them suppressed the increase in the share of labor compensation, and the coefficient of the composition of fixed capital formation products in information transmission, software and information technology services1 coefficient was positive, contributing to the increase in the LS; across all 20 important coefficients, the number of coefficients that showed an increase in the coefficient and the number of coefficients that showed a decrease in the coefficient were roughly the same, and since the weights were all positive, half of the important coefficients' changes led to an increase in the LS and half of the important coefficients' changes led to a decrease in the LS, which could explain why the overall change in the composition of the products of final demand contributed to the LS This also explains why the overall change in the composition of final demand products contributes less to the change in the LS; the coefficient that has the largest impact on the change in the LS is the coefficient on the ratio of fixed capital formation to total fixed capital formation for sector 27, construction2, which has a negative impact on the LS, and its large contribution is partly due to a large change in the coefficient itself.

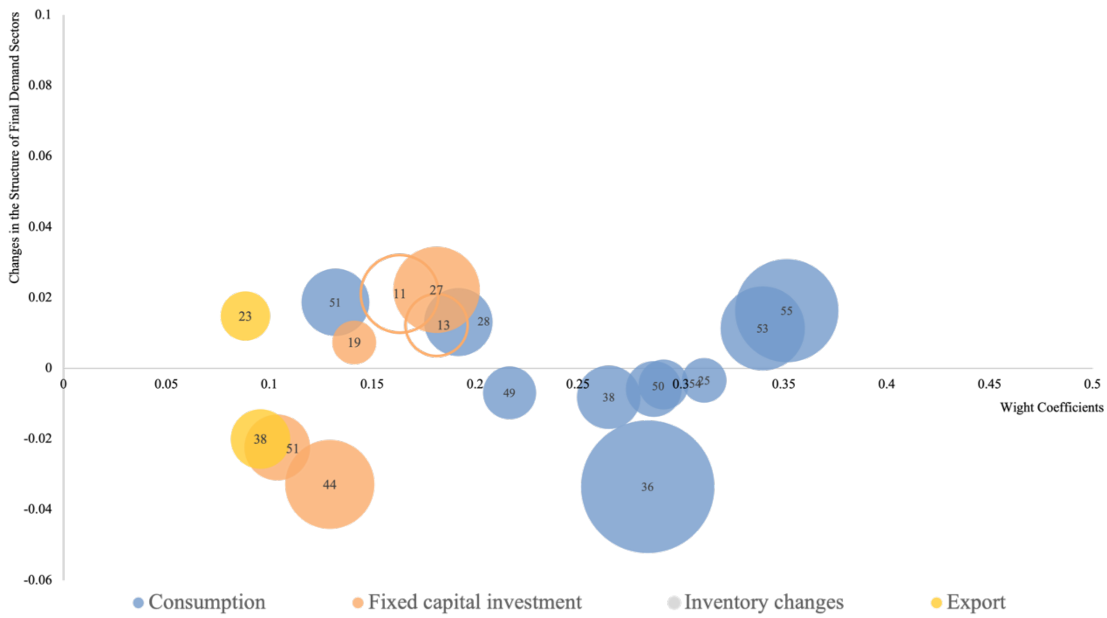

Fig. 10 Important coefficients in the changing composition of final demand, 2017-2020

5. Conclusions

Based on the input-output tables of the non-competitive digital economy in 2012, 2017, and 2020, the impact of the development of the digital economy on the evolution of theLS in China is found by using a structural decomposition model:

The development of the digital economy had a negative impact in 2012-2017 and a positive impact in 2017-2020. The increased interdependence between the digital economy and the traditional sector (the degree of digital-real integration) is critical to the shift from a negative to a positive impact of the digital economy on the share of labor compensation during the 2017-2020 period. The effect of the digital economy on the share is partially explained by the various digital economy sectoral correlation coefficients, and the research in this paper may underestimate the effect of the digital economy to some extent. For example, if firms do not choose to outsource the process of digitization but instead set up their departments to carry out the digital transformation, the development of digitization may not be reflected in an increase in the coefficient of input of the digital economy sectors, but rather in an increase in the coefficient of value added.

Between 2012 and 2020, the share of labor compensation in the traditional economy increased period by period. Interestingly, the development of the digital economy has played a dampening and then a boosting role, a trend similar to the change in the share of labor compensation in the country as a whole, which has contributed to the shift from negative to positive in the share of labor compensation in the traditional economy in specific periods. The main reason for this change is the increase in the share of value added to the digital economy sector in the aggregate. In addition, the increased integration of the digital economy with the traditional economy sectors has also been an essential factor in driving up the share of labor compensation in the conventional economy. Before 2017, the employee compensation factor was the dominant factor driving the increase in the share of labor compensation in the conventional economy. However, after 2017, reduced import dependence on intermediate goods dampened the momentum of further increases in the labor compensation share of the conventional economy. The increase in the value-added share of the digital economy sector became the main contributing factor to offset this negative impact. In addition, the adverse effects of structural characteristics in the final demand sector of the digital economy have increased, a phenomenon that stems mainly from the adjustment of weights.

To further analyze the causes of the contribution pattern, this article decomposes the contributions of various factors at the elemental level, revealing the uneven development of labor share growth among industries. The decline in the labor share of the digital manufacturing sector reflects a "substitution effect," while the increase in the labor share of the digital services sector reflects a "pull effect." From 2012 to 2020, the changes in important coefficients in the former stage had a much greater impact on the labor share than in the latter stage, which also explains the phenomenon of the slowing trend in the increase of the labor share in China. Although the role of the digital economy in the growth of the labor share is initially suppressive and then promotive, the number of digital economy-related industries making the main contribution has increased.

Based on the above findings, it is recommended that consideration be given to the development of incentive policies to promote digital-real integration. Encourage enterprises to carry out innovation and R&D in the digital economy. By providing tax incentives and financial support for R&D, enterprises should be prompted to increase their investment in digital transformation to raise the income level of workers in the digital economy industry. It also encourages the integration of the digital economy with traditional industries to balance the development of digitalization and traditional sectors. This will help the digital transformation of traditional industries while providing more digital jobs and contributing to higher labor remuneration.

Consideration should be given to implementing extensive digital skills training and education programs. Improve the digital literacy and skill level of the workforce, which will help workers better adapt to the development of the digital economy and increase their employment opportunities and employee compensation levels in digital industries. Provide more employment services and career planning support to help workers better adapt to the employment needs of the digital economy. This includes providing vocational training, guidance on career planning, and support to help workers adapt quickly to changes in the industry. To better protect the rights and interests of workers in the digital economy, labor market policies should be proactively adjusted, including the formulation of more flexible labor regulations, such as regulating the employment status, working hours, and compensation of platform workers. Improve social security benefits for freelancers and provide support for freelancers; establish flexible hiring mechanisms adapted to the digital economy to ensure that workers can receive better compensation and benefits in the digital economy; and improve the social security system, including raising the level of welfare such as occupational annuities and unemployment insurance, etc., to ensure that, while AI brings about social progress, workers will truly enjoy corresponding social security and welfare benefits.

Appendix

Table A.1 Sector classification of input-output table

Code	Type	Sector	Code	Type	Sector
01	Digital Product Manufacturing Sectors	Paper Printing and Educational, Sports, and Cultural Supplies 1	29	Traditional Sectors	Research and Experimental Development 2
02		Chemical Products 1	30		Culture, Sports and Entertainment 2
03		General Equipment 1	31		Agriculture, hunting, forestry, and fishing
04		Special Equipment 1	32		Coal
05		Electrical1 Machinery and Equipment 1	33		Petroleum & Natural Gas
06		Communications Equipment, Computers, and Other Electronic Equipment	34		Metal
07		Instruments and Apparatus 1	35		Non-Metal Mineral and Other Mining
08	Digital Product Services Sectors	Wholesale and Retail 1	36		Food, beverages, and tobacco
09		Leasing and Business Services 1	37		Textile Production
10		Residential Services 1	38		Leather, leather products, and footwear
11	Digital Technology Application Sectors	Information Transmission, Software and Information Technology Services	39		Wood and products of wood and cork
12		Comprehensive Technical Services 1	40		Petroleum, Coking and Nuclear Fuel Processing
13	Digital Factor-driven Sectors	Construction 1	41		Non-Metal Mineral Product
14		Finance 1	42		Metal Smelting & Pressing
15		Research and Experimental Development1	43		Fabricated Metal Product
16		Culture, Sports and Entertainment 1	44		Transportation Equipment
17	Traditional Sectors	Paper Printing and Educational, Sports, and Cultural Supplies 2	45		Other Manufacturing
18		Chemical Products 2	46		Electricity, Heat Production & Supply
19		General Equipment 2	47		Gas Production & Supply
20		Special Equipment 2	48		Water Production & Supply
21		Electrical1 Machinery and Equipment 2	49		Transport, Storage & Post
22		Instruments and Apparatus 2	50		Hotels and restaurants
23		Wholesale and Retail 2	51		Real estate services
24		Leasing and Business Services 2	52		Water Conservancy, Environment & Utility Management
25		Residential Services 2	53		Education
26		Comprehensive Technical Services 2	54		Health and social work
27		Construction 2	55		Public administration and defense; compulsory social security
28		Finance 2			

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